The Barra Integrated Model (BIM303)

Empirical Notes

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Contents

1 Executive Summary

This paper describes BIM303, a new version of the Barra Integrated Model (BIM).

This new version incorporates the latest Barra equity models, includes several new and updated Barra fixed income models, and completes the history of the private equity and private real estate components. Other local models that form the complete BIM are the same as those in BIM301, the previous integrated model. BIM303, like BIM301, comes in versions for multiple horizons: Short, Long, and Extra Long[1].

1.1 Practitioner Overview

The Barra Integrated Model (BIM) is a multi-asset-class risk model that couples breadth of coverage (global equities, global bonds, currencies, commodities, and hedge funds) with the depth of analysis provided by local models. Users need not choose between granularity of local model analysis, on the one hand, and the broad scope of global analysis, on the other. BIM can be used by institutional investors in their investment processes, from analyses of a single-market portfolio to a planwide international portfolio of equities, bonds, and alternatives.

BIM is a valuable addition to an investment management process for two simple reasons. First, one needs to understand risk in order to manage it, and risk factors provide a parsimonious way to visualize and forecast portfolio risk. Second, risk forecasts find their ultimate usefulness when combined with return forecasts; by definition in an optimal portfolio, the risk of each segment is aligned with the expected return. BIM is thus central to the process of risk budgeting.

BIM has four main features that make it superior to other factor-type risk models.

- It provides local detail, market by market, including both traded and private asset classes. Specifically, it provides **fundamental factor**[2] covariance forecasts over multiple horizons for assets in 90 equity markets, 60 bond markets, 161 currencies, 34 commodities, 31 private real estate markets, 9 hedge fund strategies, and global private equity and debt[3].
- It provides global aggregation of those markets for a multi-asset-class (MAC) portfolio.
- It can forecast risk over multiple horizons, and thus provides the right amount of responsiveness to recent events.
- It is robust: By modeling the structure underlying assets’ behavior, it can differentiate between noise and information.

[1] Models Direct BIM 303 includes Long and Short horizons only

[2] A fundamental factor risk model is one in which the factors are constructed using observable security characteristics, such as industry, market capitalization weights, valuation metrics for equities, and credit quality, duration, and industry for fixed income. Other types of factor models include macroeconomic models and statistical models. See Grinold (1994) for more information about factor risk models.

[3] Models Direct BIM 303 will not cover private real estate, hedge fund and global private equity asset classes. For a list of equity and fixed income models covered please refer to the BIMe 303 and BIMef 303 Datasheets

A new version of BIM – rather than an update – has been introduced for several reasons:

- The new integrated model's "global factor structure," which is the mechanism to simplify and provide robustness to cross-market factor covariances, has been redesigned to take advantage of Barra's new Global Equity Model (GEM3); the previous integrated model (BIM301) used the previous global model's (GEM2) factor structure.
- The new integrated model incorporates nine updated Barra country equity models, including the new Emerging Markets Model (EMM1) for frontier markets. Equity security coverage in BIM303 has increased by roughly 20%[4].
- The new integrated model incorporates two new Barra country bond models and three updated country models (all emerging markets).
- The new integrated model provides deeper history for a number of fixed income and alternatives models.

What parts of this note should I read?

- Part 2: Description of changes from BIM301 to BIM303.
- Part 3 and Appendix A: Description of empirical tests showing model performance.
- Part 4: Use cases for the integrated model in BarraOne.
- Appendix B: Detailed description of integrated model components and coverage.

1.2 Description of BIM Coverage and Scope[5]

The integrated model is delivered to clients in four ways: (a) as the risk model engine of BarraOne, a software platform/interface providing portfolio management, data management, automated input/output, and customized report creation; (b) via the BarraOne Developer's Toolkit (BDT) programmatic connection to BarraOne's servers, which enables clients to download risk forecasts directly into their own applications;(c) via Models Direct, which provides the covariance matrix (and other market and security data) that clients can integrate into their own software platforms; and (d) via Barra PortfolioManager, a cloud-based, interactive platform that enables clients to share strategies, analytics, and reports across their organizations.

- BIM natively covers over 104,000 global equity securities in 71 country models and 3 regional models.
- Global bond coverage includes over 500,000 sovereign and corporate bonds, 900,000 municipal bonds, and 2,200,000 structured products (MBS/ABS/CMO) through 52 sovereign bond models, 8 developed currency credit models, and 118 hard currency emerging market sovereign and corporate credit factors.

[4] Models Direct BIM 303 does not incorporate EMM1.

[5] See BIMe 303 Datasheet and BIMef 303 Datasheet for coverage details for Models Direct

- Over 290,000 mutual funds are covered via the Mutual Fund Model (MFM2).
- Alternatives coverage includes: 161 currencies; 34 commodities; nine (9) global hedge fund styles (via the Hedge Fund Model HFM2); 17 regional strategy factors for private equity and debt; 31 country private real estate markets (including 460 submarkets), and 10 markets with Equity Volatility Futures.
- Data on all factors and securities goes back to 1/1/2003 within the BarraOne platform, and back to 10/1/1997 in Models Direct.

1.3 The Innovation of the Integrated Model[6]

Risk models face four competing challenges: to be detailed, global, responsive, and robust. Detail requires that a model distinguish between every return driver 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 enables 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 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 original Barra Integrated Model (BIM), all four of these goals were addressed together for the first time. 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.

BIM303 continues to use the methodology introduced in version BIM301, which eliminates the need to choose between our best set of global factors and our best local models.[7] It incorporates the Barra Global Equity Model (GEM3)[8], and the new Barra Emerging Markets Model (EMM1).[9] It also comprises short-, long-, and extra-long horizon versions (BIM303S, BIM303L, BIM303XL), and it improves the relationships between local and global factors.

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6 Adapted from Shepard (2011)

7 See Shepard (2007)

8 See Menchero, et al. (2012)

9 See Mozorov, et al. (2014)

Together, the Barra Integrated Model:

- Achieves full accuracy and detail of local models within markets
- Offers a global structural model that aggregates intermarket risk
- Incorporates GEM3, our best set of global equity factors
- Provides statistical estimators to reduce errors and correct issues of asynchronous trading and serial correlation
- Avoids spurious correlations both within and between markets
- Captures local correlations when meaningful
- Consistently aggregates risk from portfolios to fund
- Intuitively decomposes risk into additive contributions

1.4 The Importance of Structure: An Experiment

The value of a structural factor model such as BIM is not the ability to predict returns (it cannot), much less predict changes in regimes. Its value is primarily in the ability to understand the drivers of asset returns and the relationships among them. In normal times, this understanding makes it possible not just to forecast risk, but to manage it. A factor model links risk to the portfolio characteristics about which investors make decisions.

A factor model can also play a role beyond normal times, when understanding the structure of the markets can help make sense of unprecedented events.

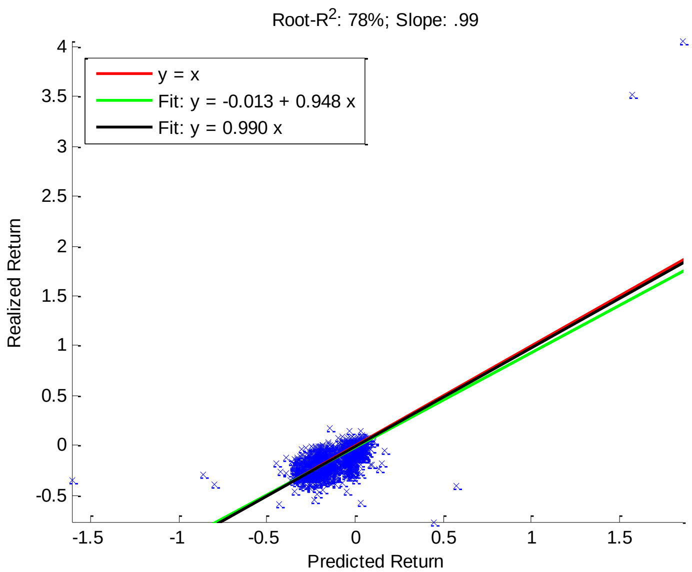
The global financial crisis of October 2008 was such an event. Few predicted such a shock to the markets (and the Barra Integrated Model was not among them). If one did see a crisis coming, could BIM, as of September 2008, predict anything about the upheaval that was to come? Is BIM accurate at propagating that shock to all other market variables, even in times of such market upheaval?

Consider the following experiment. In September 2008, the short-horizon BIM301S predicted the monthly volatility of US B Financial spreads to be about 2%; the actual spread movement in October 2008 of over 16% was an "8 standard deviation" event. Given[10] such an event, how well could BIM have predicted the behavior across the rest of the markets? In the hands of a prescient market participant expecting a financial crisis, could BIM say anything about what was to come? Or did the market dislocations of the crisis render BIM useless?

Figure 1 shows the result of this experiment. Given just one key return to define the scenario, the actual October 2008 returns of USB Financial spreads, BIM's forecasts are remarkably accurate for the behavior of all other factors. Returns of this magnitude had never occurred, but the structure within BIM was persistent, and its forecasts are 88% correlated with the crisis that unfolded the following month.

[10] Note that there was no "cherry picking" to choose this factor. In this experiment, the US Financials B factor was first and alone selected – using financial intuition and experience – to embody the shock of the GFC, and then propagated to all other factors.

Figure 1: A Simple Out-of-Sample Test of the Integrated Model. Predicted factor returns as of September 2008 are shown on the horizontal axis, conditioned on the actual returns of US B Financial Spreads. The actual October 2008 factor returns are shown on the vertical axis. The scatterplot shows how well the risk model predicted all factor returns based on the movement of a single factor. A perfect prediction of all factors would result in all return pairs falling on the red line (y=x). The correlation of actual to predicted return was 88%, meaning that the factor structure alone explained 0.88^2 = 78% of the variability in the actual returns.



1.5 Summary of the Model's Performance

The rest of this note is devoted to a more systematic test of the accuracy of BIM in providing useful, timely, accurate, and unbiased risk forecasts. To this end, we performed numerous tests of the new model, BIM303 (a) against actual results; (b) versus the old model, BIM301; and (c) to our global equity model, GEM3. These tests are described in section 3 and in Appendix A. A list of all the portfolios used in the tests (some 1552 in all) is given in Appendix C.

Tests of model performance include the following metrics. First is the "R^2" test, which shows for each portfolio the average (over all the securities in the portfolio) portion of security return explained by the model factors as a proportion of the variability of total security return. Second is the "Bias" test, which shows over a class of portfolios how close the model predicted volatility was to the actual volatility over a given period (usually the entire estimation period). Third, since an important use of a risk model is in predictions of one asset's sensitivity to movements in another reference asset, is the "beta" test. This test compares the model predicted betas to actual betas for a number of portfolios.

Results can be broadly summarized as follows: BIM303 performed as well as or better than BIM301 on the vast majority of these tests. Where comparisons with GEM3 are relevant, BIM outperformed GEM3 (a global model without local detail). Finally, for the majority of portfolios, BIM303 produced forecasts that were neither too low nor too high compared to the actual range of outcomes.

2 Changes: BIM303 versus BIM301

This section lists the differences between the latest and previous risk models. For readers not familiar with the structure of the integrated models, a complete list of model components can be found in Appendix B, and it should be reviewed before continuing with this section.

2.1 New and Revised Component Factor Models

2.1.1 Equity

BIM303 incorporates the following newly updated equity models:

GEM3: Global Equity Model. This model is also used extensively in the new mapping of local to global equity factors, described in the next section

EUE4: Europe

USE4: United States

JPE4: Japan

AUE4: Australia

CAE5: Canada

CNE5: China

KRE3: Korea

ZAE4: South Africa

EMM1: Emerging Equity Markets Model (new) provides coverage of "Frontier Markets" not covered in BIM301

In addition to newly estimated models, BIM303 provides native coverage of approximately 20% more equity issuers.

2.1.2 Fixed Income

The following new and updated fixed income models are part of BIM303L, for which the government curve and factors are now based on the government bond spot curve (rather than the swap curve), and for which the curve estimations now use the new parametric curve methodology[11]

CXF1: China Offshore [12]

NGF1: Nigeria

PHF4: Philippines [13]

THF4: Thailand

TWF3: Taiwan

BIM303 provides new coverage of the China Offshore and Nigerian bond markets.

2.2 New Data

2.2.1 Data Frequency and Covariance Estimation

As discussed in Appendix B4, BIM employs consistent covariance matrix parameters across local models, even though initial stand-alone versions of the local models used different parameters in each country. The following tables indicate the changes in the frequency of data used to estimate Correlation (Column 3) and Volatility (Column 4).Table 1 shows changes in existing BIM component models, and Table 2 shows the parameters used in new models included in BIM303.

[11] See Reference: Fox, J., et al. (2011) and DeMond, A., et al. (2015)

[12] new government bond factors

[13] generic swap spread factor replaced with new government bond factors

Table 1: Estimation of Correlations and Volatility: data frequency changes from BIM301 to BIM303

Component Model (both L and S versions)	ASSET_CLASS	Correlation freq BIM301 -> BIM303	Volatility freq BIM301 -> BIM303
COM2	Commodity	Weekly → Daily	Weekly → Daily
CUR2	Currency	Weekly → Daily	Weekly → Daily
EVX1	Equity Implied Volatility	Weekly → Daily	Weekly → Daily
AUF3	Fixed Income	Same (Weekly)	Weekly → Daily
CAF3	Fixed Income	Same (Weekly)	Weekly → Daily
DKF2	Fixed Income	Same (Weekly)	Weekly → Daily
EMF2	Fixed Income	Same (Weekly)	Weekly → Daily
EMF3	Fixed Income	Same (Weekly)	Weekly → Daily
EUF3	Fixed Income	Same (Weekly)	Weekly → Daily
GBF3	Fixed Income	Same (Weekly)	Weekly → Daily
JPF4	Fixed Income	Same (Weekly)	Weekly → Daily
MYF4	Fixed Income	Same (Weekly)	Weekly → Daily
NOF2	Fixed Income	Same (Weekly)	Weekly → Daily
NZF2	Fixed Income	Same (Weekly)	Weekly → Daily
PLF2	Fixed Income	Same (Weekly)	Weekly → Daily
SEF2	Fixed Income	Same (Weekly)	Weekly → Daily
USF4	Fixed Income	Same (Weekly)	Weekly → Daily
ZAF2	Fixed Income	Same (Weekly)	Weekly → Daily

Table 2: Estimation of Correlations and Volatility: data frequency used in BIM303 New Component Models

New Component Model (both L and S versions)	ASSET_CLASS	Correlation freq in BIM303	Volatility freq in BIM303
AUE4	Equity	New Model → Daily	New Model → Daily
CAE5	Equity	New Model → Daily	New Model → Daily
CNE5	Equity	New Model → Daily	New Model → Daily
EMM1	Equity	New Model → Daily	New Model → Daily
EUE4DUK	Equity	New Model → Daily	New Model → Daily
GEM3	Equity	New Model → Daily	New Model → Daily
JPE4	Equity	New Model → Daily	New Model → Daily
KRE3	Equity	New Model → Daily	New Model → Daily
USE4	Equity	New Model → Daily	New Model → Daily
ZAE4	Equity	New Model → Daily	New Model → Daily
CXF1	Fixed Income	New Model → Weekly	New Model → Weekly
NGF1	Fixed Income	New Model → Weekly	New Model → Weekly
PHF4	Fixed Income	New Model → Weekly	New Model → Weekly
THF4	Fixed Income	New Model → Weekly	New Model → Weekly
TWF3	Fixed Income	New Model → Weekly	New Model → Weekly

There is some variation of half-life parameters among the component models of the Barra Integrated Model, but the following parameters are typical:

MODEL	Volatility Half-Life	Correlation Half-Life
Short Horizon (S)	90 days	2 years
Long-Horizon (L)	1 year	3 years
Extra-long Horizon (XL)	8 years	8 years

2.2.2 Expanded History

BIM303 extends the available history in two important ways. The Private Equity (PEQ2) and Private Real Estate (PRE2) model history was previously available beginning from 2013. In BIM303, history for both of these models is extended back to 2003. This enables portfolio analysis, including stress tests, to be run on these additional historical periods. Secondly, the extra-long (XL) version of BIM303 is also available back to 2003 (previously 2013), enabling consistent risk analysis in all periods.

2.3 Global Factors

2.3.1 What are Global Factors?

The integrated model is built from roughly 150 distinct equity, bond, and alternative component models. Altogether, there are thousands of distinct factors. Correlations of factors within each local model are estimated without regard to other asset classes. When the models are combined, the local factors are completely retained, but there remains a serious question of how to estimate the millions of cross-model correlations. Aside from purely econometric issues, it is difficult to imagine that meaningful or robust relationships could be computed between, say, the Peru Value factor and the Malaysian Twist factor. The innovation of the Barra Integrated Model is the selection of a smaller number of global factors to simplify the relationships among disparate local factors. The choice of these global factors, and the separation of risk between exposure to a global factor and a residual exposure to a pure local factor, is what enables so many local factors to coexist and provide meaningful results both locally and as part of a global diversified portfolio.

Readers not familiar with this aspect of BIM will find a more complete explanation of global factors in Appendix D and Shepard (2011). A complete list of all global factors is found in Appendix B, part 3.

2.3.2 Equity

There are (coincidentally) 303 global factors in total. Of these, 111 are Equity factors. BIM303 inherits most global equity factors from GEM3 (as did BIM301 from GEM2), with additional factors to cover emerging and frontier markets not covered in GEM3 (additions and changes are noted in italics):

- 9 Regional Factors
  - World Market factor
  - Europe Market, Emerging Markets, and *Asia Pacific market factor*
  - *5 Emerging Markets regional factors for countries not in GEM3*
    - *Emerging Markets: Latin America, Asia, Europe, Africa, Middle East*
- 57 Country factors
  - All 23 Developed market country factors (all countries included in MSCI World Index)
  - All 21 Emerging market country factors (all countries included in MSCI Emerging Markets Index)
  - 13 Frontier market country factors (subset of countries included in MSCI Frontier Markets Index)
- *All 11 Equity Style factors from GEM3 (BIM301 had 8 Style factors from GEM2)*
- All 34 Equity Industry factors from GEM3

Table 3: Summary of BIM303 Global Equity Factors

Factor Group	BIM301 #	BIM303 #	Comments
Market	1	1	GEM2/GEM3 WORLD factor
Style	8	11	GEM2/GEM3 Style factors
Industries	34	34	GEM2/GEM3 Industry factor
Countries	57	57	All 46 ACWI countries + 15 Frontier Markets
Regions	2	8	Europe, Emerging Mkts, 5 new EM regions, Asia-Pacific
Currencies	55	-	Separate global currency block in 303
Total:	157	111	46 fewer factors in global block

2.3.3 Fixed Income

Fixed Income global factors number 100 in total:

- Term Structure (75 total)
  - Shift: 40 (3 new: CX, MX, NG)
  - Twist: 13 (same as BIM301)
  - Swap: 14 shift and 1 twist (3 new: HK, MX, SE)
  - IPB: 7 (same as BIM301)
- Spread Factors (25 total)
  - 16 country specific
    - 9 DM
    - 7 EM (less one: Mexico)
  - 6 Regional
    - Europe
    - 5 EM regions (new: Africa, Asia, E. Europe, Latin Am., Mid-East)
    - Less old EM global factor (from BIM301)
  - 3 credit sectors (same as BIM301)

There is a small change in methodology in the combination of individual local fixed income factors into global factors. For example, the Global Implied Volatility Factor is constructed from eight local implied volatility factors (AU, CA, CH, EU, GB, JP, SE, US). BIM301 used inverse absolute deviation weighted averages to combine factors; this method weights each factor inversely to the typical scale of its return. By contrast, BIM303 uses the market capitalization weight of the respective country in the bond universe to weight each factor. Capitalization weights are more intuitive and enable important factors to contribute more to a global factor. This new methodology was used in the construction of the following factors:

- Global Average Twist
- Global Average Swap Twist
- Global Average Covered Bond
- Global Average Financial Credit
- Global Implied Volatility

Table 4: Summary of BIM303 Bond Factors and BIM303 Bond Global Factors

Bond Sector	Total	Comments	Global
Government	157	57 shift, 53 twist, 47 butterfly	52
Swap	69	29 shift, 22 twist, 18 butterfly	15
Credit (ex MBS, Muni)	282	84 US, 65 EU, 35 UK, 31 CA, 24 CH, 21 JP, 16 AU	11
Muni	17	US STB, US, AU, CA, CH, EU, JP ratings	1
MBS	10	5 Spread, 5 Refinance	1
IPB	23	13 shift, 7 twist, 3 butterfly	7
EM	151	Dollar denominated sovereign spreads, sector ratings	12
Implied Vol	8	EU, GB, JP, US, AU, CA, CH, SE	1
Total:	717		100

2.3.4 Other Asset Classes

The following factors round out the set of global factors.

- 5 Commodity factors (as in BIM301)
- 10 Equity Implied Volatility factors, including 8 new markets:
  - Australia, Spain, Germany, Great Britain, Hong Kong, Japan, Korea, Switzerland
- 77 Currency factors
  - Same countries as in BIM301, including 22 new Frontier Market factors:
  - Bangladesh, Bulgaria, Bosnia & Herzegovina, Cyprus, Estonia, Croatia, Iceland, Jamaica, Kazakhstan, Kenya, Lebanon, Sri Lanka, Lithuania, Latvia, Mauritius, Nigeria, Romania, Serbia, Slovenia, Tunisia, Ukraine, Vietnam

Note that some classes of local factors are not mapped directly to any global factors. Private Real Estate is integrated via local factors to ensure accurate relationships with listed real estate in each country. The Pure Private Equity factors and Pure Hedge Fund Strategy factors are constructed as residuals to public factors. Although these residuals may be correlated with each other, the correlations with public factors are already absorbed by regression betas.

2.3.5 Core vs. Global Factors

As in earlier versions of BIM, a subset of Global factors, called Core factors, is used to ensure robustness in correlation forecasts across asset classes. BIM303 employs a total of 303 global factors 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.

Table 5: Summary of Core and Global Factors in BIM301 and BIM303

ASSET BLOCK	Number of Core Factors		Number of Global Factors	
	BIM 301	BIM 303	BIM 301	BIM 303
Equity	47	66	101	111
Fixed Income	52	54	90	100
Currency	34	34	55	77
Commodity	5	5	5	5
Equity Implied Vol.	0	0	2	10
Total	138	159	253	303

For core equity factors, BIM303 takes the global country factors of all 45 countries in MSCI's All Country World Index (ACWI), a subset of nine countries in the MSCI Frontier Market Index, eight regional factors, and the World factor, for a total of 66 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 (as in BIM301).

BIM303 retains a similar set of core fixed income factors as BIM301, including 39 Shift and 15 credit spread factors, for 54 in total. Three shift factors are new: China, Mexico, and Nigeria, and one credit factor was dropped (Mexico hard currency spread)

BIM303 uses as core factors the currency factors for the 14 Developed and 20 Emerging Markets for which there are separate country fixed income models, for a total of 34 core currency factors, the same as BIM301. These factors are important for events that tend to drive the equity, bonds, and currency of a country to move in unison.

BIM303 retains all 5 of BIM301's global commodity factors as core factors. These core factors capture significant correlations 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 BIM303 (as in BIM301). For hedge funds and private equity, BIM303'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.

A table of all global and core factors is found in Appendix B3. For a more complete discussion of Core Factors, see Appendix D and Shepard (2011).

3 Empirical Results of Model Performance

3.1 Process of Model Validation

The investment industry, like the rest of the financial sector, relies on models to simplify a complex and noisy world by focusing on key factors and relationships that explain the common behavior among securities. Risk models such as BIM303 are used by practitioners to understand the drivers of performance in their portfolios and to forecast the likely sources of uncertainty in future performance. Whether a model is old or new, it is important periodically to evaluate the model's ability to do these two tasks. There are other features that may affect a model's quality and usefulness, but we focus here on the two uses mentioned above.

We first test whether the model explains a significant portion of the variation in returns over past periods. We look at both the ability to capture performance variation across securities (called cross-sectional) and the ability to capture the variation in diversified portfolios of securities over time. We expect that any model would be better at the latter task as the importance of the common factors increases and the idiosyncratic variation is diversified away. To measure both types of variation, we use the metric called "R-squared", or R^2, which is the fraction of variance captured in a regression across securities or across time. The closer R^2 is to the value 1.0, the higher the explanatory power of the model.

Second, we test how well the model's predictions of volatility (and indirectly, of correlations) accord with the range of realized outcomes in periods after the forecast. We do not expect the model's predictions to exactly agree with the subsequent realized volatility, given sampling error and ever changing markets, but we do expect that it will provide forecasts that are not systematically biased (neither too high nor too low). The metric we use is called the Bias statistic, and an accurate model should produce bias statistics close to 1.0.

We report, in the figures below and the tables in Appendix A, a number of tests of each type. There are several dimensions across which models are tested:

- Statistics: These refer to the two practitioner use cases above – explaining the past and predicting the future.
- Portfolios: We group portfolios as Equity (indexes and portfolios constructed using model factors), Fixed income (government, credit, and diversified), and Multi-Asset Class. Details are given in the sections below.
- Model Horizon: As explained in Appendix B.5, the integrated model comes in several variants for different horizons. The Short ("S") model has a horizon of one month; the Long ("L") model has a six to twelve month horizon; and the Extra Long ("XL") model has a horizon of eight years or more. In most instances, we show results for five models: BIM301S, BIM303S, BIM301L, BIM303L, and BIM303XL. The 301XL model was introduced in 2013 and does not have sufficient history to evaluate.
- Total vs Active Risk: Where applicable, we show the active (benchmark-relative) risk as well as the total (absolute) risk.

3.2 Tests and Statistics

Results are shown in the form of "Box and Whisker" plots. Each plot shows the statistics for the models tested, identified on the horizontal axis. The observations, either R^2 statistics or Bias statistics, are indicated along the vertical scale. The rectangular "box" encompasses the middle 50% of the distribution, between the 25th and 75th percentiles. The horizontal line through the box indicates the median. The vertical lines ("whiskers") extending above and below the box indicate the upper and lower quartiles plus or minus 1.5 times the interquartile range (IQR), respectively. For a normal distribution, the whiskers would include plus or minus 2.7 standard deviations, or more than 99% of the data. Individual observations outside this range are indicated by dots above and below the whiskers.

For R^2, the maximum value is 1.0. For the Bias statistic, the ideal value is 1.0, with statistics larger than 1 indicating a tendency to under forecast risk, and vice versa. Hence, a good result occurs when the bulk of either distribution is located close to 1.0.

A complete list of all portfolios tested is found in Appendix C.

3.2.1 Capturing In-Sample Systematic Sources of Return Variation

3.2.1.1 The R-Squared Test

This statistic measures the extent to which the factor model captures the in-sample variability in realized returns. The maximum score is 1.0; that is, the model explains 100% of the variation. The proportion of variability not explained by the model is then $1 – R^2$. R^2 depends only on the model factor structure, not on the model horizon, thus comparisons are made only between BIM301 and BIM303.

The statistic is computed in two ways. First we look at the ability of the model to capture systematic factors for each security, and then we average across all securities in the market ("cross sectional"). Second, we look at the ability of the model to capture systematic factors for each market, which itself a weighted average of securities ("portfolio").

3.2.1.2 Portfolios Tested (individual model regressions) and Summary Results

Cross Sectional (Security level) R-Squared:

- Equity: seven (7) single country equity models + the Europe model
- Government Bonds: 41 sovereign yield curve models
- Credit: eight (8) developed markets, sector by ratings factors for the following currencies
  - AUD, CAD, EUR, JPY, CHF, SEK, GBP, USD / Total return and credit spread return

Portfolio level R-Squared:

- EQUITY: 54 MSCI Country Indexes / BONDS: 52 Sovereign and Credit Indexes[14]

[14] Unless otherwise indicated, all fixed income indexes are source (or derived from) BofA Merrill Lynch Global research, used with permission.

Figure 2: Equity Models Cross Sectional R^2. This figure shows the distributions of factor regression R^2 values over the model history. The left panel ("daily") includes the country models for Australia, Canada, China, Japan, Korea, South Africa. Statistics were calculated for BIM301 and BIM303 using daily observations. BIM303 provides a slight improvement in explanatory power. The right panel ("mixed") compares the two models for Europe and the United States. Here, the data is not strictly comparable, in that BIM301 statistics were generated using regressions on monthly returns, while BIM303 statistics were generated with daily returns. We see an apparent advantage to the older model, as monthly data is less noisy. However, the BIM303 statistics in the right panel are consistent with those in the left panel.

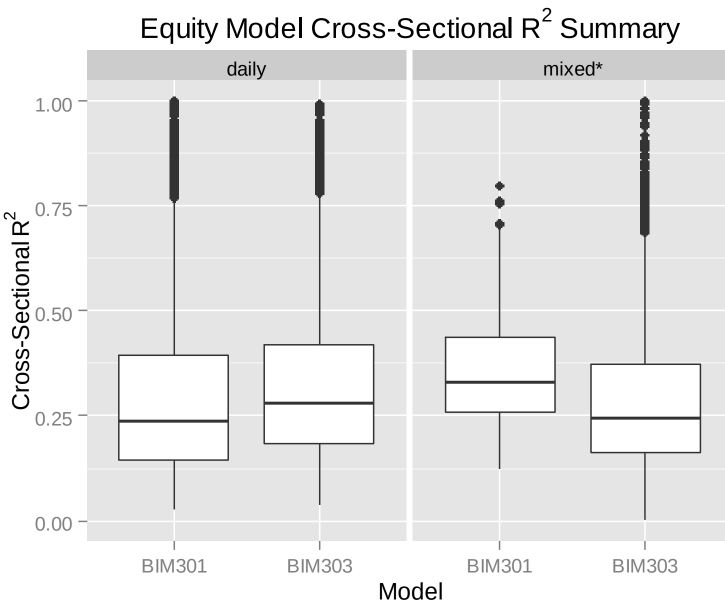


Figure 3: Fixed Income Models Cross Sectional R^2. This figure shows the distribution of average cross-section R^2 values across MSCI's fixed income models. Each observation is the average R^2 of the estimation universe over the period of March 2006 to March 2015. The top left panel ("gov") includes the 50 country bond models for which government yield curves are estimated from bonds. Statistics were calculated for BIM301 using weekly data and BIM303 using daily data. Because sovereign bond returns are well explained by a small number of factors, the cross-sectional R-squared is very high. The top right panel ("all credit") evaluates the eight developed market credit models. The bottom left and right panels segregate credit into Investment Grade ("ig") and High Yield ("hy"). The lower explanatory power in credit is consistent with the more idiosyncratic nature of these assets, most noticeable at the equity-like end of the spectrum, in high-yield. The higher explanatory power in BIM303 may be attributed to the enhancements in the credit model factor estimation.

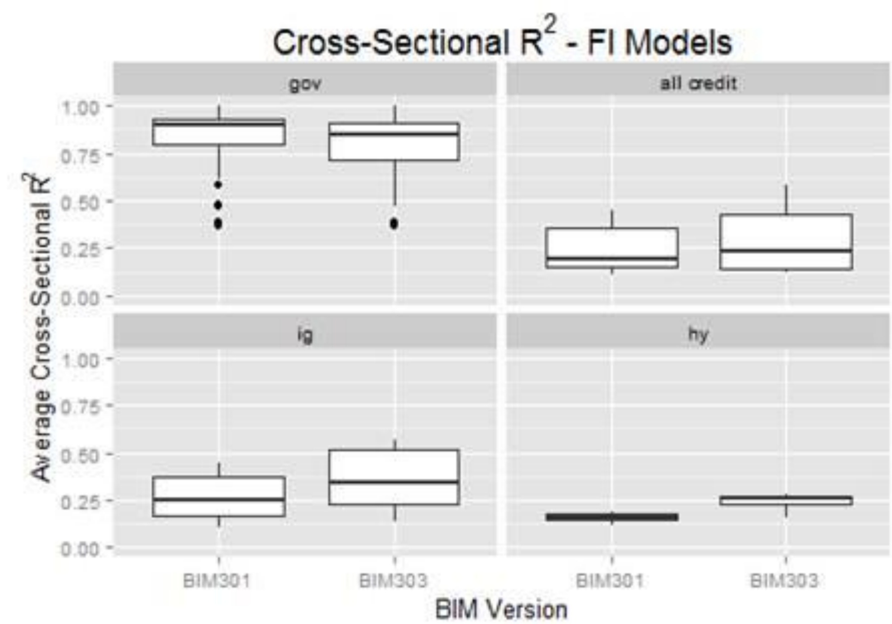
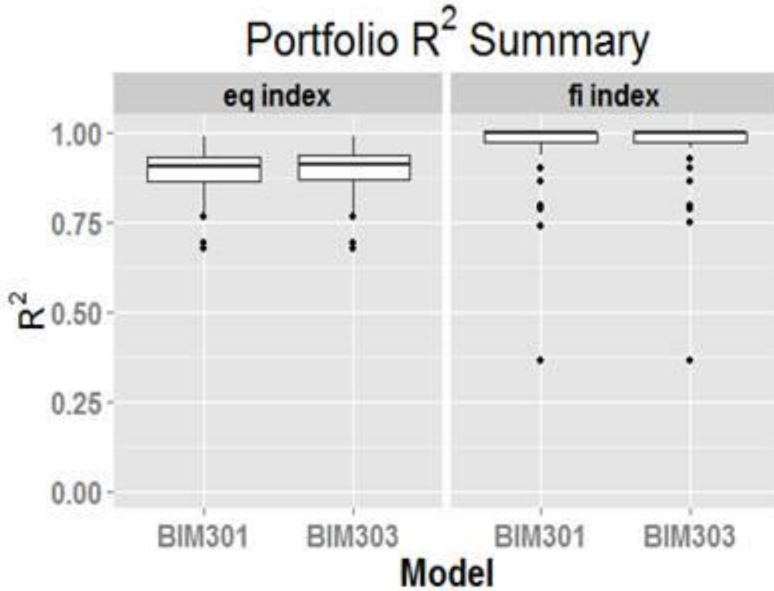


Figure 4: Equity Country Index and Fixed Income Sovereign and Credit Index Portfolio R-squared. This figure shows the distributions of R-squared values for the new equity models at the portfolio level. Each observation is a monthly average R-squared for all securities in each index. Equity indexes are shown in the left panel, and fixed income indexes are shown in the right. Again, BIM303 provides a slight improvement in explanatory power for both asset classes. Note that these values are much higher than the R-squared values in the cross-sectional regressions among assets, because the idiosyncratic risk is largely diversified away in a diversified portfolio, leaving more common factor sources of risk. (Unless otherwise indicated, all fixed income indexes are source BofA Merrill Lynch Global research, used with permission.)



3.2.2 Forecasting Volatility over a Given Horizon

3.2.2.1 The Bias Statistic Test

Given a model that forecasts (security/portfolio) volatility, we want to test how well the forecasts fit the subsequent data.

The bias statistic is a useful measure of the accuracy of a risk model, particularly the existence of systematic inaccuracies; for example, missing factors, inaccurate exposures, 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. However, even a perfect risk forecast would not lead to a bias statistic of exactly 1 due to sampling error in the realized volatility.

A detailed discussion of bias statistic can be found in the appendix. For all the following bias statistic tests, we calculate the statistic using calendar year data.

3.2.2.2 Portfolios Tested and Summary Results

EQUITY:

- Global Portfolios based on GEM3 factors
  - 77 Equity Country *factor portfolios* based on GEM3 Countries (23 DM, 22 EM, 32 FM[15])
  - 34 Equity Industry *factor portfolios* based on GEM3 Industries
  - 22 Equity Style *factor portfolios* (each portfolio contains the securities with the top 20% or bottom 20% of exposures to each of 11 equity styles)
- Concentrated Equity *factor* portfolios: each combination below, provided there are more than 15 assets meeting the criteria (a total of 831 eligible portfolios)
  - GEM3 country x industry (161 portfolios)
  - GEM3 country x top 20% style (332 portfolios) / bottom 20% style (338 portfolios)
- Country Index Portfolios
  - 54 MSCI single country *equity indexes* (23 DM, 22 EM, 9 FM)
  - MSCI All Country World Index (ACWI)

In Figure 5 below, we see the bias statistics for the six groups of equity portfolios listed above. The first row of blocks shows statistics for total risk forecasts; the second shows statistics for active risk, where the common benchmark used is the MSCI ACWI; and the third row shows statistics for active risk (concentrated portfolios only), where each country portfolio uses the MSCI equity index for that country. The following observations apply to the forecasts:

- In virtually all cases, the forecasts for BIM303 are as good as, or marginally better than, the forecasts for BIM301.
- The distribution of statistics for the Short models (both BIM301 and BIM303) is centered closer to 1.0 than for the corresponding Long models (both BIM301 and BIM303). This indicates that it is easier to construct an unbiased forecast at a shorter horizon. The world at time of forecast is more similar to the forecast period if the latter period is shorter.
- The forecasts for the Extra-long model suffer from an overforecast bias at this return horizon, or the largest dispersion, or both. (There was one exception, for Active risk for the “country x style” portfolios)
- There are very few extreme cases of overforecasting risk, but many 12-month periods in which risk forecasts were lower than the realized volatility (the presence of individual observations above the upper “whisker”). The great majority of these occurred during the global financial crisis and the unanticipated spike in volatility.

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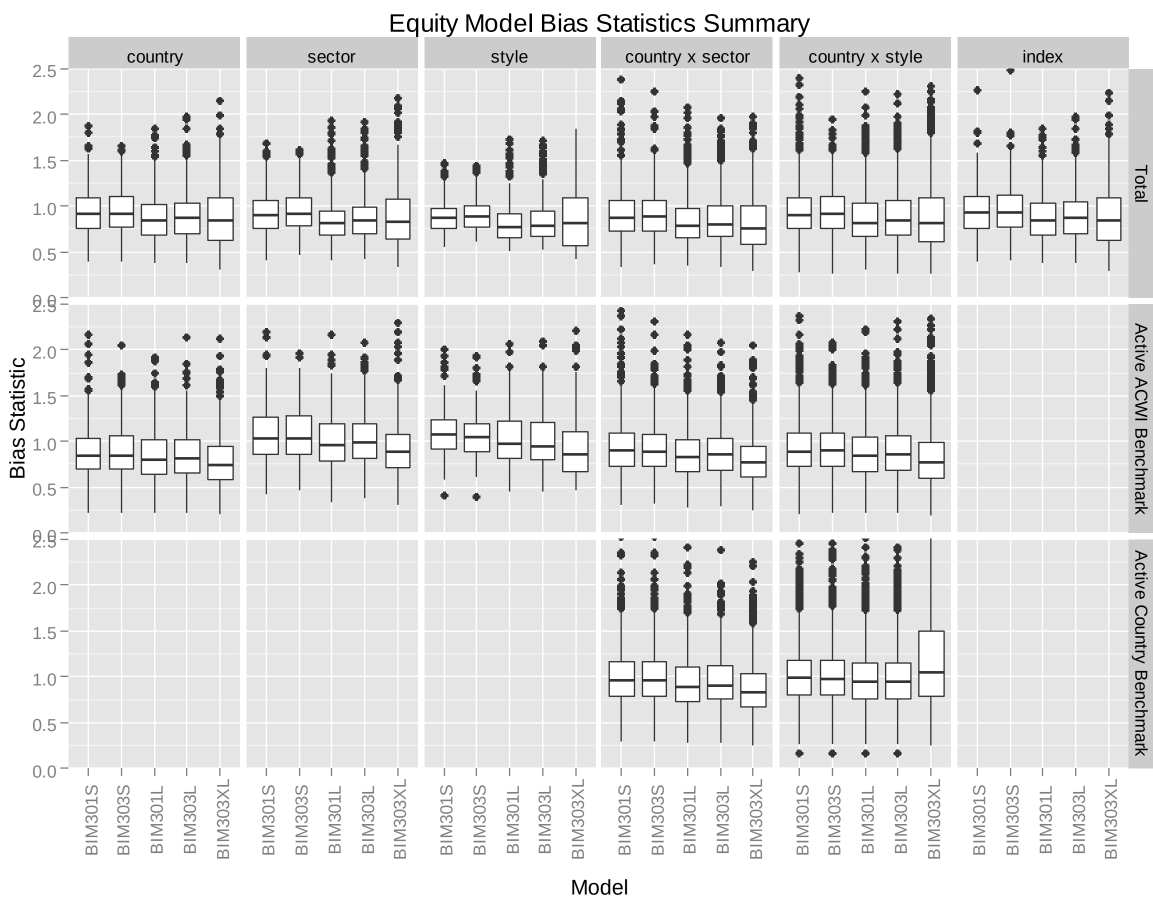
[15] DM = “Developed Markets,” EM = “Emerging Markets,” FM = “Frontier Markets” using the classification of the MSCI Global Equity Indexes.

- In spite of this longer under forecasting "tail," forecasts for the middle 50% of the years were biased to the upside (indicated by bias statistics of less than one). That is, there is a tendency of all versions to slightly over forecast risk relative to the realized volatility. This can be understood as due to the inclusion of the possibility of very large tail events that *could* recur, but did not in these years.

Figure 5: Equity Factor Portfolios and Index Portfolios Bias Statistics. Bias statistics in the form of "Box and Whisker plots" are shown for the six groups of equity portfolios listed above (each column shows a separate group of portfolios). Each observation is an annual bias statistic for a portfolio in a calendar year from 2006-2014. The first row of blocks shows statistics for total risk forecasts; the second, for active risk, where the common benchmark used is the MSCI ACWI; and the third row shows statistics for active risk (concentrated portfolios only) in which each country portfolio uses the MSCI equity index for that country. Within each block we see the distribution of bias statistics for each model tested: BIM301 Short and Long, BIM303 Short and Long, and BIM303 Extra Long.



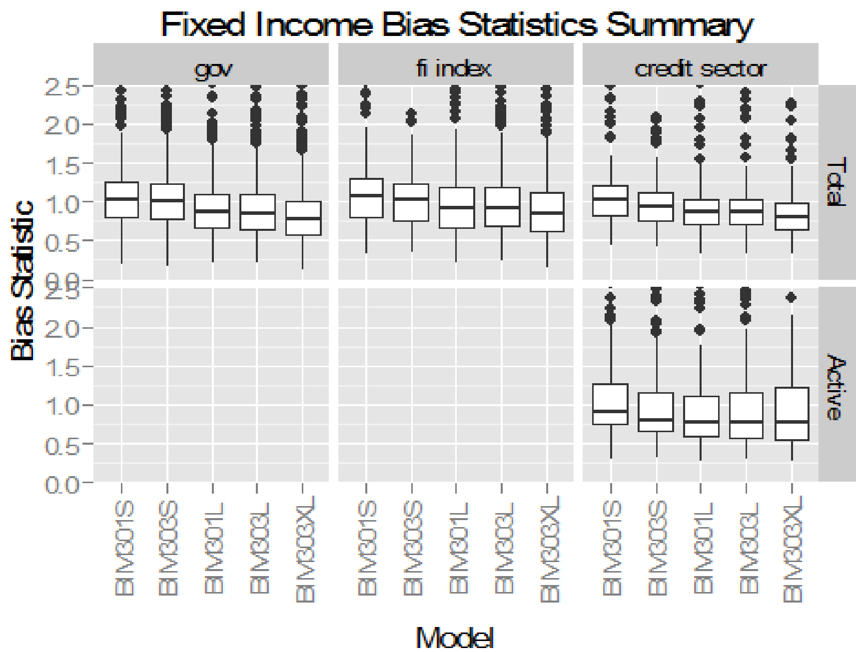
BONDS:

- Concentrated portfolios of government bonds of similar duration
  - 5 Duration portfolios for each of the 50 government bond markets tested in section 3.2.1 for the following maturity ranges: 1-3 years / 3-5 years / 5-7 years / 7-10 years / 10+ years, provided that there are bonds in the category
- 52 Diversified FI Indexes (unless otherwise indicated, all fixed income indexes are source BofA Merrill Lynch Global Research, used with permission)
  - Government Bonds: 34 country government bond indexes (22 DM, 10 EM, 2 Global)
  - Credit Markets: US (7), UK (1), Euro (6), Global (4) credit sector indexes
- 123 Sector x Rating factor portfolios for each of the eight (8) hard currencies tested in section 3.2.1
  - AUD, CAD, EUR, JPY, CHF, SEK, GBP, USD
  - For the benchmarks used to compute active risk, see Gold, et al. (2011), Table 12. Active portfolios are duration-matched to their benchmark so that the net interest rate duration of the portfolio is zero. https://support.msci.com/docs/DOC-3631.

In Figure 6 below, we see the bias statistics for the three groups of bond portfolios listed above. The first row of blocks shows statistics for total risk forecasts; the second, active risk, where the benchmarks used are customized to the currency and sector, as shown in detail in tables beginning with Table 17 in Appendix A. The following observations apply to the forecasts:

- BIM303 performed on par with BIM301, except for the credit sector, short horizon model, where it underperformed marginally.
- Similar to equity, all models showed the same pattern of an extreme “tail” during 2008-2009.
- The Short model performed better than the Long and Extra Long models
- The medians of the distributions were centered closer to 1.0, indicating unbiased forecasts.

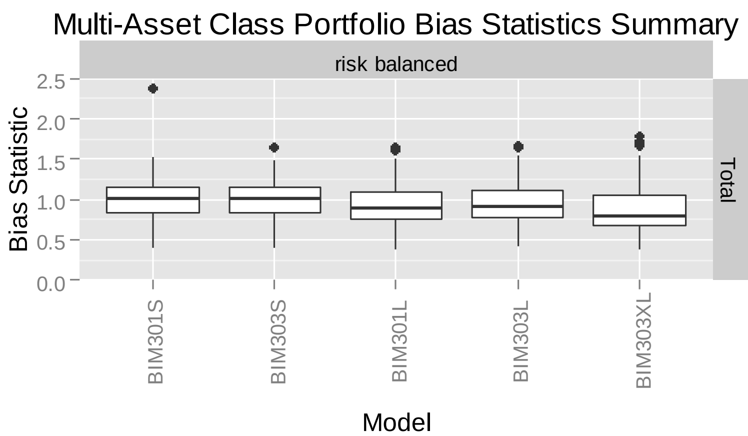
Figure 6: Fixed Income Portfolio Bias Statistics. Bias statistics, in the form of "Box and Whisker plots," are shown for the three groups of fixed income portfolios listed above (each column show a separate group of portfolios). The first row of blocks shows statistics for total risk forecasts; the second, for active risk, where the individual benchmarks used depend on the currency and sector (e.g., high yield sector portfolios are compared to a high yield market benchmark). Within each block, we see the distribution of bias statistics for each model tested: BIM301 Short and Long, BIM303 Short and Long, and BIM303 Extra Long.



MULTI-ASSET CLASS:

- 41 "risk balanced" portfolios constructed so approximately 50% of the contribution to total risk is attributed to equities and 50% to bonds
- For each of these "risk balanced" portfolios, we choose stocks from the MSCI country equity index and bonds from the country's aggregate bond portfolio. We adopt a 20/80 weighting with bond assets being the majority asset class. So, in Japan for example, we use the securities in the MSCI Japan IMI Index (for equity), and we use all the bonds in the Barra Japan bond estimation universe (for bonds). We then change the weights so that equity comprises 20% of the capital.

Figure 7: Risk-Balanced Portfolios Bias Statistics. These portfolios were constructed to test the model's ability to forecast risk when equity and fixed income contribute roughly the same to total volatility. Volatility balancing provides better tests of the model's cross-asset-class predictions than testing more traditional "balanced" portfolios, for which risk tends to be dominated by equity. Since we have shown separate tests of risk forecasts for equity and bonds, this is primarily a test of the correlation between these key drivers of most institutional portfolios. Overall, BIM303 performs slightly better than BIM301. As above, BIM303XL is slightly biased toward over forecasting risk.

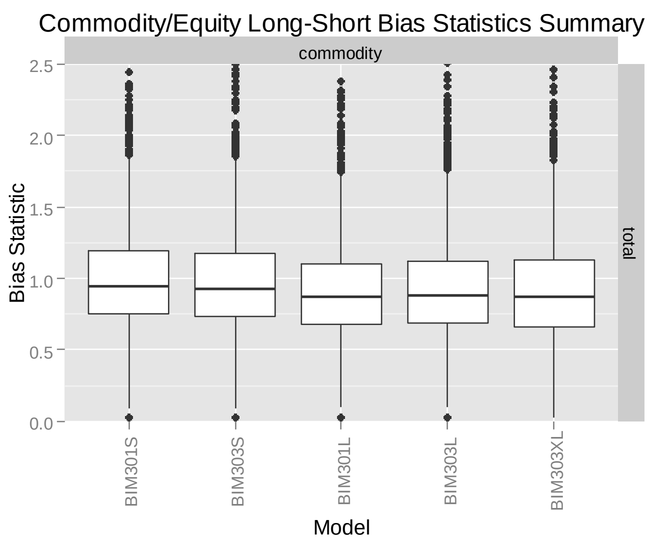


COMMODITIES:

34 commodity-equity portfolios constructed by going long each of 34 commodities and short one of six equity portfolios[16]

[16] These are: MSCI ACWI Index, Australia Equity Index, Airlines sector, Diversified Financials sector, Gold and Precious Metals sector, and the Oil and Gas Exploration and Production sector.

Figure 8: Commodity Portfolios Bias Statistics. This figure summarizes the bias statistics for the 204 commodity portfolios formed by going long each of 34 commodities and short one of six equity portfolios that might be used for hedging purposes. We find the bias statistics generally closer to 1.0, with lower dispersion, than was seen in the single asset class portfolios.



3.2.3 Estimating the Sensitivities of One Market to Another

3.2.3.1 Market Beta

Often an investor wants to have a summary statistic of a portfolio's sensitivity to some reference portfolio, whether a policy or client benchmark, a major market, or a hedgeable instrument. This sensitivity represents the typical return of the first portfolio conditioned on a unit return in the reference portfolio. A beta of 0.7 means that for every 10% return on the reference portfolio, the first portfolio would be expected to have a return of 7%. For historical reasons, this quantity is called beta. The prediction of this exposure is an important output of the risk model, precisely because it gives a shorthand method to gauge risk and design hedges for various positions.

3.2.3.2 Asset Pairs Tested and Summary Results

- Sensitivity of country equity to global equity
  - 54 MSCI Country Equity Indexes to MSCI ACWI Index
- Sensitivity of country equity to same country sovereign bonds
  - 41 MSCI Country Equity Indexes to corresponding Government Bond Market Shift Factor

- Sensitivity of 14 selected Cross-Asset-Class pairs
  - Emerging Markets (EM) Equity – Developed Markets (DM) Equity
  - EM Equity – Copper
  - EM Equity – Crude Oil
  - EM Sovereign Debt – DM Sovereign Debt
  - Europe High Yield to Europe Equity
  - Non-US DM Equity – Copper
  - Non-US DM Equity – Crude Oil
  - US Equity to Copper
  - US Equity to Oil
  - US HY to US Equity
  - US IG Credit to US Equity
  - US IG Credit to US Treasury
  - US ILB to US Equity
  - US ILB to US Treasury

To test the accuracy of beta forecasts, we can draw on the interpretation of beta as the slope coefficient of a given time series against another. For example, if a portfolio's beta is 2, then the portfolio returns plotted versus the market returns would cluster around a line with a slope of 2. Depending on the correlation of the portfolios, these plots may or may not cluster tightly: Perfect correlation would lead all points to fall exactly on the line, while low correlation would introduce a "buckshot" scatter around the line.

The slope interpretation is complicated slightly by the fact that betas change over time: There is no single slope of the line. To account for such time dependence, we can instead plot each portfolio return $r_{i,t}$ against the beta-scaled market returns $\beta_{i,t} \times r_{m,t}$, and now we expect the points to cluster around a line with slope 1 (at 45-degrees to the axes).

Motivated by these relationships, we can test beta predictions by plotting portfolio returns $r_{i,t}$ against market returns scaled by the forecast betas $\hat{\beta}_{i,\boldsymbol{t-1}}$. Accurate beta forecasts lead to plots with a slope of 1, while inaccuracies tilt the scatterplots away from the 45° line. (A "beta bias statistic" can be defined simply as the slope of the best fit line, and interpreted exactly like more traditional volatility bias statistics.)

Figure 9 shows such out-of-sample tests of the model's predicted equity betas. (The predicted betas themselves are in Appendix A3.) Each of the pictures shows an MSCI Country Equity Index,[17] relative to the global equity index, the MSCI ACWI. The dots are monthly return observations from 2006 through 2014, along with the line of best fit (solid blue line) and target 45 degree[18] line y=x.

Some countries, such as the Netherlands (NLD) and the United States (USA), are highly correlated with global equity, leading to nearly straight lines. Other markets, such as Brazil (BRA) and Turkey (TUR), are more idiosyncratic and cluster more loosely. A range in volatility is also apparent in the spread of returns, from low volatility Japan (JPN) to high volatility Greece (GRC). But these are all aspects of the markets themselves, not of the beta forecasts.

The accuracy of the beta forecasts is reflected in the slope of the lines of best fit: Across the wide range of correlations and volatility levels, the best fit lines tend to be well aligned with the 45-degree targets.

[17] See the three-letter country code in each title bar.

[18] Note: In a scatterplot where the X and Y axes have the same scale, the line y=x will be at a 45 degrees. If the scales are not the same, the same line will have a different slope.

Figure 9: Tests of beta forecasts of Equity Country Markets to the Global Index. In most cases, the line of best fit is closely aligned to the line of slope = 1.0, indicating the accuracy the accuracy of the beta forecasts. Inaccurate beta forecasts would be reflected in misalignment between the best-fit lines and the slope=1 line. The tightness of the fit indicates the intrinsic correlation of the country with the World, and it is not an indicator of forecast accuracy.

Figure 10: Tests of forecast sensitivity of Equity to Bond Markets in the same country. In most cases, the line of best fit is closely aligned to the line of slope = 1.0, indicating that the time-varying beta estimate captures much of the local relationship of stocks and bonds. There is, however, more dispersion around the line than in the case of equity (above), a reflection of the low equity-bond correlations.

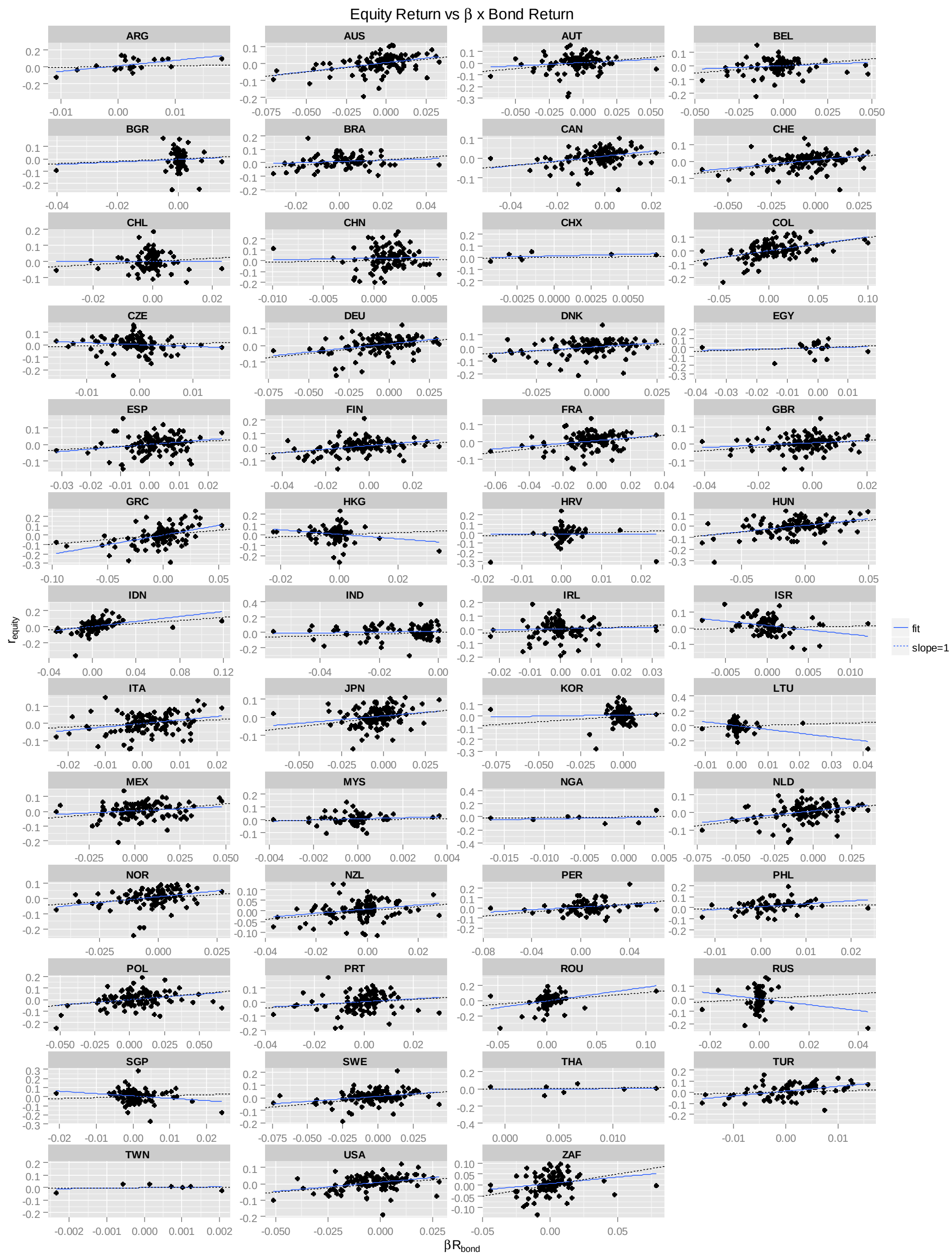
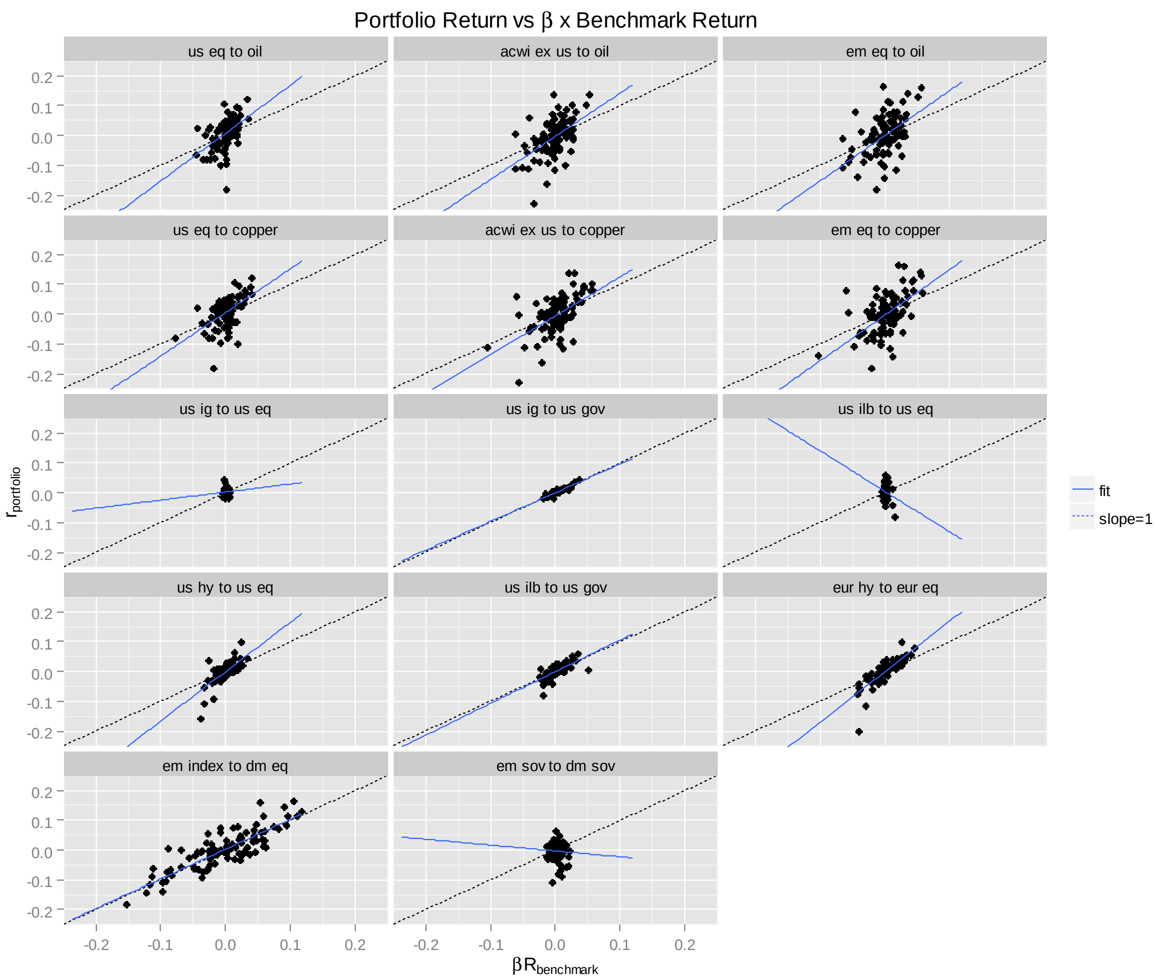


Figure 11: Tests of forecast sensitivity of selected cross-asset-class relationships. The beta forecasts are generally more accurate (as indicated by the alignment of the fit and slope=1 lines) when the assets are more closely related (as indicated by less dispersion, such as US IF Credit to US Treasury). In cases where the relationship is very weak (Emerging Market Sovereign to Developed Markets or Sovereign or US ILB to US Equity), almost any line can fit the cloud of points. The high-yield equity relationships are notable for being very good fits most of the time, except for underforecasting the relationship during the crisis, when correlations rose significantly.



3.2.4 Model Responsiveness Comparison

Unlike the statistical tests summarized above, we now turn to an example of greater economic than statistical significance. Figure 12 depicts the actual return of the MSCI AWCI global equity index (blue crosses) over the 2006-2015 period. The three lines show the volatility forecasts (one standard deviation) of this index using the three different models: BIM303S, BIM303L, and BIM303XL. As described in Appendix B.5., the forecast horizons of the models are one month, 6-12 months, and eight years, respectively. The return for each month lines up with the forecast as of the month before, so this chart shows out-of-sample forecasts.

Contrasting the shortest and longest horizon, we see that the “S” model more quickly adapts to large returns; by December 2009 the model’s forecast captured the actual (negative) market return. The XL model tends to over forecast when volatility is low, and under forecast when it is high. In periods of moderate volatility (2012-2014), all models do fairly well.

Figure 12: Risk Forecasts, Realized Return, and Responsiveness. The actual returns of the MSCI AWCI global equity index (blue crosses) are shown over the 2006-2015 period. The three lines show the volatility forecasts (± one standard deviation) of this index using the three different models: BIM303S, BIM303L, and BIM303XL.

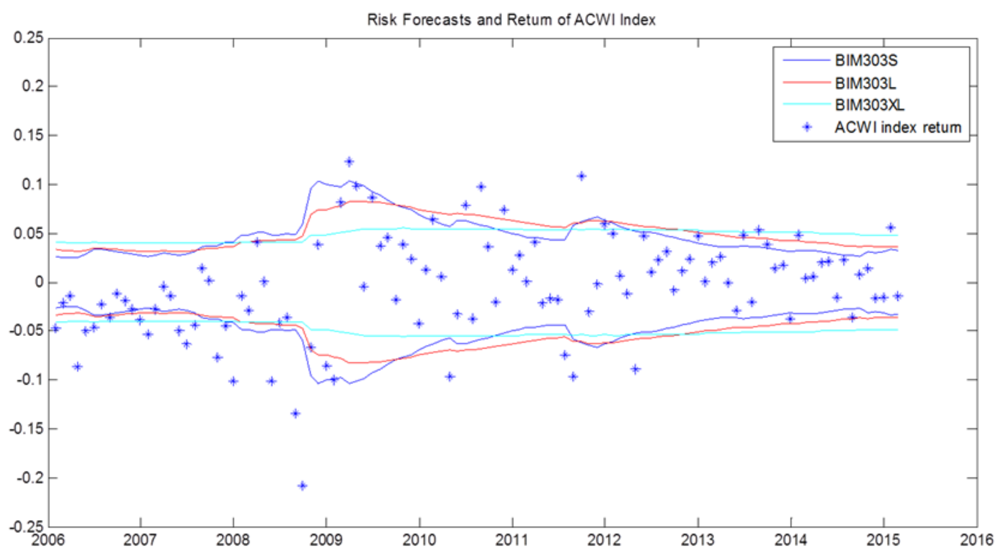


Figure 13: Risk Forecasts, Realized Return, and Responsiveness: The MSCI United Kingdom Equity Index

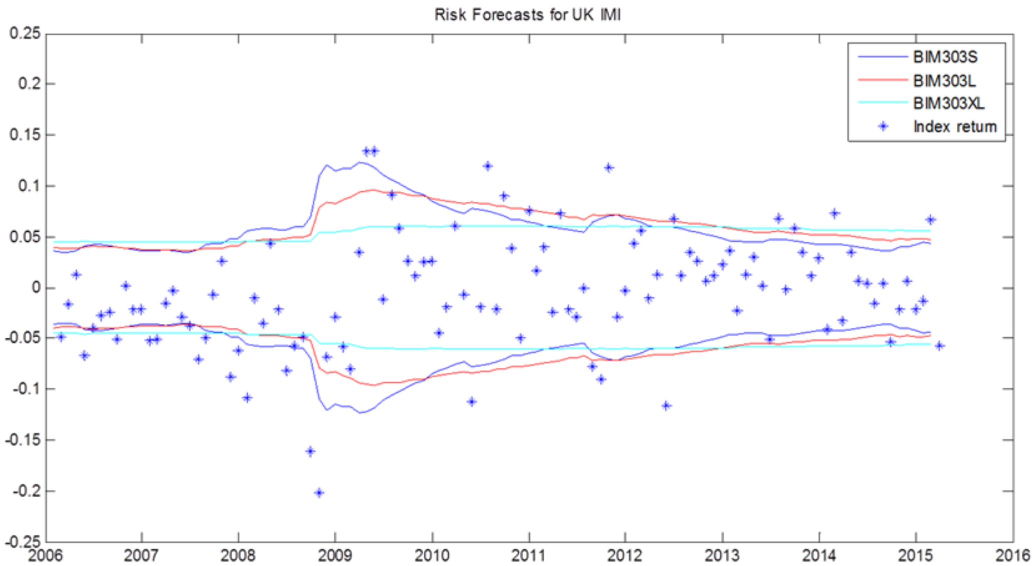


Figure 14: Risk Forecasts, Realized Return, and Responsiveness: The Japan Equity Index

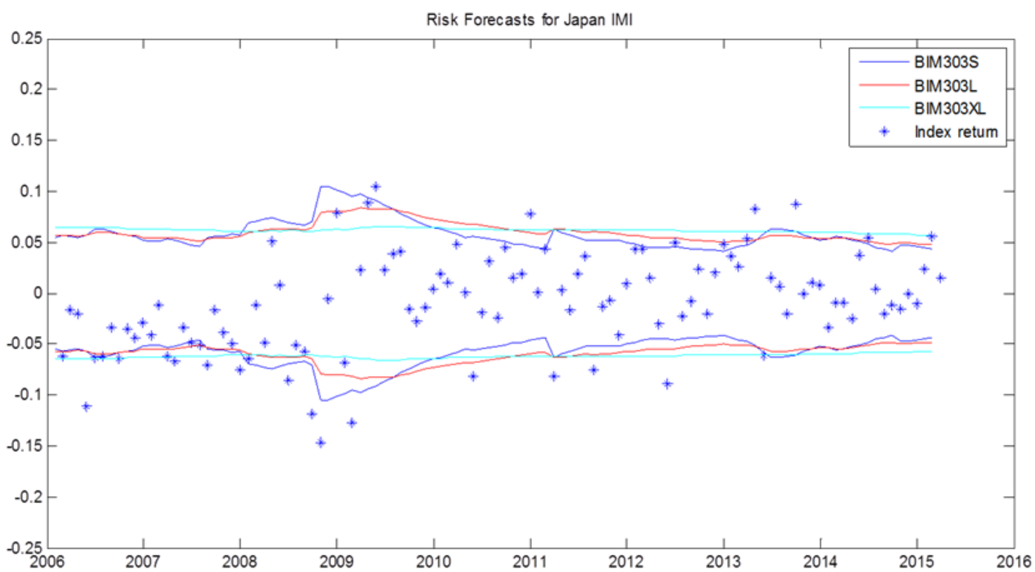


Figure 15: Risk Forecasts, Realized Return, and Responsiveness: The MSCI Government Bond Estimation Universe, currency hedged to USD

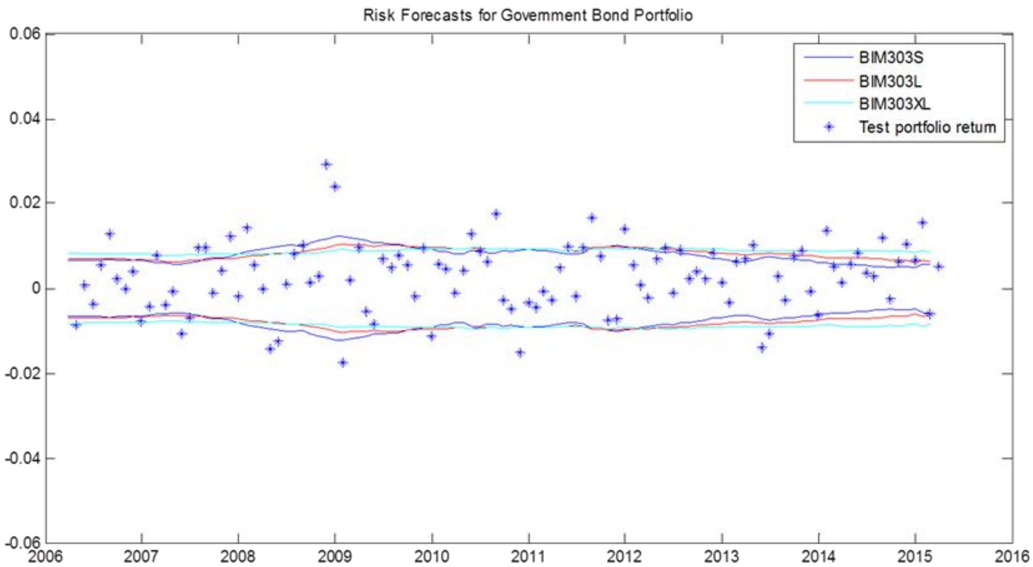


Figure 16: Risk Forecasts, Realized Return, and Responsiveness: The MSCI Developed Markets Corporate Investment Grade Bond Estimation Universe, currency hedged to USD

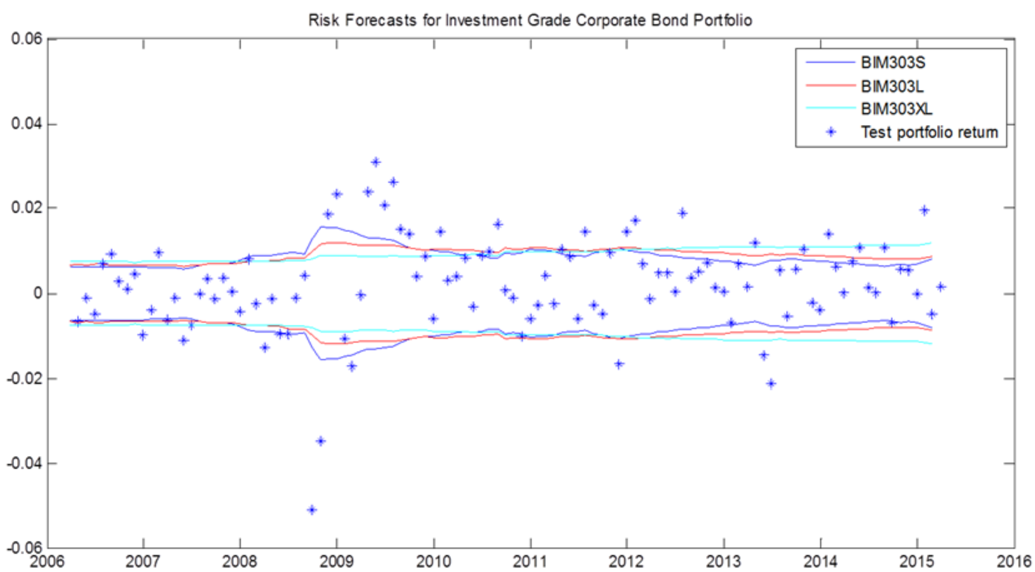
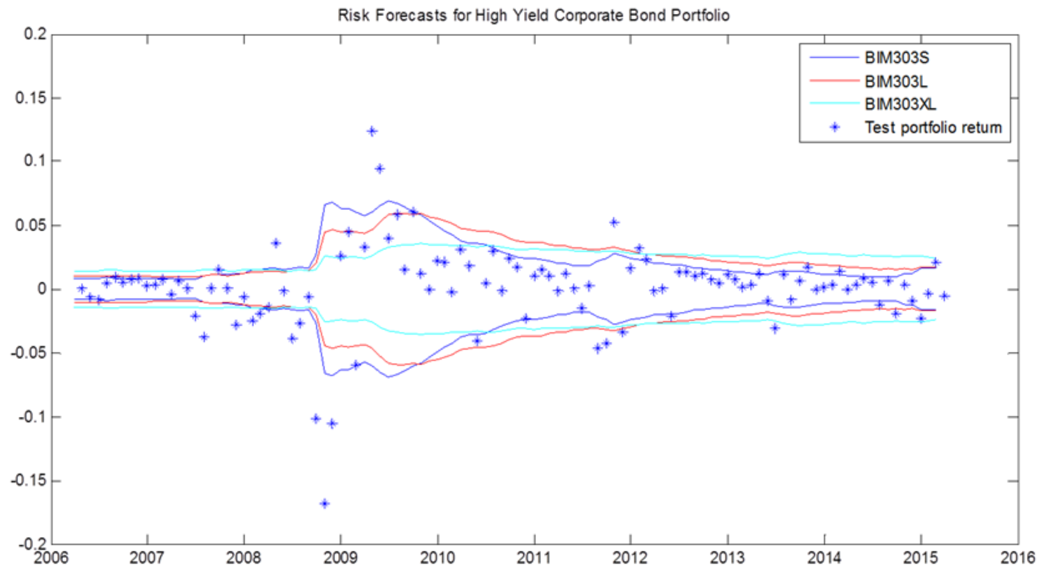


Figure 17: Risk Forecasts, Realized Return, and Responsiveness: The MSCI Developed Markets Corporate High Yield Bond Estimation Universe, currency hedged to USD



3.2.5 The Value of Granularity: Integrated vs. Global Models

The Barra Integrated Model incorporates dozens of component equity models, which together have over a thousand factors to capture each facet of these local markets. In contrast, the Global Equity Model (GEM3) and the Emerging Markets Model (EMM1) employ a far more parsimonious set of factors to model global equity. Is one view always superior to the other? Is it necessary to include a specific US Banks factor, or can we capture US Banks based on the behavior of the broader US equity market and Global Banks?

Figure 18 and Figure 19 study this question for a range of test portfolios by looking at the models' explanatory power. As in Section 3.2, the "Global" collection of country, global industry, and global style portfolios are constructed along the classes of the factors of the global equity model. The "Concentrated" portfolios consist of single-sector and single-style portfolios in each country. The portfolios are viewed from the perspective of total return, active return relative to the MSCI ACWI IMI[19] benchmark, and active return relative to the appropriate country benchmark in the case of the concentrated portfolios.

For both the Global and Concentrated portfolios, the more parsimonious GEM and EMM1 are able to capture nearly as much of the total return as the more granular BIM (see the first two sets of columns in the figures). This indicates that even concentrated portfolios are significantly driven by the broad country returns, which the global models capture well. The global models are also fairly accurate in capturing the active returns of the concentrated portfolios relative to the global benchmark (ACWI), reflecting the

[19] IMI = "Investible Market Index," the broadest index of large and small capitalization stocks representing the entire equity market, subject to liquidity constraints.

importance of broad country effects in these returns (see the third and fourth sets of columns in the figures).

The greatest differences between the global models and the integrated model are apparent in the active returns of the country-concentrated portfolios, for which BIM has a large advantage of about twice the explanatory power (see the fifth set of columns in the figures). These concentrated portfolios are intrinsically more idiosyncratic, and looking at active returns cancels out the overall market component, reducing the systematic component and the overall explanatory power.

It is notable that the importance of granularity is similar in the developed and emerging markets, despite structural differences among these markets. The magnitude of the total explanatory power is likely due to two offsetting contributions: Strong country effects in the emerging markets make them easier to explain with fewer factors (Brazilian stocks boom and bust together, e.g.), but the remaining returns are very heterogeneous across countries (Brazilian banks bear little relation to Russian banks, e.g.).

Most real portfolios will fall somewhere between the extremes of these test portfolios. Some portfolios are well aligned with the global factors, and simplicity may favor the use of a global model. Other portfolios have tilts and concentrations in individual markets, and the added detail of the full integrated model is needed to accurately understand them.

Figure 18: Model Average R-Squared – BIM vs. Global Equity Model averaged over five collections of global and concentrated factor portfolios. The two models have similar performance for Total risk and for Active risk relative to ACWI (the global equity benchmark). For the concentrated active risk relative to the country benchmark, BIM has significantly larger explanatory power.

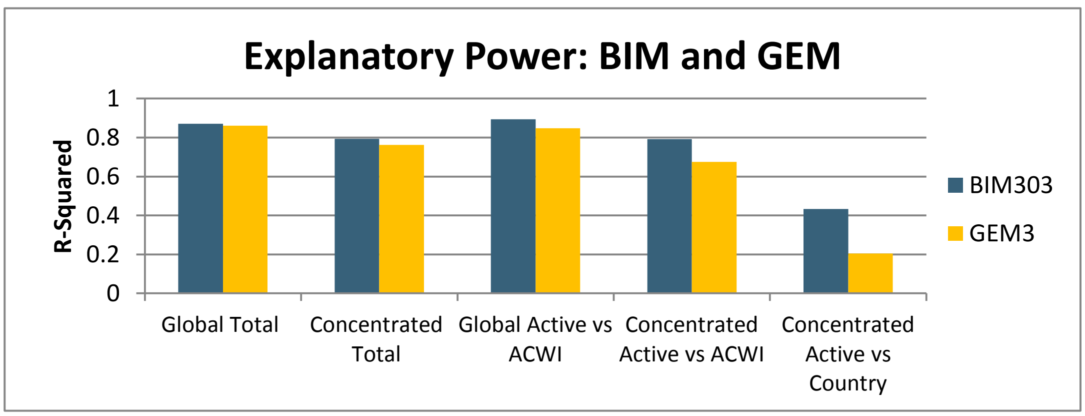
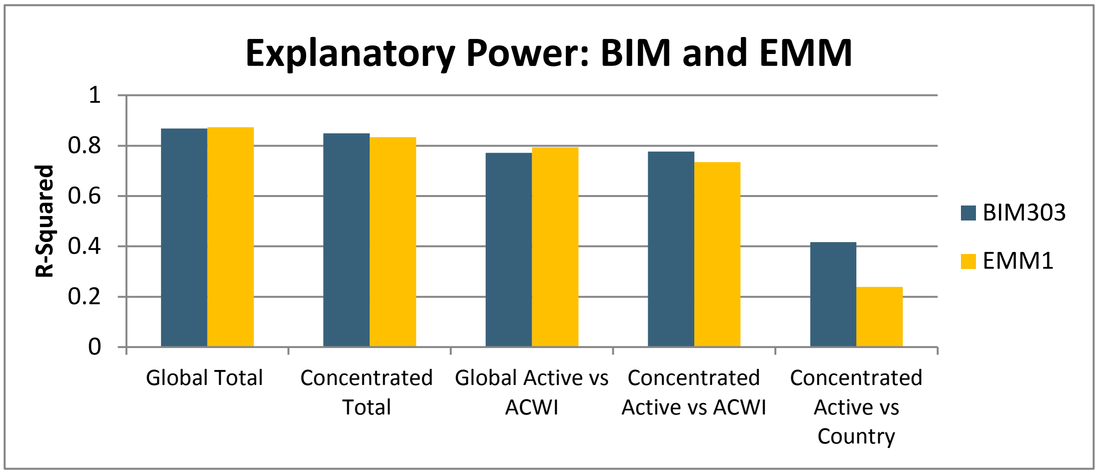


Figure 19: Equity Model R-Squared – BIM vs. Emerging Markets Model averaged over five collections of global and concentrated factor portfolios. The two models have similar performance for Total risk and for Active risk relative to ACWI (the global equity benchmark). For the concentrated active risk relative to the country benchmark, BIM has significantly larger explanatory power.



4 Use Cases for BIM in BarraOne

4.1 Typical Uses of a Risk Model in the Investment Process

There are many ways a risk model can be a tool for understanding and managing a complex multi-asset-class portfolio. This section provides a brief overview of these uses; the next provides several examples.

The primary use of a risk model – and the platform in which it is embedded – is to identify and quantify the multiple sources of risk in a portfolio. Not only are forecasts provided for individual securities, but also for arbitrary groups within a portfolio, and for groups of related portfolios (e.g., all emerging market equity portfolios in a multi-asset-class fund). Any security characteristic that is important to the decision-making process can be identified as an attribute and used to sort and group securities. Some examples that investors find useful to classify holdings: security type, membership in a subportfolio, country of issuer, currency, industry sector, issuer, credit rating, effective duration, ESG[20] rating, economic exposure[21], etc.

Not only can total volatility be computed for any arbitrary subset of a portfolio, but the portfolio total forecast volatility can be decomposed into these same subdivisions. So an investor could ask, how much of the total forecast risk is attributed to high-yield bonds? Or high yield bonds in the energy sector? Or, exposure to the slope of the yield curve (vulnerability to steepening or flattening of the curve)? Or if benchmarks are relevant, how much active (benchmark-relative) risk is attributable to overweights in the technology sector, or underweight to the 10-year Treasury Key Rate? Similar statistics can be computed relative to liability benchmarks.

These forecast risk decompositions are driven by the correlations among securities and groups of securities; the investor may want to see those correlations directly. One valuable byproduct of security or portfolio correlations is called the “implied returns” or “hurdle returns.”[22] For any portfolio, the marginal risk of each subportfolio is proportional to the expected return required to make that portfolio optimal (in a mean-variance sense). Hence, implied returns are used as a beginning point for asset allocation. Comparing the investor’s expected returns with the computed implied returns reveals whether each asset is expected to compensate the owner for the risk it contributes to the portfolio, or if the portfolio can be made more risk-return efficient by reweighting the components.

Although it is valuable to understand the current portfolio’s vulnerabilities, it is also useful to have a context for those statistics. Most risk managers and portfolio managers also want to understand evolution of risk forecasts. This can include (a) tracking changes in forecast risk between portfolio and benchmark over time, (b) tracking changes in forecast risk / forecast active risk among similar portfolios over time, (c)

[20] ESG = Environmental, Social, and Governance factors used to describe long-run risks other than market price volatility.

[21] Economic exposure refers to all the country/countries in which a company does business. This information highlights equity or bond risk in countries and currencies different from the country of domicile.

[22] For a good introduction and bibliography, see Herold (2005).

tracking the changes in a portfolio's risk decomposition over time. In addition to seeing this evolution, it is useful to determine whether the change in forecast risk from one period to the next results from changes in exposures, changes in forecast volatility, or changes in forecast correlations. Related to this type of inquiry is a "what-if?" or trade analysis of the risk effect of given asset substitutions or changes in asset allocation. By changing the exposure of a single asset or group of assets, the investor can simulate changes in portfolio risk, active risk, risk decomposition, or implied returns.

If an investor has adopted a risk budget for the portfolio, a risk model is almost a necessity. A fund manager may have a top-down risk budgeting framework ("risk allocation") on a multiple-portfolio structure. Alternatively, a portfolio manager (PM) may have a single portfolio with risk budgets for multiple strategies; for example, risk is allocated to country exposures, to industry sector exposures, and to currency exposures, each of which is determined separately. Just as BIM provides volatility and correlation forecasts for securities, which are then combined to yield a volatility estimate for a portfolio, the same process can work in reverse. That is, given a total portfolio risk budget and the volatility, correlations, and expected returns of the country, industry, and currency strategies, the PM can (a) determine an optimal allocation of risk to each of the three strategies, and (b) monitor actual risk taking relative to that overall budget, making sure that neither too much nor too little risk is utilized by the strategy teams in pursuit of their return objectives.

The final application in this brief tour is stress testing, which has become a popular — and in many cases required — form of assessing the vulnerabilities of a portfolio. Unlike a volatility forecast, a stress test simulates the profit or loss ("P&L") that results from a particular event (set of market changes, or stresses) on a set of portfolios. The result is an amount denominated in the user's base currency, and also expressed as a percentage of the portfolio (or portfolio segment). In BarraOne, an investor can generate two types of tests. An Historical Stress Test applies the actual returns experienced by the portfolio's elements between a given start and end date. If any particular security did not exist at the time of the stress event, BIM uses the factor exposures of that security and the factor returns from that period to estimate that portion of the P&L. The second type of test is called a Predictive Stress Test. In this case, the user supplies a (small) set of shocks to given market factors (equity markets, interest rate curves, credit spreads, currencies, commodities, and privately held assets) to represent a given hypothetical event or scenario. This type of stress test is discussed in more detail in Section 4.2.3 below.

4.2 Examples

4.2.1 Macro Factor Risk Decomposition

The methodology of the integrated model solves the econometric problem of estimating the covariances among the thousands of factors driving the world's markets. By understanding the layers of structure driving relationships among factors, the integrated model avoids the spurious correlations that would arise from directly estimating millions of parameters.

While the many detailed factors are important (Greek and German bonds are not quite the same thing, it turns out), they leave the economic problem of making sense of so many dimensions. For some investment problems, it is important to understand each and every intra-market driver of returns. For others, it is essential not to be blind to the forest for the trees. The Macro Factor methodology in BarraOne makes this possible.

The Macro Factor methodology introduces tiers of broader and broader factors sitting atop BIM's granularity. At the highest level, just six factors are used to describe the behavior of all the markets. These multi-asset-class factors can provide a basis for a risk-factor-based asset allocation approach that some pension funds and institutional investors are using to supplement traditional asset allocation.

While the top tier factors may provide the appropriate lens for board-level decisions, additional granularity is needed further down in the organization. Lower tiers capture greater detail to traverse the board to the CIO, asset class heads, and portfolio managers.

In all cases, all the views provide consistency with the full BIM, and a set of factor residuals to indicate when the simplified view is missing important details: Factor residuals capture the component of granular factors net of the macro factors. For the total risk of a broadly diversified global portfolio, these residuals often diversify away completely. For the active risk of a more concentrated portfolio, these residuals are essential to understanding the active strategy.

Figure 20 shows a macro factor analysis of a sample multi-asset-class portfolio from the point of view of the Tier 2 macro factors. This broad portfolio is exposed to risk from nearly every one of BIM's thousands of factors, but this view shows that most of its total risk can be understood in terms of a much smaller set of factors. In this case, 21 basis points of the total 8.46% are attributed to the factor residuals. For more concentrated portfolios, and for active risk, the factor residual is often much larger, indicating that the macro factors are unable to capture important details.

Figure 20: Sample Tier 2 Macro Factor Risk Decomposition for a Multi-Asset-Class portfolio. Portfolio risk contributions for individual elements are derived from the product of the standalone risk of that element, the exposure of that element, and the correlation of that element to the total portfolio.

	Risk Source	Standalone Risk	Portfolio Exposure	Portfolio Correlation	Portfolio Risk Contrib
	Total Risk	8.46		1.00	**8.46**
Equity	US Equity Market	13.84	0.32	0.94	4.10
	Developed Equity Markets (ex. US)	11.67	0.18	0.88	1.85
	Emerging Equity Markets	11.40	0.04	0.85	0.35
	Defensive	3.22	0.11	-0.46	-0.17
	Cyclical	0.84	0.42	0.46	0.16
	Value	1.56	-0.06	0.19	-0.02
	Size	1.34	-0.01	0.30	0.00
	Momentum	2.70	0.03	-0.31	-0.02
	Volatility	4.02	0.04	0.84	0.12
Fixed Income	Credit	0.30	3.65	0.72	0.79
	Interest Rates	0.35	1.47	-0.24	-0.12
	Steepener	0.16	0.25	-0.10	0.00
Alts	Hedge Funds	1.41	0.07	0.01	0.00
	Real Estate	7.28	0.10	0.45	0.32
	Private Equity	11.05	0.10	0.00	0.00
	Factor Residual Risk	1.76		0.12	**0.21**
	Selection Risk	0.71		0.08	0.06
	Currency Risk	5.40	0.29	0.53	0.83

4.2.2 Multi-Asset-Class Correlations

Figure 21 shows the long-horizon volatility and correlations of a sample of indexes spanning global equity, bonds and alternatives. The differences are generally small, with the largest differences associated with the enhanced US Credit model.

Figure 21: Correlations of major market indexes. Correlations from BIM303L (BIM301L) are in the lower (upper) triangle. Correlation differences greater than 5% and relative volatility differences greater than 10% are in italics.

BIM301L Correlations

BIM303L Correlations

Correlations April 30, 2015	MSCI DM Equity	MSCI EM Equity	MSCI Globl Small Cap	ML Global Gov	ML Global Gov IL	ML Global Broad Corp	ML Global High Yield	ML US MBS	Global EM Bonds	GSCI Energy Index	GSCI Non-Energy	BIM Global Prvt Equity	BIM Global Real Estate	BIM Global Hedge Fnd
MSCI Developed Equity	1.00	0.82	0.96	0.00	0.27	0.30	0.65	-0.11	0.56	0.38	0.43	0.67	0.75	0.85
MSCI Emerging Equity	0.81	1.00	0.84	0.09	0.35	0.40	0.69	-0.03	0.66	0.40	0.48	0.54	0.69	0.66
MSCI Global Small Cap	0.96	0.83	1.00	0.01	0.28	0.31	0.67	-0.10	0.58	0.39	0.46	0.67	0.74	0.82
ML Global Gov	-0.01	0.08	0.00	1.00	0.78	0.81	*0.29*	0.52	*0.47*	0.01	0.22	-0.09	0.34	-0.09
ML Global Gov Infl Lnkd	0.26	0.35	0.28	0.77	1.00	0.86	*0.61*	0.46	0.70	0.23	0.39	0.12	0.52	0.17
ML Global Broad Corp	0.34	0.44	0.36	0.77	0.86	1.00	0.69	0.55	0.79	0.17	0.38	0.15	0.53	*0.20*
ML Global High Yield	0.68	0.69	0.70	*0.18*	*0.52*	0.65	1.00	0.13	0.88	0.44	0.52	0.44	0.66	*0.56*
ML US MBS	-0.10	-0.02	-0.08	0.54	0.49	0.54	0.08	1.00	0.24	-0.21	-0.05	-0.08	0.04	-0.09
Global EM Sov & Credit	0.59	0.68	0.61	*0.41*	0.65	0.78	0.87	0.24	1.00	0.36	0.50	0.35	0.65	0.44
GSCI Energy Index	0.38	0.40	0.38	0.00	0.23	0.19	0.45	-0.20	0.37	1.00	0.47	0.23	0.33	0.31
GSCI Non-Energy Index	0.45	0.48	0.46	0.21	0.39	0.40	0.52	-0.03	0.50	0.47	1.00	0.26	0.47	0.35
BIM Global Private Equity	0.66	0.53	0.67	-0.10	0.12	0.18	0.47	-0.07	0.38	0.22	0.27	1.00	0.46	0.60
BIM Global Real Estate	0.75	0.69	0.74	0.30	0.49	0.53	0.64	0.06	0.64	0.32	0.47	0.46	1.00	0.59
BIM Global Hedge Fund	0.84	0.65	0.82	-0.09	0.17	*0.25*	*0.61*	-0.08	0.49	0.33	0.36	0.59	0.59	1.00
BIM 303 Volatility	12.4	15.8	13.1	5.1	6.4	4.6	*6.6*	5.4	7.4	26.4	11.4	15.2	8.6	3.5
BIM 301 Volatility	13.0	15.8	14.0	5.5	6.6	4.6	*5.6*	5.4	7.0	28.1	11.8	15.6	8.9	3.7

4.2.3 Stress Testing

Risk measures that are largely data driven have an advantage of objectivity, but it is important to complement them with more subjective views of risks from possible "tail events."

Some such events may be similar to crises that have occurred before. In these cases, a factor model can be a powerful tool to translate historical scenarios to the current portfolio. For example, Facebook and Google did not yet exist during the Internet Bubble, and although Microsoft did exist then, it was a very different company than it is today. In all these cases, a factor model can be used to explore the hypothetical bursting of "Internet Bubble 2.0" by projecting the factor returns from the historic Internet Bubble onto these assets today, based on their fundamental characteristics. See Shepard (2013) for more on this example.

Other scenarios may pose dangers that have never occurred. At the time of this writing, many investors are concerned about a possible hard landing in China or a Greek exit from the euro, neither of which has ever happened. Other possible scenarios, such as an interest rate hike or an increase in the price of crude oil, have occurred, but only in the context of significantly different market environments.

To explore these scenarios requires a form of forward-looking stress testing. Figure 22 shows examples of such stress tests, in which the investor chooses one or two principal risk drivers and simulates the effect of stresses to those factors on her portfolio. In BarraOne, this can be done in one of two ways. The first and simpler way is to propagate the shock to only those assets directly affected by a factor. For example, a "15% correction in the US Equity market" would be applied to all US stocks in the portfolio according to their sensitivity to the overall market, but it would not affect anything other than US stocks. Since global equity markets and other asset classes have become closely correlated with the US, such a treatment could significantly understate the effect on a broader portfolio.

The second way is to make use of the model's structure (as introduced in the example in Section 1.4). Using BarraOne's "correlated mode," a shock can be propagated to all securities in the portfolio. A shock to any part of the market affects all other assets in proportion to the magnitude of the shock and the strength of the relationship among factors. Thus, a shock to US Equity would affect not only other equity markets, but also bonds, real estate, and private equity portfolios (to name a few). The examples below show this second, correlated method applied to one of the multi-asset-class Target Date portfolios analyzed in Section 3.

When conducting stress tests, it is crucial to think carefully about which extreme scenarios pose dangers, and how to represent these scenarios with a core set of market variables. What is the economic intuition behind the event? For example, the effect of a rise in interest rates may be quite different if the real rate is rising, as opposed to the expected inflation premium. Once the scenario is defined with core market variables, a factor model can then be used to propagate the shocks to rest of the market.

Sometimes, what seems like a simple scenario requires more careful specification. A common example, as discussed in Shepard (2013), is an "Oil Shock" that actually has very different effects if the shock is driven by changing supply or demand. Although the price of oil is more frequently driven by changing demand expectations, it is a supply shock that investors typically fear.

To study the effect of an oil supply shock, it is therefore necessary to specify not just an increase in the price of oil, but also an indicator of the corresponding economic slowdown. Our research[23] based on the study of a long history of oil supply shocks indicates that this slowdown can be captured by a decrease in equity of 0.25 times the relative increase in the price of oil. With these two inputs, the model can propagate the shock to all other parts of the market.

[23] See Phillips (2015).

Figure 22: Stress Test Results by Asset Class using BIM303. The three stress tests include the following shocks: (a) The MSCI ACWI is shocked by -16%, which is approximately a two-standard-deviation annual move, extended over a three-month period. All other market factors are shocked in relation to the sensitivity of those factors to movements in the ACWI index. (b) In the Credit shock, the bond spreads of financial issuers in USD, CAD, EUR, GBP, CHE, and JPY currencies rise by 100 bp; these shocks are propagated to other factors using factor sensitivities. (c) In the crude Oil supply shock, we assume crude oil jumps by +50%, causing a drop in economic activity, and an equity correction of 12.5%; these shocks are propagated to other factors using factor sensitivities.

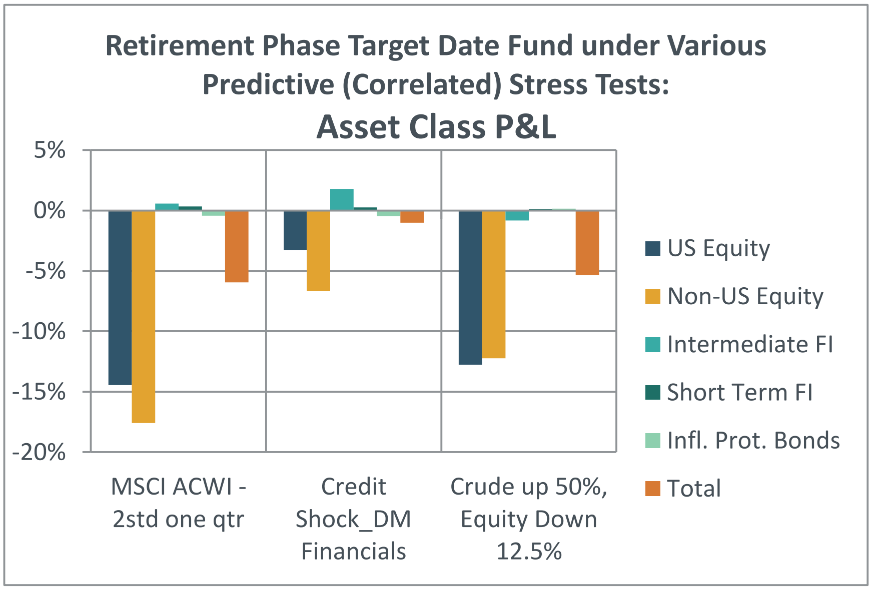
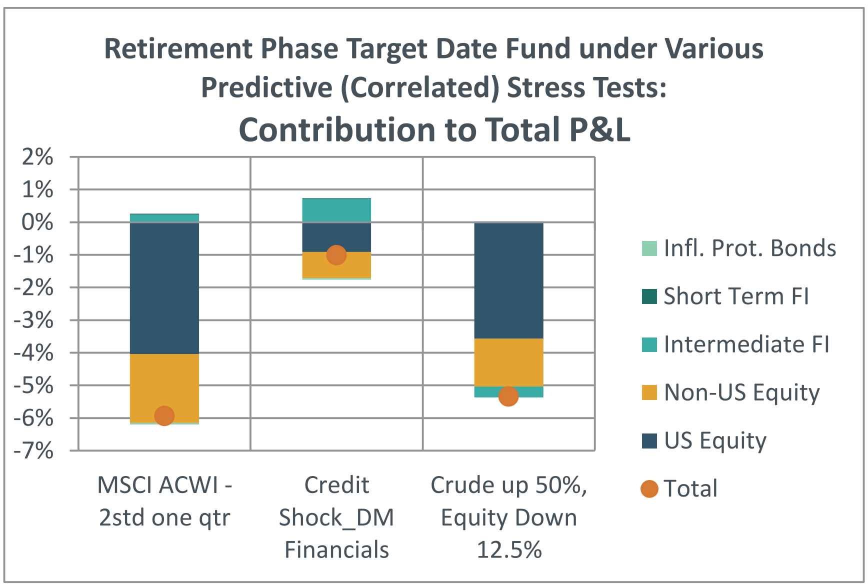


Figure 23: Stress Test Results by Contribution to Total Return. This chart shows the same stress test results, but decomposes the total return into the major asset class effects.



4.3 Functionality of BarraOne Supported by BIM303

- Supported Modules. Users can choose BIM303 models for use in the following areas of BarraOne:
  - Analysis tab:
    - All Risk Reports
    - Multiple Portfolio Comparison (MPC)
    - Asset-Liability Management (ALM)
    - Portfolio Optimization
  - Simulation tab
  - Portfolio Admin tab
  - Data Admin tab (Attributes, Factors, Screen, and User Assets)
  - Import tab
  - Export tab (Portfolio Analysis, Multiple Portfolio Comparison, Stress Test Simulation, and Monte Carlo VaR)
  - Accounts tab (My Profile)
- BIM303L, BIM303S, and BIM303XL support the feature that enables users to select a Covariance Date different from the Analysis Date.
- Hedge Fund and Mutual Fund factor exposures are generated using BIM301 and converted to BIM303 factor exposures using a factor mapping. A new Barra Fund Model that generates exposures directly to BIM303 will be released later in 2015.
- The following functions of BarraOne are not supported for BIM303:
  - Returns Calculator
  - Performance Attribution

5 Summary

The Barra Integrated Model is a multi-asset-class risk model that couples breadth of coverage (global equities, global bonds, currencies, commodities, hedge funds, private real estate, and private equities) with the depth of analysis provided by local models. The new version, BIM303, updates fixed income and equity models and adds private asset coverage. This new version performs as well or better than BIM301 in explaining returns and forecasting risk for most portfolios across a broad set of tests. BIM303 supports a range of use cases, including risk analysis at multiple levels of detail (from the highest level asset-class decomposition into six groups to a zoomed-in view of single country details) and multiple types of stress tests that take advantage of its structured approach to risk analysis.

Appendix A: Empirical Results — Detail

A.1 R-Squared

A.1.1 Equity Portfolio and Cross-Sectional R^2

Table 6: MSCI EQUITY Country Index Portfolio Regressions: comparison of BIM301L and BIM303L

Developed Markets	301L	303L	Emerging Markets	301L	303L	Frontier Markets	301L	303L
Australia	0.93	0.93	Brazil	0.96	0.96	Argentina	0.97	0.97
Austria	0.93	0.93	Chile	0.87	0.87	Bahrain	0.69	0.69
Belgium	0.87	0.87	China International	0.99	0.99	Jordan	0.82	0.82
Canada	0.91	0.91	Colombia	0.84	0.84	Kuwait	0.95	0.95
Denmark	0.87	0.88	Czech Republic	0.86	0.92	Oman	0.94	0.94
Finland	0.88	0.87	Egypt	0.91	0.91	Pakistan	0.94	0.94
France	0.9	0.9	Greece	0.94	0.95	Qatar	0.9	0.9
Germany	0.9	0.91	Hungary	0.93	0.95	Saudi Arabia	0.94	0.94
Hong Kong	0.89	0.89	India	0.94	0.94	UAE	0.91	0.91
Ireland	0.86	0.88	Indonesia	0.94	0.94			
Israel	0.68	0.68	Korea	0.91	0.91			
Italy	0.92	0.93	Malaysia	0.76	0.76			
Japan	0.81	0.82	Mexico	0.88	0.88			
Netherlands	0.89	0.89	Morocco	0.83	0.83			
New Zealand	0.84	0.84	Peru	0.78	0.78			
Norway	0.94	0.94	Philippines	0.89	0.89			
Portugal	0.9	0.91	Poland	0.92	0.94			
Singapore	0.91	0.91	Russia	0.8	0.82			
Spain	0.91	0.92	South Africa	0.93	0.9			
Sweden	0.92	0.92	Taiwan	0.92	0.92			
Switzerland	0.77	0.77	Thailand	0.93	0.93			
United Kingdom	0.87	0.87	Turkey	0.94	0.95			
United States	0.84	0.84						

Table 7: Equity Model Security (Cross Sectional) Regressions: comparison of BIM301L and BIM303L

Country / Region	model	301 mean R2	model	303 mean R2
Australia	AUE3	0.27	AUE4	0.32
Canada	CNE4	0.33	CAE5	0.32
Japan	JPE3	0.24	JPE4	0.29
China	CHE2	0.35	CNE5	0.35
Korea	KRE2	0.26	KRE3	0.30
South Africa	SAE3	0.43	ZAE4	0.35

Country / Region*	model	301 mean R2	model	303 mean R2
United States	USE3	0.38	USE4	0.33
Europe excl. UK	EUE3DUK	0.36	EUE4DUK	0.29
* results for these model are not strictly comparable: for the BIM301 statistics, monthly data was used; for BIM 303 statistics, daily data was used				

A.1.2 Fixed Income Portfolio and Cross-Sectional R^2

Table 8: Fixed Income Indexes Portfolio R-Squared: comparison of BIM301L and BIM303L

CODE	BofA Merrill Lynch Indexes	301L	303L	CODE	BofA Merrill Lynch Indexes	301L	303L	CODE	BofA Merrill Lynch Indexes	301L	303L
G0T0	Australian Governments	1.00	1.00	G0CL	Chile Government Index	1.00	1.00	C0D0	US Domestic Industrial	0.98	0.98
G0H0	Austrian Governments	1.00	1.00	G0CN	China Government Index	1.00	1.00	C0Z0	US Domestic Yankee Master (incl CAN)	0.95	0.96
G0G0	Belgian Governments	1.00	1.00	G0HK	Hong Kong Government Index	1.00	1.00	C0A0	ML US Investment Grade Corporate bonds	0.97	0.97
G0C0	Canadian Governments	1.00	1.00	G0ID	Indonesia Government Index	0.99	0.99	C0J0	The BofA Merrill Lynch US Insurance & Financial Services Index	0.80	0.80
G0M0	Danish Governments	1.00	1.00	G0IN	India Government Bond Index	1.00	1.00	C0R0	The BofA Merrill Lynch US Telecommunications Index	0.96	0.96
G0K0	Finnish Governments	1.00	1.00	G0MY	Malaysian Government Index	1.00	1.00	C0Q0	US Domestic Utilities	0.98	0.99
G0F0	French Governments	1.00	1.00	G0SK	South Korean Government Index	1.00	1.00	H0HB	US High Yield Homebuilders/Real Estate	0.86	0.86
G0D0	German Federal Governments	1.00	1.00	G0SP	Singapore Government Index	1.00	1.00				
G0R0	Irish Governments	1.00	1.00	G0IS	Israel Government Bond Index	1.00	1.00	EJ00	EMU Corporates Industrials Index	0.96	0.96
G0I0	Italian Governments	1.00	1.00	G0PL	Polish Governments	1.00	1.00	EP00	EMU Pfandbrief Index	0.96	0.96
G0Y0	Japanese Governments	1.00	1.00	G0RU	Russia Government Index	0.99	0.99	EB00	The BofA Merrill Lynch Euro Financial Index	0.90	0.90
G0N0	Dutch Governments	1.00	1.00	G0TR	Turkey Government Index	1.00	1.00	HPC0	Euro High Yield Constrained Index	0.98	0.98
G0Z0	New Zealand Governments	1.00	1.00	G0SA	South Africa Governments G0SA	1.00	1.00	HE30	The BofA Merrill Lynch CCC & Lower Euro High Yield Index	0.79	0.79
G0U0	Portuguese Governments	1.00	1.00	G0BC	Global Investment Grade Corporate bonds	0.90	0.90	HEFA	The BofA Merrill Lynch Euro Fallen Angel High Yield Index	0.36	0.36
G0E0	Spanish Governments	1.00	1.00	IC00	Global Emerging Markets Credit Index	0.74	0.75				
G0W0	Swedish Governments	1.00	1.00	IP00	Global Emerging Markets Sovereign Plus Index	0.94	0.93	W0G1	ML Global Government Index	1.00	1.00
G0S0	Swiss Governments	0.97	0.97					W0GI	ML Global Inflation-linked Sovereign bonds	1.00	1.00
G0L0	UK Gilts	1.00	1.00	UC00	Sterling Corporate Index UC00	0.99	0.99				
G0Q0	US Treasury Master	1.00	1.00	UKL0	Sterling Large Cap Index	1.00	1.00				

Table 9: Government Bond Models Cross-Sectional R-squared: comparison of BIM301L and BIM303L (BIM301 uses weekly data and BIM303 uses daily data.)

Country	301	303	Country	301	303
ARG	1.00	1.00	IRL	0.91	0.83
AUS	0.97	0.97	ISR	0.86	0.86
AUT	0.93	0.90	ITA	0.90	0.87
BEL	0.93	0.90	JPN	0.86	0.84
BGR	0.58	0.58	KOR	0.88	0.88
BRA	0.92	0.92	LTU	0.61	0.61
CAN	0.93	0.88	MEX	0.84	0.84
CHE	0.86	0.82	MYS	0.48	0.60
CHL	0.64	0.64	NGA	N/A	0.78
CHN	0.65	0.65	NLD	0.93	0.92
CHX	N/A	0.50	NOR	0.94	0.96
COL	0.37	0.37	NZL	0.97	0.97
DEU	0.94	0.93	PER	0.80	0.80
DNK	0.92	0.90	PHL	N/A	0.63
EGY	1.00	1.00	POL	0.87	0.80
EMU	0.95	0.90	PRT	0.89	0.82
ESP	0.93	0.89	ROU	0.39	0.39
FIN	0.95	0.93	RUS	0.39	0.39
FRA	0.93	0.90	SGP	0.79	0.79
GBR	0.94	0.94	SWE	0.95	0.93
GRC	0.90	0.81	THA	N/A	0.71
HKG	0.90	0.90	TUR	0.87	0.87
HRV	0.47	0.47	TWN	N/A	0.75
IDN	0.61	0.61	USA	0.93	0.92
IND	0.80	0.80	ZAF	0.92	0.92

Table 10: Credit Market Models Cross-Sectional Asset R-squared: comparison of BIM301L and BIM303L. The upper left panel shows results for all credit bonds; the upper right shows results for Investment Grade only, and the bottom left shows High Yield only.

All Credit Cross Sectional	Average non-treasury overall R^2		Average non-treasury credit R^2	
	301	303	301	303
AUD	0.65	0.68	0.35	0.42
CAD	0.59	0.66	0.36	0.47
CHF	0.29	0.16	0.17	0.14
EUR	0.19	0.29	0.11	0.12
JPY	0.63	0.62	0.45	0.58
SEK	0.67	0.56	0.16	0.16
GBP	0.33	0.41	0.21	0.31
USD	0.14	0.22	0.12	0.13

IG Cross Sectional	Average non-treasury overall R^2		Average non-treasury credit R^2	
	301	303	301	303
AUD	0.65	0.68	0.35	0.50
CAD	0.69	0.70	0.44	0.56
CHF	0.29	0.16	0.17	0.14
EUR	0.31	0.41	0.11	0.24
JPY	0.61	0.61	0.44	0.57
SEK	0.67	0.56	0.16	0.22
GBP	0.50	0.52	0.31	0.45
USD	0.31	0.37	0.19	0.23

HY Cross Sectional	Average non-treasury overall R^2		Average non-treasury credit R^2	
	301	303	301	303
CAD	0.28	0.39	0.17	0.27
EUR	0.11	0.12	0.15	0.25
GBP	0.13	0.14	0.19	0.28
USD	0.09	0.12	0.12	0.16

A.2 Bias Statistics

A.2.1 Equity

Table 11: MSCI Country Equity Indexes Bias Statistics: comparison of BIM301 and BIM303

Equity Indexes	Total Risk					Equity Indexes	Total Risk				
	301S	303S	301L	303L	303XL		301S	303S	301L	303L	303XL
ARE IMI	1.27	1.29	1.17	1.21	1.16	ITA IMI	1.00	1.05	1.01	1.06	1.12
ARG IMI	1.18	1.08	1.08	1.05	1.03	JPN IMI	0.86	0.83	0.82	0.8	0.78
AUS IMI	1.01	1.06	1.00	1.04	1.21	JOR IMI	0.92	0.94	0.9	0.91	0.92
AUT IMI	1.02	1.08	1.05	1.13	1.21	KOR IMI	1.13	0.91	0.93	0.88	0.74
BEL IMI	1.04	1.06	1.07	1.10	1.15	KWT IMI	0.99	0.95	0.83	0.79	0.73
BHR IMI	1.21	1.24	1.02	1.09	0.90	MAR IMI	0.94	0.98	0.80	0.95	0.90
BRA IMI	0.95	0.99	0.94	0.94	0.92	MEX IMI	0.98	0.97	0.87	0.87	0.76
CAN IMI	1.00	1.02	0.99	1.00	1.13	MYS IMI	0.98	1.02	0.92	0.95	0.95
CHE IMI	0.89	0.96	0.89	0.94	0.98	NLD IMI	1.01	1.02	1.02	1.04	1.10
CHL IMI	0.98	0.98	0.98	0.97	1.03	NOR IMI	1.05	1.08	1.05	1.10	1.15
CHX IMI	0.88	0.87	0.83	0.80	0.73	NZL IMI	0.91	1.05	0.96	1.03	1.10
COL IMI	1.10	1.18	1.02	1.09	1.04	OMN IMI	0.98	1.05	0.77	0.82	0.59
CZE IMI	0.98	0.95	0.96	0.93	0.95	PAK IMI	0.90	0.86	0.73	0.77	0.62
DEU IMI	1.01	1.06	1.00	1.07	1.16	PER IMI	0.99	1.07	0.97	0.99	0.92
DNK IMI	0.98	1.06	1.00	1.08	1.11	PHL IMI	1.00	0.97	0.89	0.93	0.86
EGY IMI	1.02	1.05	1.01	1.02	0.97	POL IMI	1.02	1.00	1.02	1.02	1.08
ESP IMI	0.99	1.05	1.01	1.07	1.17	PRT IMI	0.99	1.04	1.00	1.05	1.07
FIN IMI	0.95	0.99	0.96	0.98	1.03	QAT IMI	0.94	0.95	0.79	0.81	0.57
FRA IMI	0.98	1.02	0.98	1.03	1.13	RUS IMI	1.07	0.99	1.07	0.99	0.76
GBR IMI	0.98	0.96	0.98	0.98	1.07	SAU IMI	1.20	1.11	1.09	1.02	0.93
GRC IMI	1.04	1.05	1.07	1.08	1.09	SGP IMI	1.01	1.03	0.93	0.95	0.87
HKG IMI	1.04	1.01	0.96	0.91	0.83	SWE IMI	0.96	1.01	0.97	1.02	1.10
HUN IMI	1.13	1.10	1.16	1.14	1.22	THA IMI	1.07	1.09	0.93	1.04	0.92
IDN IMI	1.08	1.05	1.01	0.99	1.01	TUR IMI	1.11	1.11	1.05	1.05	0.81
IND IMI	1.01	0.95	0.88	0.94	0.73	TWN IMI	0.97	1.01	0.86	0.97	0.86
IRL IMI	0.98	1.03	0.99	1.01	1.03	USA IMI	1.06	1.11	1.01	1.03	1.05
ISR IMI	0.87	0.85	0.80	0.80	0.82	ZAF IMI	0.94	0.98	0.96	0.93	0.94

Table 12: GEM3 Country Factor Portfolios Bias Statistics: comparison of BIM301L and BIM303L

Equity Country Factors	Total Risk					Active Risk - ACWI Benchmark				
	301S	303S	301L	303L	303XL	301S	303S	301L	303L	303XL
ARGENTINA	1.29	1.16	1.22	1.18	1.14	1.14	1.09	1.08	1.08	0.98
AUSTRALIA	1.01	1.06	0.99	1.04	1.20	0.96	1.04	0.90	0.95	0.97
AUSTRIA	1.02	1.08	1.04	1.13	1.21	0.93	1.01	0.95	1.02	1.03
BELGIUM	1.04	1.07	1.07	1.10	1.15	0.84	0.90	0.88	0.90	0.84
BRAZIL	0.95	0.99	0.94	0.94	0.92	0.95	0.98	0.95	0.96	0.83
CANADA	1.00	1.02	0.99	1.00	1.13	0.91	0.97	0.87	0.92	0.98
CHILE	0.98	0.98	0.98	0.97	1.03	0.98	0.99	0.97	1.00	1.02
CHINA INTER	0.94	0.94	0.86	0.84	0.77	0.94	0.94	0.82	0.81	0.68
COLOMBIA	1.10	1.18	1.02	1.09	1.04	1.01	1.01	0.94	0.97	0.87
CZECH REPUBLIC	0.98	0.95	0.96	0.93	0.95	0.90	0.87	0.87	0.79	0.73
DENMARK	0.98	1.06	1.00	1.08	1.11	0.83	0.89	0.85	0.88	0.82
EGYPT	1.02	1.05	1.01	1.02	0.97	0.92	0.92	0.86	0.88	0.81
FINLAND	0.95	0.99	0.96	0.98	1.03	0.91	0.99	0.92	0.96	0.92
FRANCE	0.98	1.02	0.98	1.03	1.13	0.85	0.97	0.86	0.95	0.96
GERMANY	1.00	1.04	0.99	1.05	1.14	0.86	0.98	0.87	0.98	0.95
GREECE	1.04	1.05	1.07	1.08	1.09	0.99	0.97	1.02	0.99	1.00
HONG KONG	1.04	1.01	0.96	0.91	0.83	0.95	0.90	0.88	0.84	0.67
HUNGARY	1.07	1.02	1.05	1.03	1.07	1.03	0.96	1.00	0.94	0.94
INDIA	1.08	1.05	1.01	0.99	1.01	1.02	0.98	0.95	0.94	0.86
INDONESIA	1.01	0.95	0.88	0.94	0.73	0.92	0.86	0.82	0.86	0.60
IRELAND	0.98	1.03	0.99	1.01	1.03	0.88	1.02	0.92	0.99	0.96
ISRAEL	0.88	0.85	0.81	0.80	0.81	0.76	0.73	0.72	0.70	0.69
ITALY	1.00	1.05	1.01	1.06	1.12	0.88	0.99	0.89	0.97	0.99
JAPAN	0.86	0.84	0.82	0.80	0.78	0.74	0.72	0.71	0.70	0.67
JORDAN	1.12	1.12	1.17	1.16	1.27	1.00	1.01	0.98	0.98	1.05
KOREA	1.13	0.92	0.93	0.88	0.74	1.05	0.88	0.85	0.80	0.56
MALAYSIA	0.94	0.98	0.80	0.95	0.90	0.83	0.83	0.71	0.80	0.64
MEXICO	0.98	0.97	0.87	0.87	0.76	0.80	0.76	0.71	0.69	0.53
MOROCCO	0.97	1.01	0.92	0.95	0.95	0.88	0.89	0.85	0.86	0.88
NETHERLANDS	0.99	1.01	0.99	1.03	1.09	0.84	0.90	0.84	0.89	0.84
NEW ZEALAND	0.91	1.05	0.96	1.03	1.10	0.76	0.84	0.77	0.81	0.79
NORWAY	1.05	1.08	1.05	1.10	1.15	1.06	1.07	1.05	1.06	1.03
PAKISTAN	1.29	1.23	1.06	1.22	1.21	1.39	1.41	1.24	1.42	1.39
PERU	1.51	1.19	1.46	1.08	1.15	1.54	1.24	1.46	1.09	1.09
PHILIPPINES	1.00	0.97	0.89	0.93	0.86	0.98	0.92	0.88	0.91	0.78
POLAND	1.02	1.00	1.02	1.02	1.08	0.99	0.96	1.01	0.97	0.93
PORTUGAL	0.99	1.04	1.00	1.05	1.07	0.91	0.95	0.91	0.91	0.90
RUSSIA	1.21	1.11	1.19	1.09	0.85	1.14	1.08	1.14	1.03	0.70
SINGAPORE	1.01	1.03	0.93	0.95	0.87	0.92	0.90	0.83	0.83	0.64
SOUTH AFRICA	0.94	0.98	0.96	0.93	0.94	0.88	0.90	0.86	0.81	0.72
SPAIN	0.99	1.05	1.01	1.07	1.17	0.94	1.06	0.99	1.07	1.12
SWEDEN	0.97	1.01	0.98	1.02	1.10	0.88	0.94	0.90	0.94	0.96
SWITZERLAND	0.89	0.96	0.89	0.94	0.98	0.72	0.83	0.72	0.78	0.74
TAIWAN	0.97	1.01	0.86	0.97	0.86	0.85	0.84	0.69	0.79	0.63
THAILAND	1.07	1.09	0.93	1.04	0.92	0.93	0.92	0.83	0.90	0.74
TURKEY	1.11	1.11	1.05	1.05	0.81	1.19	1.14	1.10	1.07	0.73
UNITED KINGDOM	0.97	0.96	0.98	0.98	1.07	0.72	0.67	0.69	0.66	0.66
USA	1.06	1.11	1.01	1.04	1.05	0.85	0.87	0.82	0.85	0.84

Table 13: GEM3 Industry Factor Portfolios Bias Statistics: comparison of BIM301L and BIM303L

Equity Sector Factors	Total Risk					Active Risk - ACWI Benchmark				
	301S	303S	301L	303L	303XL	301S	303S	301L	303L	303XL
Airlines	1.12	1.11	1.05	1.05	1.06	1.40	1.38	1.32	1.30	1.22
Aluminum Diversified Metals	1.05	1.08	1.05	1.07	1.22	1.22	1.27	1.19	1.23	1.32
Automobiles and Components	0.97	0.99	0.93	0.96	1.01	0.96	0.95	0.92	0.92	0.91
Banks	1.09	1.08	1.05	1.07	1.16	1.04	1.03	1.03	1.06	1.11
Biotechnology	1.05	1.10	0.97	0.98	0.82	1.09	1.17	1.02	1.10	0.83
Capital Goods	1.06	1.08	1.05	1.07	1.15	1.27	1.24	1.20	1.20	1.14
Chemicals	1.03	1.04	1.00	1.03	1.13	1.20	1.14	1.12	1.10	1.02
Commercial and Professional Services	1.15	1.14	1.10	1.10	1.12	1.17	1.10	1.13	1.07	0.94
Communications Equipment	1.03	1.09	0.99	1.04	0.99	1.07	1.07	1.01	1.00	0.83
Computers Electronics	1.10	1.11	1.05	1.08	1.04	0.98	1.00	0.91	0.95	0.81
Construction Containers Paper	1.09	1.12	1.07	1.10	1.18	1.28	1.27	1.23	1.23	1.15
Consumer Durables and Apparel	1.13	1.12	1.09	1.09	1.16	1.22	1.12	1.17	1.10	1.11
Diversified Financials	1.08	1.08	1.02	1.03	1.02	1.19	1.20	1.11	1.13	1.01
Energy Equipment and Services	1.10	1.12	1.05	1.09	1.04	1.18	1.23	1.06	1.18	0.97
Food and Staples Retailing	1.05	1.09	0.99	1.02	1.02	1.06	1.05	0.99	1.00	0.93
Food Beverage and Tobacco	1.17	1.23	1.13	1.16	1.15	1.12	1.11	1.01	1.02	0.93
Gold and Precious Metals	1.04	1.13	1.04	1.12	1.21	1.17	1.31	1.13	1.29	1.36
Health Care Equipment and Services	1.22	1.22	1.16	1.16	1.15	1.12	1.08	1.02	1.01	0.93
Hotels Restaurants and Leisure	1.06	1.07	1.01	1.02	1.04	0.89	0.89	0.84	0.85	0.80
Household and Personal Products	1.04	1.15	0.98	1.08	0.98	0.99	0.99	0.93	0.96	0.85
Insurance	1.14	1.13	1.09	1.10	1.17	1.08	1.03	1.02	1.01	1.00
Internet Software and Services	1.02	1.15	0.93	1.05	0.89	0.87	1.12	0.77	1.04	0.79
IT Services and Software	1.09	1.10	1.02	1.03	0.94	0.89	0.88	0.82	0.84	0.64
Media	1.15	1.20	1.10	1.15	1.13	1.03	1.03	0.96	0.98	0.83
Oil and Gas Exploration and Production	1.10	1.09	1.06	1.06	1.07	1.27	1.18	1.18	1.13	1.03
Oil Gas and Consumable Fuels	1.02	1.06	0.98	1.02	1.06	1.11	1.13	1.05	1.09	0.98
Pharmaceuticals and Life Sciences	1.15	1.17	1.08	1.10	1.03	1.10	1.11	1.03	1.04	0.92
Real Estate	1.13	1.16	1.06	1.09	1.14	1.27	1.29	1.18	1.18	1.12
Retailing	1.12	1.11	1.05	1.03	1.02	1.15	1.11	1.09	1.06	0.91
Semiconductors	1.02	1.02	0.93	0.96	0.86	0.87	0.92	0.78	0.86	0.65
Steel	1.03	1.01	1.02	1.02	1.11	1.29	1.26	1.25	1.21	1.20
Telecommunication Services	1.00	1.03	0.95	0.98	0.94	1.17	1.10	1.08	1.04	0.89
Transportation Non-Airline	1.01	1.03	0.99	1.00	1.06	1.07	1.07	1.02	1.02	0.95
Utilities	1.02	1.07	0.99	1.02	1.04	1.30	1.20	1.19	1.15	1.06

Table 14: GEM3 Style Factor Portfolios Bias Statistics: comparison of BIM301L and BIM303L

Equity Style Factors	Total Risk					Active Risk - ACWI Benchmark				
	301S	303S	301L	303L	303XL	301S	303S	301L	303L	303XL
Bottom Beta	1.12	1.16	1.05	1.10	1.10	1.17	1.11	1.15	1.08	1.11
Bottom Book-to-Price	1.13	1.14	1.09	1.10	1.14	1.22	1.22	1.14	1.18	1.08
Bottom Dividend Yield	1.07	1.07	1.06	1.07	1.14	1.07	1.05	1.05	1.04	1.02
Bottom Earnings Yield	1.08	1.07	1.03	1.03	1.06	1.21	1.15	1.08	1.06	0.83
Bottom Growth	1.02	1.05	0.99	1.01	1.07	1.08	1.04	1.03	1.00	0.88
Bottom Leverage	1.03	1.04	1.02	1.03	1.09	0.94	0.92	0.88	0.89	0.78
Bottom Liquidity	1.10	1.15	1.04	1.07	1.09	1.05	0.99	0.99	0.96	0.91
Bottom Momentum	1.10	1.08	1.08	1.09	1.14	1.21	1.19	1.24	1.21	1.21
Bottom Non-linear Size	0.98	0.98	0.94	0.94	0.98	0.82	0.83	0.77	0.78	0.70
Bottom Residual Volatility	1.08	1.12	1.05	1.08	1.15	1.09	1.00	1.02	0.96	0.87
Bottom Size	1.12	1.10	1.07	1.07	1.09	1.11	1.07	1.05	1.02	0.93
Top Earnings Yield	1.08	1.10	1.06	1.09	1.18	1.24	1.24	1.19	1.22	1.23
Top Beta	1.02	1.01	1.00	1.00	1.08	1.06	1.00	1.05	1.00	1.07
Top Book-to-Price	1.09	1.10	1.06	1.08	1.16	1.23	1.24	1.21	1.24	1.24
Top Dividend Yield	1.08	1.11	1.05	1.08	1.15	1.27	1.22	1.25	1.21	1.17
Top Growth	1.08	1.08	1.06	1.05	1.09	1.28	1.24	1.22	1.19	1.00
Top Leverage	1.08	1.09	1.05	1.07	1.13	1.10	1.12	1.10	1.13	1.13
Top Liquidity	1.02	1.03	0.99	1.00	1.04	1.06	1.04	0.99	0.99	0.90
Top Momentum	1.05	1.08	1.03	1.05	1.11	1.31	1.28	1.30	1.27	1.22
Top Non-linear Size	1.08	1.10	1.05	1.07	1.12	1.16	1.11	1.07	1.04	0.89
Top Residual Volatility	1.11	1.09	1.07	1.07	1.10	1.30	1.24	1.18	1.19	1.07
Top Size	1.07	1.09	1.04	1.06	1.12	1.18	1.10	1.07	1.03	0.89

A.2.2 Fixed Income

Table 15: Bias Statistics for Government Bond Duration Groups: comparison of BIM301L and BIM303L

Developed	Bias statistic		Developed	Bias statistic		Developed	Bias statistic		Emerging	Bias statistic		Emerging	Bias statistic	
Country x Duration	301	303	Country x Duration	301	303	Country x Duration	301	303	Country x Duration	301	303	Country x Duration	301	303
AUS_1-3	0.96	0.94	FIN_1-3	0.93	0.95	NLD_1-3	0.91	0.93	BGR_1-3	1.29	1.27	KOR_1-3	0.94	0.94
AUS_3-5	0.97	0.97	FIN_3-5	0.93	0.92	NLD_3-5	0.95	0.96	BGR_3-5	1.16	1.15	KOR_3-5	0.95	0.94
AUS_5-7	0.97	0.96	FIN_5-7	0.99	1.03	NLD_5-7	0.99	1.01	BGR_5-7	1.10	1.11	KOR_5-7	0.95	0.94
AUS_7-10	0.96	0.94	FIN_7-10	1.05	1.14	NLD_7-10	1.06	1.08	BGR_7-10	1.07	1.08	KOR_7-10	1.06	1.05
AUS_10+	0.93	0.86	FIN_10+	1.19	1.25	NLD_10+	1.18	1.20	BRA_1-3	0.97	0.97	KOR_10+	0.92	0.92
AUT_1-3	0.95	0.95	FRA_1-3	0.86	0.88	NOR_1-3	0.96	0.94	BRA_3-5	0.91	0.91	MEX_1-3	1.03	1.03
AUT_3-5	0.93	0.93	FRA_3-5	0.93	0.94	NOR_3-5	0.94	0.93	BRA_5-7	0.83	0.83	MEX_3-5	1.11	1.11
AUT_5-7	0.98	0.99	FRA_5-7	0.99	1.00	NOR_5-7	1.00	0.98	BRA_7-10	0.86	0.86	MEX_5-7	1.03	1.03
AUT_7-10	1.01	1.01	FRA_7-10	1.03	1.04	NOR_7-10	0.92	0.91	BRA_10+	0.89	0.89	MEX_7-10	1.04	1.04
AUT_10+	1.10	1.11	FRA_10+	1.07	1.09	NZL_1-3	1.00	1.03	CHL_1-3	1.25	1.26	MEX_10+	1.07	1.07
BEL_1-3	1.00	1.03	GBR_1-3	0.93	0.92	NZL_3-5	1.15	1.15	CHL_3-5	1.33	1.34	MYS_1-3	0.86	0.86
BEL_3-5	0.96	0.98	GBR_3-5	0.97	0.97	NZL_5-7	1.01	0.98	CHL_5-7	1.27	1.28	MYS_3-5	0.90	0.91
BEL_5-7	0.99	1.02	GBR_5-7	1.05	1.05	NZL_7-10	0.91	0.93	CHL_7-10	1.12	1.13	MYS_5-7	1.10	1.13
BEL_7-10	1.05	1.09	GBR_7-10	1.12	1.11	NZL_10+	1.38	1.76	CHL_10+	0.74	0.74	MYS_7-10	1.02	1.04
BEL_10+	1.09	1.15	GBR_10+	1.11	1.09	PRT_1-3	1.39	1.38	CHN_1-3	1.16	1.16	MYS_10+	1.11	1.12
CAN_1-3	0.93	0.91	HKG_1-3	0.66	0.66	PRT_3-5	1.33	1.31	CHN_3-5	1.04	1.04	PER_1-3	0.93	0.93
CAN_3-5	1.04	1.01	HKG_3-5	1.16	1.16	PRT_5-7	1.27	1.25	CHN_5-7	0.97	0.97	PER_3-5	0.95	0.95
CAN_5-7	1.14	1.10	HKG_5-7	1.29	1.29	PRT_7-10	1.20	1.20	CHN_7-10	0.92	0.92	PER_5-7	0.92	0.92
CAN_7-10	1.17	1.13	HKG_7-10	1.25	1.25	PRT_10+	0.96	0.98	CHN_10+	0.94	0.94	PER_7-10	0.90	0.90
CAN_10+	1.19	1.14	HKG_10+	1.25	1.25	SGP_1-3	0.68	0.68	COL_1-3	0.98	0.97	PER_10+	0.91	0.90
CHE_1-3	0.91	0.91	IRL_1-3	1.02	1.01	SGP_3-5	0.84	0.84	COL_3-5	1.11	1.10	POL_1-3	0.97	1.00
CHE_3-5	0.98	0.98	IRL_3-5	1.16	1.12	SGP_5-7	0.86	0.86	COL_5-7	0.85	0.85	POL_3-5	1.04	1.06
CHE_5-7	0.99	0.99	IRL_5-7	1.12	1.10	SGP_7-10	0.84	0.84	COL_7-10	0.74	0.73	POL_5-7	1.11	1.13
CHE_7-10	1.02	1.02	IRL_7-10	1.16	1.15	SGP_10+	0.69	0.69	GRC_1-3	1.94	1.92	POL_7-10	1.09	1.10
CHE_10+	1.11	1.10	IRL_10+	0.79	0.82	SWE_1-3	1.15	1.16	GRC_3-5	1.63	1.61	POL_10+	0.57	0.61
DEU_1-3	0.94	0.94	ISR_1-3	0.85	0.84	SWE_3-5	0.94	0.95	GRC_5-7	1.50	1.48	ROU_1-3	1.14	1.11
DEU_3-5	0.94	0.94	ISR_3-5	1.00	0.99	SWE_5-7	1.12	1.12	GRC_7-10	1.23	1.21	ROU_3-5	1.22	1.21
DEU_5-7	0.97	0.96	ISR_5-7	1.00	1.00	SWE_7-10	1.09	1.09	GRC_10+	1.13	1.14	ROU_5-7	0.87	0.86
DEU_7-10	1.02	1.06	ISR_7-10	1.06	1.06	SWE_10+	1.15	1.15	HRV_1-3	3.02	2.87	ROU_7-10	1.02	1.02
DEU_10+	1.13	1.13	ISR_10+	1.18	1.18	USA_1-3	0.82	0.78	HRV_3-5	1.40	1.40	RUS_1-3	1.48	1.49
DNK_1-3	0.97	0.97	ITA_1-3	1.30	1.28	USA_3-5	0.92	0.89	HRV_5-7	1.50	1.50	RUS_3-5	1.32	1.30
DNK_3-5	1.00	0.99	ITA_3-5	1.25	1.23	USA_5-7	1.03	0.99	HRV_7-10	0.46	0.46	RUS_5-7	1.07	1.07
DNK_5-7	1.07	1.07	ITA_5-7	1.24	1.21	USA_7-10	1.09	1.03	IDN_1-3	1.45	1.45	RUS_7-10	0.93	0.93
DNK_7-10	1.10	1.10	ITA_7-10	1.18	1.16	USA_10+	1.04	1.00	IDN_3-5	1.32	1.32	TUR_1-3	0.91	0.91
DNK_10+	1.11	1.11	ITA_10+	1.00	0.99				IDN_5-7	1.23	1.23	TUR_3-5	0.82	0.82
ESP_1-3	1.25	1.22	JPN_1-3	0.95	0.93				IDN_7-10	1.19	1.19	TUR_5-7	0.74	0.74
ESP_3-5	1.16	1.13	JPN_3-5	0.83	0.80				IDN_10+	1.27	1.27	ZAF_1-3	1.11	1.13
ESP_5-7	1.13	1.10	JPN_5-7	0.89	0.85				IND_1-3	1.08	1.08	ZAF_3-5	1.06	1.12
ESP_7-10	1.09	1.06	JPN_7-10	0.99	0.96				IND_3-5	1.07	1.06	ZAF_5-7	1.04	1.08
ESP_10+	1.03	1.01	JPN_10+	0.89	0.85				IND_5-7	1.10	1.09	ZAF_7-10	1.33	1.37
									IND_7-10	0.78	0.78	ZAF_10+	1.13	1.13
									IND_10+	0.64	0.64			

Table 16: Bias Statistics for Bank of America Merrill Lynch Fixed Income Indexes: comparison of BIM301L and BIM303L

CODE	Index Name	Bias Statistics				
		301S	303S	301L	303L	303XL
G0T0	Australian Governments	1.01	0.98	0.98	0.98	0.90
G0H0	Austrian Governments	1.16	1.09	1.03	1.03	1.09
G0G0	Belgian Governments	1.18	1.12	1.05	1.09	1.17
G0C0	Canadian Governments	1.21	1.13	1.12	1.08	0.87
G0M0	Danish Governments	1.25	1.19	1.14	1.13	1.09
G0K0	Finnish Governments	1.19	1.15	1.04	1.11	1.02
G0F0	French Governments	1.11	1.07	1.03	1.04	1.04
G0D0	German Federal Governments	1.16	1.09	1.05	1.04	1.07
G0R0	Irish Governments	1.12	1.10	1.17	1.14	1.66
G0I0	Italian Governments	1.15	1.08	1.14	1.11	1.12
G0Y0	Japanese Governments	0.96	0.87	0.83	0.79	0.53
G0N0	Dutch Governments	1.20	1.15	1.08	1.10	1.10
G0Z0	New Zealand Governments	1.16	1.11	1.12	1.09	1.02
G0U0	Portuguese Governments	1.13	1.13	1.24	1.23	1.84
G0E0	Spanish Governments	1.10	1.03	1.11	1.09	1.24
G0W0	Swedish Governments	1.16	1.10	1.08	1.08	0.93
G0S0	Swiss Governments	1.20	1.18	1.03	1.03	0.91
G0L0	UK Gilts	1.18	1.13	1.10	1.09	1.02
G0Q0	US Treasury Master	1.10	1.01	1.03	0.97	0.97
G0CL	Chile Government Index	1.39	1.39	1.06	1.06	0.91
G0CN	China Government Index	0.93	0.92	0.94	0.94	0.71
G0HK	Hong Kong Government Index	1.37	1.44	1.20	1.20	0.74
G0ID	Indonesia Government Index	1.22	1.21	1.15	1.14	1.14
G0IN	India Government Bond Index	1.41	1.45	1.25	1.25	0.99
G0MY	Malaysian Government Index	1.26	1.19	1.06	1.07	0.75
G0SK	South Korean Government Index	1.11	1.09	0.97	0.97	0.90
G0SP	Singapore Government Index	0.86	0.85	0.76	0.76	0.64
G0IS	Israel Government Bond Index	1.23	1.23	1.02	1.01	0.80
G0PL	Polish Governments	1.21	1.18	1.08	1.10	0.85
G0RU	Russia Government Index	1.22	1.20	1.13	1.12	1.10
G0TR	Turkey Government Index	0.86	0.83	0.80	0.80	0.59
G0SA	South Africa Governments G0SA	1.20	1.17	1.09	1.13	0.76
W0G1	ML Global Government Index	1.11	1.07	1.04	1.02	0.96
W0GI	ML Global Inflation-linked Sovereign bonds	1.23	1.19	1.22	1.22	1.42
G0BC	ML Global Investment Grade Corporate bonds	1.24	1.15	1.19	1.16	1.25
UC00	Sterling Corporate Index UC00	1.26	1.15	1.16	1.16	1.09
C0D0	US Domestic Industrial C0D0	1.27	1.11	1.23	1.15	1.25
C0Z0	US Domestic Yankee Master (incl CAN) C0Z0	1.27	1.13	1.19	1.11	1.05
C0A0	ML US Investment Grade Corporate bonds	1.24	1.12	1.20	1.14	1.25
C0J0	The BofA Merrill Lynch US Insurance & Financial Services Index	1.58	1.45	1.61	1.57	1.77
C0R0	The BofA Merrill Lynch US Telecommunications Index	1.23	1.09	1.16	1.11	1.20
C0Q0	US Domestic Utilities C0Q0	1.15	1.03	1.11	1.06	1.13
H0HB	US High Yield Homebuilders/Real Estate H0HB	1.93	1.52	1.92	1.60	2.15
EJ00	EMU Corporates Industrials Index EJ00	1.09	1.06	1.03	1.06	1.06
EP00	EMU Pfandbrief Index EP00	0.98	0.96	0.92	0.92	0.93
EB00	The BofA Merrill Lynch Euro Financial Index	1.14	1.12	1.06	1.09	1.11
HPC0	Euro High Yield Constrained Index	1.98	1.92	1.21	1.56	0.65
HE30	The BofA Merrill Lynch CCC & Lower Euro High Yield Index	1.35	1.29	1.30	1.32	1.26
HEFA	The BofA Merrill Lynch Euro Fallen Angel High Yield Index	1.17	1.05	1.06	1.03	1.01
IC00	The BofA Merrill Lynch Global Emerging Markets Credit Index	2.70	2.36	2.68	2.57	2.14
IP00	The BofA Merrill Lynch Global Emerging Markets Sovereign Plus Index	1.21	0.98	1.08	0.97	0.65
UKL0	The BofA Merrill Lynch Sterling Large Cap Index	1.17	1.12	1.09	1.09	1.00

A.2.3 Credit Portfolios by Currency

In this and the following tables, please note: (1) “Total risk” refers to the total return of the credit portfolios, which includes both rates and credit exposures. (2) “Active risk” is calculated relative to a duration-matched broad credit benchmark, so the remaining exposure is the credit risk of the particular sector.

Table 17: USD Credit Bias Statistics by Sector: comparison of BIM301 and BIM303

US dollar		Total risk bias statistics					Active risk bias statistics				
Portfolio	Benchmark	301S	303S	301L	303L	303XL	301S	303S	301L	303L	303XL
Corporate (All)	NA	1.18	1.07	1.13	1.08	1.19					
Auto	Corporate (All)	1.47	1.19	1.47	1.32	1.52	1.39	1.11	1.56	1.36	2.04
Banks	Corporate (All)	1.30	1.23	1.23	1.25	1.50	1.83	1.92	2.01	2.14	2.83
Consumer Discretionary excl. Auto	Corporate (All)	1.22	1.07	1.16	1.10	1.17	1.43	1.14	1.21	1.19	1.23
Consumer Staples	Corporate (All)	1.15	1.01	1.09	1.02	1.09	1.60	1.60	1.65	1.80	2.28
Corporate Non-Financial	Corporate (All)	1.20	1.06	1.16	1.09	1.18	1.46	1.44	1.58	1.64	2.41
Diversified Financial Services	Corporate (All)	1.24	1.14	1.19	1.18	1.35	1.16	1.12	1.26	1.42	1.99
Energy	Corporate (All)	1.23	1.08	1.19	1.11	1.23	1.54	1.36	1.61	1.52	2.02
Financial	Corporate (All)	1.39	1.29	1.34	1.33	1.53	1.76	1.77	1.99	2.10	3.16
Health	Corporate (All)	1.22	1.08	1.18	1.11	1.21	1.57	1.47	1.54	1.63	2.06
Industrial	Corporate (All)	1.22	1.10	1.19	1.13	1.21	1.38	1.28	1.26	1.33	1.47
Materials	Corporate (All)	1.47	1.27	1.44	1.37	1.49	1.51	1.37	1.78	1.67	2.65
Technology	Corporate (All)	1.17	1.03	1.11	1.06	1.09	1.38	1.29	1.23	1.31	1.40
Telecommunications	Corporate (All)	1.19	1.05	1.12	1.07	1.17	1.10	1.00	1.01	1.08	1.08
Transportation	Corporate (All)	1.28	1.12	1.24	1.16	1.24	1.55	1.39	1.53	1.57	1.89
Utility	Corporate (All)	1.12	1.00	1.08	1.02	1.08	1.40	1.25	1.32	1.37	1.71
Non-Corporate (All)	NA	1.00	0.93	0.92	0.86	0.84					
Agency	Non-Corporate (All)	1.01	0.93	0.95	0.89	0.90	2.39	2.00	2.93	2.45	3.63
Foreign Agency	Non-Corporate (All)	1.01	0.94	0.91	0.87	0.82	1.07	0.97	1.11	1.00	1.28
Sovereign	Non-Corporate (All)	1.13	1.06	1.01	0.96	0.94	1.47	1.27	1.30	1.27	1.21
Supranational	Non-Corporate (All)	1.02	0.95	0.92	0.88	0.84	1.14	1.01	1.23	1.07	1.39
High Yield (All)	NA	1.67	1.42	1.62	1.48	1.57					
High Yield Consumer Disc.	High Yield (All)	1.52	1.13	1.48	1.20	1.73	1.34	0.93	1.27	0.95	1.31
High Yield Consumer Staples	High Yield (All)	1.58	1.34	1.48	1.36	1.29	0.84	0.76	0.78	0.74	0.63
High Yield Energy	High Yield (All)	1.74	1.47	1.67	1.51	1.64	1.48	1.26	1.42	1.33	1.25
High Yield Finance	High Yield (All)	1.73	1.36	1.78	1.46	1.81	1.67	1.28	1.84	1.47	1.83
High Yield Health	High Yield (All)	1.57	1.35	1.40	1.32	1.25	1.28	1.15	1.12	1.12	0.96
High Yield Industrial	High Yield (All)	1.71	1.41	1.61	1.45	1.69	1.16	0.99	1.08	1.03	0.97
High Yield Materials	High Yield (All)	1.84	1.45	1.78	1.54	1.80	1.26	0.92	1.22	1.02	1.09
High Yield Telecommunications	High Yield (All)	1.31	1.11	1.14	1.13	0.89	0.76	0.65	0.63	0.60	0.50
High Yield Utility	High Yield (All)	1.30	1.05	1.12	1.01	0.91	1.25	1.04	1.09	1.03	0.87
Emerging Markets	NA	1.27	1.00	1.13	0.99	0.62					
Conventional 15yr Mortgage	NA	0.95	0.88	0.85	0.81	0.84					
Conventional 30yr Mortgage	NA	0.85	0.79	0.82	0.77	0.89					
GNMA 15yr Mortgage	NA	0.93	0.86	0.77	0.73	0.70					
GNMA 30yr Mortgage	NA	0.91	0.85	0.86	0.81	0.93					

Table 18: Euro Region Credit Bias Statistics by Sector: comparison of BIM301 and BIM303

EURO		Total risk bias statistics					Active risk bias statistics				
Portfolio	Benchmark	301 S	303 S	301 L	303 L	303 XL	301 S	303 S	301 L	303 L	303 XL
Corporate (All)	NA	1.23	1.23	1.16	1.26	1.31					
Auto	Corporate (All)	1.20	1.14	1.18	1.17	1.28	1.73	1.67	1.89	1.91	1.98
Consumer Disc. excl. Auto	Corporate (All)	1.05	1.05	0.99	1.06	1.02	1.33	1.35	1.22	1.41	1.18
Consumer Staples	Corporate (All)	1.03	1.02	0.97	1.01	1.02	2.32	2.43	2.24	2.55	2.45
Corporate Non-Financial	Corporate (All)	1.08	1.06	1.04	1.07	1.08	2.70	2.98	2.79	3.19	2.85
Diversified Financial Services	Corporate (All)	1.38	1.41	1.39	1.51	1.34	1.75	1.71	1.53	2.00	1.10
Energy	Corporate (All)	1.04	1.00	0.97	0.98	0.98	2.19	2.21	2.01	2.24	2.09
Financial	Corporate (All)	1.44	1.46	1.45	1.52	1.61	3.52	4.00	3.69	4.28	3.16
Health	Corporate (All)	1.01	1.01	0.96	1.00	1.00	2.25	2.42	2.16	2.45	2.22
Industrial	Corporate (All)	1.13	1.14	1.12	1.18	1.21	1.61	1.98	1.67	2.10	1.71
Materials	Corporate (All)	1.17	1.17	1.17	1.25	1.30	1.94	2.29	2.19	2.70	2.46
Telecommunications	Corporate (All)	1.08	1.05	1.03	1.07	0.97	1.23	1.19	1.12	1.31	0.96
Transportation	Corporate (All)	1.05	1.04	0.98	1.03	0.98	1.53	1.70	1.54	1.72	1.46
Utility	Corporate (All)	1.05	1.04	0.99	1.03	1.01	2.33	2.56	2.41	2.71	2.42
Non-Corporate (All)	NA	1.02	0.99	0.93	0.95	0.95					
Agency	Non-Corporate (All)	1.00	0.98	0.92	0.94	0.95	1.03	0.92	1.06	1.00	1.23
Muni	Non-Corporate (All)	1.01	0.97	0.93	0.94	0.95	1.51	1.30	1.50	1.33	1.55
Sovereign	Non-Corporate (All)	1.08	1.03	0.98	0.99	0.97	1.73	1.57	1.89	1.75	2.17
Supranational	Non-Corporate (All)	1.08	1.05	0.99	1.01	1.02	1.15	1.04	1.03	1.01	1.16
High Yield (All)	NA	1.40	1.41	1.45	1.54	1.48					
High Yield Finance	High Yield (All)	1.76	1.46	1.57	1.34	1.81	1.22	1.09	1.32	1.21	1.41
Covered Bonds(All)	NA	1.00	1.01	0.93	0.96	0.97					
Non-Pfandbrief Covered	Covered Bonds (All)	1.00	1.03	0.94	0.98	0.99	1.01	1.12	1.00	1.11	1.21
Pfandbrief	Covered Bonds (All)	0.96	0.94	0.90	0.90	0.91	1.01	1.12	1.00	1.11	1.21

Table 19: Canadian Dollar Credit Bias Statistics by Sector: comparison of BIM301 and BIM303

Canadian Dollar		Total risk bias statistics					Active risk bias statistics				
Portfolio	Benchmark	301 S	303 S	301 L	303 L	303 XL	301 S	303 S	301 L	303 L	303 XL
Corporate (All)	NA	1.09	1.04	0.99	0.98	0.79					
Banks	Corporate (All)	1.07	1.01	0.95	0.92	0.76	1.04	0.98	1.07	1.11	1.19
Corporate Non-Financial	Corporate (All)	1.13	1.07	1.04	1.03	0.85	1.34	1.19	1.38	1.35	1.40
Diversified Financial Services	Corporate (All)	1.45	1.35	1.40	1.34	1.16	3.04	2.88	3.38	3.45	3.98
Energy	Corporate (All)	1.13	1.06	1.05	1.05	0.87	1.57	1.44	1.62	1.61	1.72
Financial	Corporate (All)	1.12	1.06	1.01	0.99	0.81	1.44	1.30	1.49	1.46	1.49
Industrial	Corporate (All)	1.11	1.05	1.01	1.02	0.87	1.16	1.22	1.22	1.32	1.41
Transportation	Corporate (All)	1.11	1.06	1.03	1.01	0.83	1.54	1.55	1.57	1.61	1.53
Utility	Corporate (All)	1.14	1.07	1.05	1.04	0.85	1.26	1.11	1.21	1.21	1.16
Non-Corporate (All)	NA	1.15	1.09	1.08	1.05	0.85					
Muni	Non-Corporate (All)	1.07	1.00	1.00	0.97	0.81	0.72	0.65	0.71	0.69	0.64
Provincial	Non-Corporate (All)	1.17	1.10	1.10	1.07	0.89	1.01	0.85	0.91	0.85	0.70

Table 20: Pound Sterling Credit Bias Statistics by Sector: comparison of BIM301 and BIM303

British Pound Sterling		Total risk bias statistics					Active risk bias statistics				
Portfolio	Benchmark	301 S	303 S	301 L	303 L	303 XL	301 S	303 S	301 L	303 L	303 XL
Corporate (All)	NA	1.39	1.32	1.37	1.40	1.38					
Banks	Corporate (All)	1.67	1.64	1.68	1.83	1.91	2.44	2.65	2.55	3.20	3.34
Consumer Disc.	Corporate (All)	1.23	1.13	1.14	1.19	1.09	1.61	1.58	1.60	1.81	1.76
Consumer Staples	Corporate (All)	1.16	1.08	1.08	1.06	1.00	2.30	2.31	2.42	2.72	2.99
Corporate Non-Financial	Corporate (All)	1.19	1.10	1.11	1.10	0.99	2.60	2.85	2.87	3.44	3.63
Diversified Financial Services	Corporate (All)	1.57	1.46	1.57	1.60	1.69	3.00	2.52	3.13	3.00	3.28
Energy	Corporate (All)	1.07	0.99	1.00	0.98	0.95	2.06	2.13	2.20	2.49	2.74
Financial	Corporate (All)	1.68	1.66	1.73	1.86	1.96	3.10	3.43	3.46	4.16	4.21
Industrial	Corporate (All)	1.18	1.10	1.10	1.10	1.01	1.50	1.48	1.48	1.65	1.68
Materials	Corporate (All)	1.41	1.26	1.36	1.41	1.42	1.36	1.39	1.50	1.59	1.72
Telecommunications	Corporate (All)	1.22	1.09	1.12	1.11	1.05	1.30	1.28	1.37	1.46	1.48
Transportation	Corporate (All)	1.12	1.05	1.05	1.04	0.98	2.21	2.16	2.31	2.49	2.74
Utility	Corporate (All)	1.19	1.09	1.09	1.08	0.88	2.05	2.15	1.99	2.55	1.86
Non-Corporate (All)	NA	1.10	1.05	1.03	1.02	0.94					
Agency	Non-Corporate (All)	1.09	1.03	1.00	0.99	0.91	0.92	0.83	0.92	0.86	0.94
Sovereign	Non-Corporate (All)	1.11	1.03	1.05	1.03	0.99	1.08	1.00	1.07	1.02	1.18
Supranational	Non-Corporate (All)	1.10	1.04	1.03	1.01	0.94	0.77	0.69	0.75	0.69	0.78
High Yield (All)	NA	0.92	0.93	0.77	0.86	0.92					
Covered Bonds (All)	NA	1.17	1.09	1.11	1.09	1.04					

Table 21: Swiss Franc and Australian Dollar Credit Bias Statistics by Sector: comparison of BIM301 and BIM303

Swiss Franc		Total risk bias statistics					Active risk bias statistics				
Portfolio	Benchmark	301 S	303 S	301 L	303 L	303 XL	301 S	303 S	301 L	303 L	303 XL
Corporate (All)	NA	1.14	1.17	1.07	1.07	1.12					
Banks	Corporate (All)	1.09	1.11	0.99	0.99	0.97	2.53	2.54	2.85	2.80	3.41
Corporate Non-Financial	Corporate (All)	1.07	1.07	0.94	0.94	0.86	2.08	2.16	2.58	2.59	2.97
Diversified Financial Services	Corporate (All)	1.39	1.43	1.34	1.34	1.55	1.61	1.69	1.71	1.71	2.48
Financial	Corporate (All)	1.18	1.22	1.13	1.13	1.23	2.39	2.46	2.99	2.99	3.38
Non-Corporate (All)	NA	1.18	1.18	1.06	1.06	0.98					
Muni	Non-Corporate (All)	1.09	1.08	0.98	0.98	0.89	1.13	1.08	1.08	1.08	1.04
Covered Bonds (All)	NA	1.13	1.13	1.03	1.03	0.98					

Australian Dollar		Total risk bias statistics					Active risk bias statistics				
Portfolio	Benchmark	301 S	303 S	301 L	303 L	303 XL	301 S	303 S	301 L	303 L	303 XL
Corporate (All)	NA	0.99	0.93	0.98	0.94	0.88					
Banks	Corporate (All)	1.01	0.94	1.00	0.96	0.90	2.12	1.52	2.48	1.74	2.90
Corporate Non-Financial	Corporate (All)	1.00	0.94	0.98	0.97	0.90	1.37	1.13	1.40	1.04	1.70
Energy	Corporate (All)	1.08	1.05	1.06	1.07	1.05	1.57	1.52	1.63	1.51	1.98
Financial	Corporate (All)	1.01	0.93	0.99	0.94	0.90	1.42	1.18	1.48	1.11	1.78
Non-Corporate (All)	NA	0.98	0.92	0.93	0.91	0.83					
Agency	Non-Corporate (All)	0.99	0.94	0.96	0.94	0.86	0.97	0.94	1.00	0.94	1.00
Muni	Non-Corporate (All)	0.99	0.93	0.94	0.93	0.84	1.63	1.39	1.48	1.25	1.60
Sovereign	Non-Corporate (All)	0.90	0.85	0.89	0.87	0.81	1.29	1.14	1.21	1.06	1.31
Supranational	Non-Corporate (All)	0.97	0.91	0.93	0.91	0.84	1.59	1.36	1.37	1.16	1.49

Table 22: Japanese Yen and Swedish Krona Credit Bias Statistics by Sector: comparison of BIM301 and BIM303 [24]

Japanese Yen		Total risk bias statistics					Active risk bias statistics				
Portfolio	Benchmark	301 S	303 S	301 L	303 L	303 XL	301 S	303 S	301 L	303 L	303 XL
Corporate (All)	NA	1.00	0.93	0.89	0.86	0.61					
AA	Corporate (All)	0.95	0.88	0.86	0.82	0.59	1.59	1.63	1.62	1.66	1.66
BBB	Corporate (All)	1.22	1.18	1.19	1.21	0.99	1.53	1.43	1.49	1.51	1.51
SAMURAI	Corporate (All)	1.20	1.18	1.25	1.26	1.42	1.44	1.53	1.56	1.66	1.66
Non-Corporate (All)	NA	0.92	0.83	0.82	0.77	0.55					
Government Guaranteed	NA	0.90	0.81	0.81	0.75	0.54					
IPB	NA	1.25	1.49	1.22	1.27	1.27					

Swedish Krona		Total risk bias statistics					Active risk bias statistics				
Portfolio	Benchmark	301 S	303 S	301 L	303 L	303 XL	301 S	303 S	301 L	303 L	303 XL
Corporate (All)	NA	0.98	0.96	0.79	0.78	0.60					
Banks	Corporate (All)	0.86	0.83	0.69	0.68	0.53	0.82	0.79	0.76	0.74	0.68
Corporate Non-Financial	Corporate (All)	0.94	0.91	0.80	0.78	0.64	0.41	0.39	0.35	0.34	0.26
Financial	Corporate (All)	0.97	0.93	0.77	0.75	0.57	0.42	0.41	0.37	0.35	0.28
Non-Corporate (All)	NA	1.12	1.07	0.92	0.90	0.73					
Agency	Non-Corporate (All)	1.08	1.02	0.90	0.86	0.71	2.00	1.43	1.49	1.18	1.04
Covered Bonds (All)	NA	0.96	0.94	0.76	0.75	0.58					

A.2.4 Multi-Asset Class

Table 23: Target Date Portfolio Bias Statistics: comparison of BIM301 and BIM303

Target Date Portfolios	Total Risk Bias Statistics				
Years to Retirement	**301S**	**303S**	**301L**	**303L**	**303XL**
45 to 25	1.03	1.04	1.03	1.05	1.15
20	1.04	1.05	1.03	1.06	1.16
15	1.04	1.05	1.04	1.06	1.17
10	1.05	1.06	1.05	1.07	1.17
5	1.05	1.07	1.05	1.08	1.18
0	1.06	1.07	1.06	1.08	1.19
-5	1.07	1.08	1.07	1.09	1.20
-10 to -30	1.08	1.09	1.08	1.10	1.20

[24] Swedish Krona backtest period is Mar 2012 to Mar 2015.

Table 24: Risk-Balanced Portfolios Bias Statistics: comparison of BIM301 and BIM303

Country	Region	Bias statistics				
		301S	303S	301L	303L	303XL
AUSTRALIA	Developed	1.05	1.05	0.97	0.98	0.96
AUSTRIA	Developed	1.01	1.00	0.94	0.95	0.90
BELGIUM	Developed	1.01	1.01	0.96	0.98	0.97
CANADA	Developed	1.02	1.01	0.94	0.96	0.93
DENMARK	Developed	0.97	0.99	0.93	0.96	0.95
FINLAND	Developed	0.98	1.00	0.96	0.98	0.99
FRANCE	Developed	0.96	0.96	0.91	0.92	0.91
GERMANY	Developed	1.01	1.01	0.94	0.95	0.91
HONG KONG	Developed	1.09	1.06	1.03	0.97	0.88
IRELAND	Developed	1.04	1.04	1.00	1.01	0.99
ISRAEL	Developed	0.97	0.95	0.89	0.89	0.89
ITALY	Developed	0.96	0.98	0.94	0.96	0.96
JAPAN	Developed	1.01	0.99	0.94	0.94	0.89
NETHERLANDS	Developed	1.00	1.00	0.94	0.95	0.91
NEW ZEALAND	Developed	0.97	0.98	0.93	0.95	0.93
NORWAY	Developed	1.05	1.05	1.01	1.03	1.03
PORTUGAL	Developed	1.03	1.04	0.98	1.00	0.96
SINGAPORE	Developed	1.09	1.11	1.01	1.02	0.93
SPAIN	Developed	1.01	1.03	0.97	0.99	0.98
SWEDEN	Developed	0.98	0.99	0.95	0.96	0.97
SWITZERLAND	Developed	0.90	0.92	0.86	0.89	0.89
UNITED KINGDOM	Developed	1.00	0.99	0.94	0.94	0.94
US	Developed	1.02	1.00	0.95	0.95	0.91
BRAZIL	Emerging	1.02	1.05	0.98	0.98	0.94
CHILE	Emerging	1.01	1.01	0.98	0.98	0.97
COLOMBIA	Emerging	1.04	1.10	0.97	1.03	0.99
CZECH REPUBLIC	Emerging	1.06	1.06	1.00	1.00	0.99
GREECE	Emerging	0.92	0.93	0.91	0.92	0.88
INDIA	Emerging	1.08	1.06	1.02	1.00	1.01
INDONESIA	Emerging	1.09	1.06	0.99	1.04	0.89
KOREA	Emerging	1.15	1.03	0.99	0.96	0.82
MALAYSIA	Emerging	0.95	1.01	0.84	0.95	0.88
MEXICO	Emerging	1.03	1.00	0.95	0.95	0.85
PERU	Emerging	1.32	1.06	1.36	1.03	1.07
ARGENTINA	Frontier	1.00	1.01	1.00	1.02	0.99
UAE	Frontier	0.84	0.86	0.71	0.74	0.60

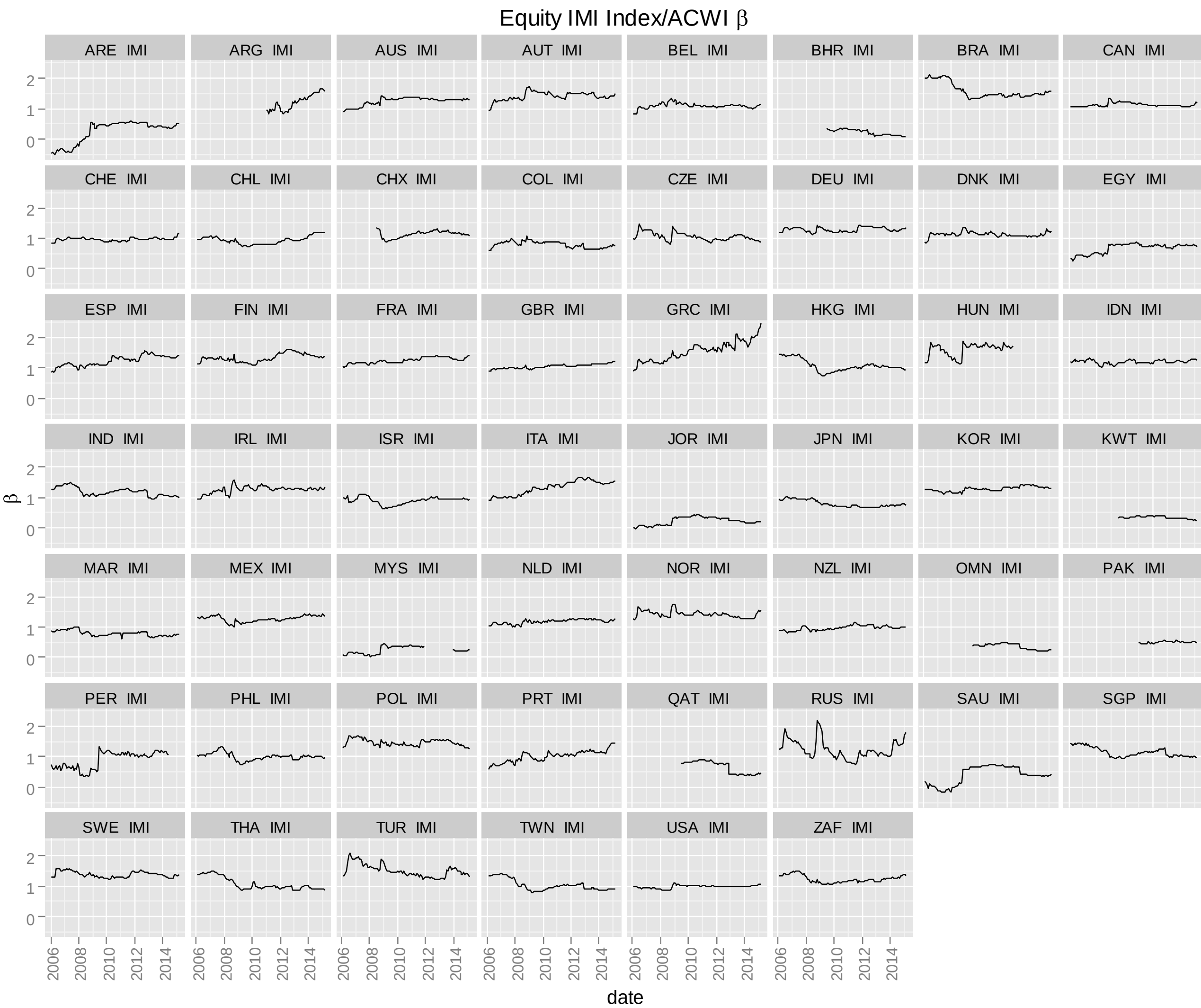
Table 25: Commodity Long/Short Portfolio Bias Statistics (Partial): comparison of BIM301 and BIM303

	Bias Statistics				
Commodity Long / Short Portfolios	**301S**	**303S**	**301L**	**303L**	**303XL**
Long_Aluminum_Short_ACWI	0.97	0.95	0.95	0.94	0.97
Long_Brent Crude_Short_ACWI	1.04	0.95	0.95	0.98	0.89
Long_Cocoa_Short_ACWI	1.00	0.90	0.90	0.88	0.86
Long_Coffee_Short_ACWI	1.12	1.04	1.04	1.05	0.92
Long_Copper_Short_ACWI	1.13	1.04	1.04	1.04	0.99
Long_Corn_Short_ACWI	1.16	1.09	1.09	1.08	1.21
Long_Cotton_Short_ACWI	0.96	0.84	0.84	0.85	0.85
Long_Crude Oil_Short_ACWI	1.02	0.93	0.93	0.95	0.92
Long_Feeder Cattle_Short_ACWI	1.08	1.02	1.02	1.03	1.08
Long_Gas Oil_Short_ACWI	1.10	0.99	0.99	1.03	0.95
Long_Gasoline_Short_ACWI	1.01	0.92	0.92	0.92	0.87
Long_Gold_Short_ACWI	1.11	1.06	1.06	1.04	1.17
Long_Heating Oil_Short_ACWI	1.01	0.91	0.91	0.93	0.89
Long_Kansas Wheat_Short_ACWI	1.18	1.14	1.14	1.14	1.24
Long_Lead_Short_ACWI	1.02	0.97	0.97	0.96	1.00
Long_Lean Hogs_Short_ACWI	1.10	1.05	1.05	1.04	1.02
Long_Live Cattle_Short_ACWI	1.13	1.04	1.04	1.04	1.08
Long_Minnesota Wheat_Short_ACWI	1.26	1.21	1.21	1.23	1.31
Long_Natural Gas_Short_ACWI	1.02	0.95	0.95	0.93	0.90
Long_Nickel_Short_ACWI	1.02	0.92	0.92	0.92	0.87
Long_NY Copper_Short_ACWI	1.13	1.02	1.02	1.01	1.04
Long_Orange Juice_Short_ACWI	0.91	0.86	0.86	0.86	0.93
Long_Palladium_Short_ACWI	1.02	0.92	0.92	0.89	0.82
Long_Platinum_Short_ACWI	1.08	1.03	1.03	1.05	1.05
Long_Robusta Coffee_Short_ACWI	1.11	1.03	1.03	1.05	0.93
Long_Silver_Short_ACWI	1.14	1.06	1.06	1.03	1.19
Long_Soybean Meal_Short_ACWI	1.10	1.03	1.03	1.05	1.09
Long_Soybean Oil_Short_ACWI	1.17	1.08	1.08	1.07	1.04
Long_Soybeans_Short_ACWI	1.13	1.05	1.05	1.07	1.07
Long_Sugar_Short_ACWI	1.06	1.00	1.00	0.98	1.02
Long_Tin_Short_ACWI	1.02	0.96	0.96	0.94	0.96
Long_Wheat_Short_ACWI	1.16	1.11	1.11	1.11	1.23
Long_White Sugar_Short_ACWI	1.05	0.99	0.99	1.00	1.08
Long_Zinc_Short_ACWI	0.97	0.92	0.92	0.91	0.93

A.3 Betas (Sensitivities)

A.3.1 MSCI Equity Country Indexes Sensitivity to MSCI ACWI Index

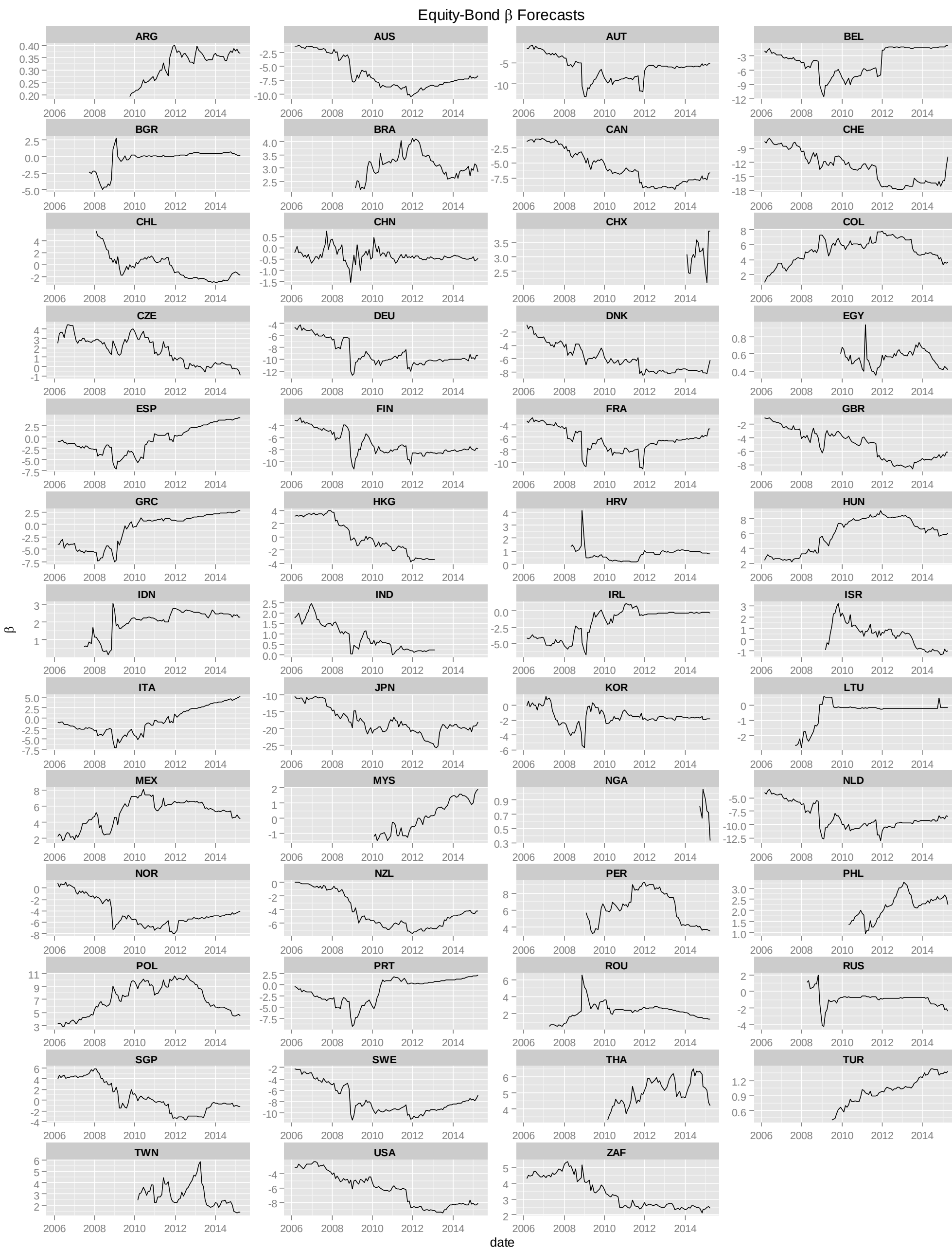
Figure 24: Forecast Betas for Equity Markets. Each small chart shows a single MSCI Index. The time series data represent the forecast betas of each country index to the global index (ACWI), as of each month in the 2006-2015 period. Many of the developed markets (and some emerging markets) have sensitivities around 1.0, and many are quite stable (see Greece and Russia, as counterexamples). Some of the emerging markets (for example, Bahrain, Jordon) have betas closer to zero.



Note: MYS IMI to ACWI beta is missing from Sept 2012 to Jul 2014, because we require our portfolios to contain more than five assets, and MYS IMI did not meet this requirement during the period.

A.3.2 MSCI Equity Country Indexes Sensitivity to corresponding Government Bond Index

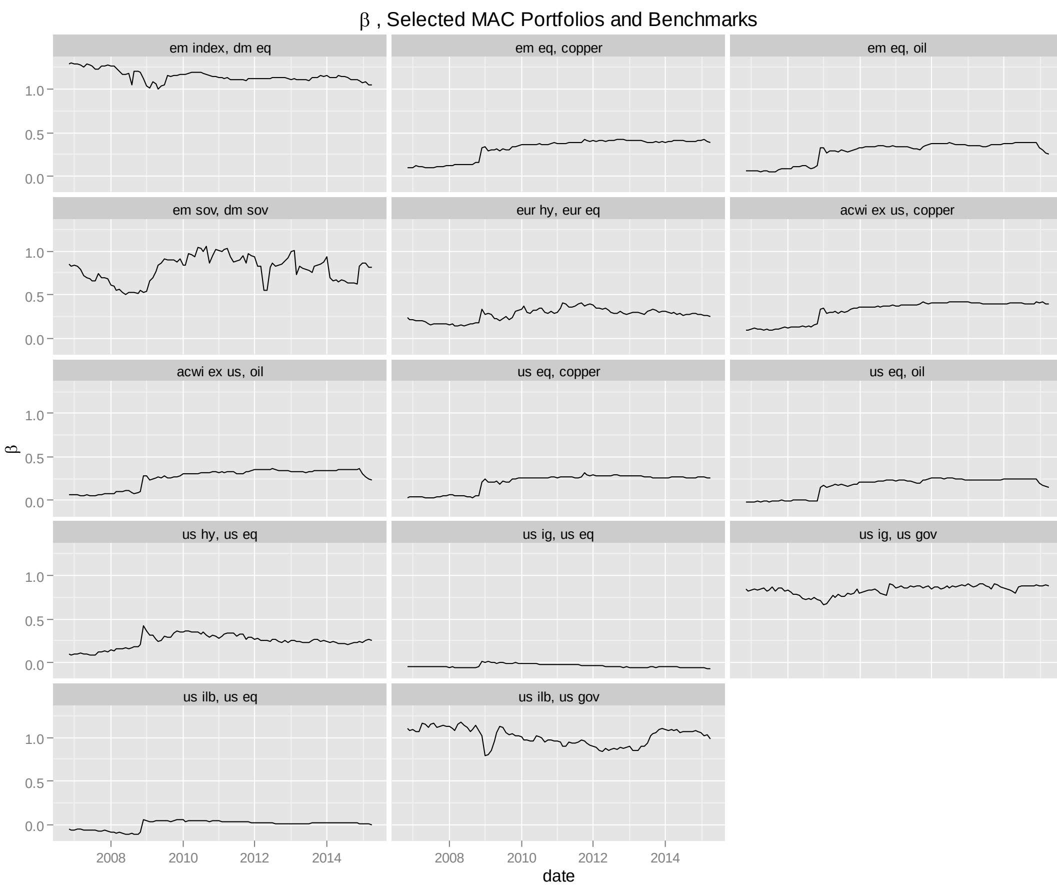
Figure 25: Time Varying Betas for Country Equity – Bond Pairs. Each small chart shows a single country. The time series data represent the forecast betas of each country's equity index to this country's government shift factor. Many of the developed markets have negative betas, while emerging markets are more prone to have positive betas. For countries like Greece, the sign flip over time is pronounced.



A.3.3 Cross-Asset Class (Selected Asset Pairs)

Figure 26: Forecast Betas for Selected Cross-Asset-Class Pairs. Each small chart shows the time series of the beta of the first series in the pair to the second series, as of each month in the 2006-2015 period. (Note that although these charts show the sensitivity of the second asset in the pair to the first asset, there is no *natural order* as in the previous two sets of sensitivities.) The charts, from left to right and top to bottom, show the following pairs:

Emerging Mkt. (EM) Equity – Devel. Mkt. (DM) Equity	EM Equity – Copper	EM Equity – Crude Oil
EM Sovereign Debt – DM Sovereign Debt	Europe High Yield to Europe Equity	Non-US DM Equity – Copper
Non-US DM Equity – Crude Oil	US Equity to Copper	US Equity to Oil
US High Yield to US Equity	US Investment Grade Credit to US Equity	US Investment Grade Credit to US Treasury
US Inflation Linked Bonds to US Equity	US Inflation Linked Bonds to US Treasury	



A.4 Bias Statistic Details

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

$$\frac{\text{realized volatility}}{\text{forecast volatility}}. \tag{1}$$

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

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

$$\mathrm{z_{p,t}} = \frac{\mathrm{R_{p,t}}}{\sigma_{\mathrm{p,t-1}}}, \tag{2}$$

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 period. If risk forecasts are accurate, then the *bias statistic*

$$B_p \equiv std(z_{p,t}) \tag{3}$$

would be close to one, in analogy with Equation (1). Indeed, in the limit that risk forecasts are constant, the Bias Statistic reduces to Equation (1).

The bias statistic is a useful measure of the accuracy of a risk model, particularly the existence of systematic inaccuracies, such as missing factors or a failure to account for serial correlation. Bias statistics greater than one suggest risk is underforecast, while bias statistics less than one indicate risk is overforecast.

Even a perfect risk forecast would not lead to a bias statistic of exactly one, due to sampling error in realized volatility. The sampling error of the bias statistic for a perfect risk forecast and a test period of T returns is approximately

$$\Delta\mathrm{B} = \sqrt{\frac{\mathrm{k}}{4(\mathrm{T}-1)}}, \tag{4}$$

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

Appendix B: Model Components — Detail

B.1 Component Equity, Fixed Income, and Real Estate Models by Country and Region

As we see in Table 26 and following, BIM includes a large number of single-country models for Equity, Fixed Income, and Real Estate. The counties are grouped by MSCI region (whether the country is included in the MSCI Developed, Emerging, or Frontier markets). Changes from BIM301 to BIM303 are indicated by the column headers.

Table 26: BIM Component Models: Developed Markets

		EQUITY		FIXED INCOME		
MSCI Region	Country	BIM 301 and 303	New in BIM 303	BIM 301 and 303	New in BIM 303	Real Estate Model
Devel	Europe**	EUE3	EUE4	EUF3		
Devel	Austria		ATEUE4	EUF3/ATF2		Y
Devel	Belgium		BEEUE4	EUF3/BEF2		Y
Devel	Denmark		DKEUE4	DKF2		Y
Devel	Finland		FIEUE4	EUF3/FIF2		
Devel	France		FREUE4	EUF3/FRF2		Y
Devel	Germany		DEEUE4	EUF3/GRF2		Y
Devel	Ireland		IEEUE4	EUF3/IEF2		Y
Devel	Italy		ITEUE4	EUF3/ITF2		Y
Devel	Netherlands		NLEUE4	EUF3/NLF2		Y
Devel	Norway		NOEUE4	NOF2		Y
Devel	Portugal		PTEUE4	EUF3/PTF2		Y
Devel	Spain		ESEUE4	EUF3/ESF2		Y
Devel	Sweden		SEEUE4	SEF2		Y
Devel	Switzerland		CHEUE4	CHF3		Y
Devel	Australia	AUE3	AUE4	AUF3		Y
Devel	Canada	CNE4	CAE5	CAF3		Y
Devel	Hong Kong	HKE1		HKF3	HKF4	Y
Devel	Israel	ILE1		ILF1		
Devel	Japan	JPE3	JPE4	JPF4		Y
Devel	New Zealand	NZE1		NZF2		Y
Devel	Singapore	SGE1		SGF3	SGF4	Y
Devel	UK	UKE7		GBF3		Y
Devel	US	USE3	USE4	USF4		Y

Table 27: BIM Component Models: Emerging Markets

		EQUITY		FIXED INCOME		
MSCI Region	Country	BIM 301 and 303	New in BIM 303	BIM 301 and 303	New in BIM 303	Real Estate Model
Emerg	Brazil	BRE2	BRE2	BRF1		
Emerg	Chile	CLE1	CLE1	CLF2		
Emerg	China	CHE2	CNE5	CNF3	CNF4	Y
Emerg	China Offshore				CXF1	
Emerg	Colombia	COE1		COF1		
Emerg	Czech Republic		CZEUE4	CZF2		Y
Emerg	Egypt	EGE1		EGF1		
Emerg	Greece		GREUE4	EUF3/GCF2		
Emerg	Hungary		HUEUE4	HUF2		Y
Emerg	India	INE1		INF3	INF4	
Emerg	Indonesia	IDE1		IDF2		Y
Emerg	Korea	KRE2	KRE3	KRF3		Y
Emerg	Malaysia	MLE1		MYF2	MYF4	Y
Emerg	Mexico	MXE1		MXF3		
Emerg	Peru	PEE1		PEF1		
Emerg	Philippines	PHE1		PHF3	PHF4	
Emerg	Poland		PLEUE4	PLF2		Y
Emerg	Russia		RUEUE4	RUF2		
Emerg	South Africa	SAE3	ZAE4	ZAF2		Y
Emerg	Taiwan	TWE1		TWF2	TWF3	Y
Emerg	Thailand	THE1		THF3	THF4	Y
Emerg	Turkey		TREUE4	TRF2		

Table 28: BIM Component Models: Frontier Markets

		EQUITY		FIXED INCOME		
MSCI Region	Country	BIM 301 and 303	New in BIM 303	BIM 301 and 303	New in BIM 303	Real Estate Model
Frontier	Argentina	ARE1		ARF1		
Frontier	Bahrain	BHE1			EMF3	
Frontier	Bangladesh		EMM1		EMF3	
Frontier	Bosnia & Herzegovina		BAEUE4		EMF3	
Frontier	Botswana		EMM1		EMF3	
Frontier	Bulgaria		BGEUE4	BGF2		
Frontier	Croatia		HREUE4	HRF2		
Frontier	Estonia		EEEUE4		EUF3	
Frontier	Ghana		EMM1		EMF3	
Frontier	Jamaica		EMM1		EMF3	
Frontier	Jordan	JOE1			EMF3	
Frontier	Kazakhstan		KZEUE4		EMF3	
Frontier	Kenya		EMM1		EMF3	
Frontier	Kuwait	KWE1	KWE1		EMF3	
Frontier	Latvia		LTEUE4		EUF3	
Frontier	Lebanon		EMM1		EMF3	
Frontier	Lithuania		LVEUE4	LTF2		
Frontier	Mauritius		EMM1		EMF3	
Frontier	Morocco	MOE1			EMF3	
Frontier	Nigeria	NGE1			NGF1	
Frontier	Oman	OME1			EMF3	
Frontier	Pakistan	PKE1			EMF3	
Frontier	Palestine		EMM1			
Frontier	Qatar	QAE1			EMF3	
Frontier	Romania		ROEUE4	ROF2	ROF2	
Frontier	Saudi Arabia	SUE1			EMF3	
Frontier	Serbia		RSEUE4		EMF3	
Frontier	Slovenia		SIEUE4		EUF3	
Frontier	Sri Lanka	LKE1			EMF3	
Frontier	Trinidad & Tobago		EMM1		EMF3	
Frontier	Tunisia		EMM1		EMF3	
Frontier	UAE	AEE1			EMF3	
Frontier	Ukraine		UAEUE4		EMF3	
Frontier	Vietnam		EMM1		EMF3	
Frontier+	Cyprus		CYEUE4		EUF3	
Frontier+	Iceland		ISEUE4	ISF2		
Frontier+	Slovakia	SKE1		SKF2		

Table 29: BIM Component Models: Other Markets

		EQUITY		FIXED INCOME		
MSCI Region	Country	BIM 301 and 303	New in BIM 303	BIM 301 and 303	New in BIM 303	Real Estate Model
N/A	Belarus				EMF3	
N/A	Cote d'Ivoire		EMM1		EMF3	
N/A	Dominican Rep.				EMF3	
N/A	Ecuador				EMF3	
N/A	El Salvador				EMF3	
N/A	Gabon				EMF3	
N/A	Georgia				EMF3	
N/A	Iraq				EMF3	
N/A	Macedonia		EMM1		EMF3	
N/A	Malta		EMM1			
N/A	Montenegro		EMM1			
N/A	Namibia		EMM1		EMF3	
N/A	Panama				EMF3	
N/A	Sierra Leone				EMF3	
N/A	Uruguay				EMF3	
N/A	Venezuela		EMM1		EMF3	
N/A	Zambia		EMM1			

B.2 Component Alternatives Models

The following tables summarize the structure of MSCI's alternative asset class models Reference links to the complete model documentation are also given.

For information on the Private Real Estate Model (PRE2), see https://support.msci.com/docs/DOC-8956.

For information on the Currency Model (CUR2), see https://support.msci.com/docs/DOC-3649.

Table 30: Private Equity Model Components

Private Equity Model (PEQ2)			
	Regions		
Strategies	**North America**	**Europe, Mid-East, Africa**	**Asia Pacific**
Large Buyout Funds	X	X	X
Small Buyout Funds	X	X	X
Early Stage Venture Capital	X	X	X
Late Stage Venture Capital	X	X	X
Mezzanine Debt	X	X	X
Distressed Debt	X	X	

https://support.msci.com/docs/DOC-9478

Table 31: Equity Volatility Futures Model Components

Equity Volatility Futures Model (EVX1)		
Equity Market	Variance Shift	Variance Relative Spot
Australia	X	
Germany	X	
Euro	X	X
Great Britain	X	
Hong Kong	X	
Japan	X	
Korea	X	
Spain	X	
Switzerland	X	
United States	X	X

https://support.msci.com/docs/DOC-4251

Table 32: Hedge Fund Model Components

Hedge Fund Model (HFM2)
Strategy Factors
Convertible Arbitrage
Distressed Securities
Equity and Market Neutral
Event Driven Multi-Strategy
Fixed-Income Arbitrage
Fund-of-Hedge-Funds
Global Macro
Managed Futures
Merger Arbitrage

https://support.msci.com/docs/DOC-3642

Table 33: Commodity Model Components

Commodity Model (COM2)							
Commodity	Shift	Twist	Butterfly	Commodity	Shift	Twist	Butterfly
Aluminum	X	X		Minnesota Wheat	X	X	
Brent Crude	X	X		Natural Gas	X	X	X
Cocoa	X	X		Nickel	X	X	
Coffee	X	X		NY Copper	X	X	
Copper	X	X		Orange Juice	X	X	
Corn	X	X		Platinum	X		
Cotton	X	X		Palladium	X		
Crude Oil	X	X	X	Robusta Coffee	X	X	
Feeder Cattle	X	X		Silver	X	X	
Gas Oil	X	X		Soybean Meal	X	X	
Gasoline	X	X		Soybean Oil	X	X	
Gold	X	X		Soybeans	X	X	
Heating Oil	X	X		Sugar	X	X	
Kansas Wheat	X	X		Tin	X	X	
Lead	X	X		Wheat	X	X	
Lean Hogs	X	X		White Sugar	X	X	
Live Cattle	X	X		Zinc	X	X	

https://support.msci.com/docs/DOC-3445

B.3 Global and Core Factors

Table 34: List of all global and core factors, grouped by asset class and subclass

ASSET CLASS	TYPE	SUB-TYPE	CORE	FACTOR NAME	COUNTRY/CURRENCY
Currency			0	GLB United Arab Emirates	United Arab Emirates
Currency			1	GLB Argentina	Argentina
Currency			1	GLB Australia	Australia
Currency			0	GLB Austria	Austria
Currency			0	GLB Belgium	Belgium
Currency			0	GLB Bangladesh	Bangladesh
Currency			0	GLB Bulgaria	Bulgaria
Currency			0	GLB Bahrain	Bahrain
Currency			0	GLB Bosnia and Herzegovina	Bosnia and Herzegovina
Currency			1	GLB Brazil	Brazil
Currency			1	GLB Canada	Canada
Currency			1	GLB Switzerland	Switzerland
Currency			1	GLB Chile	Chile
Currency			1	GLB China Domestic	China Domestic
Currency			1	GLB Colombia	Colombia
Currency			0	GLB Cyprus	Cyprus
Currency			1	GLB Czech Republic	Czech Republic
Currency			0	GLB Germany	Germany
Currency			0	GLB Denmark	Denmark
Currency			1	GLB Egypt	Egypt
Currency			1	GLB Euro	Euro
Currency			0	GLB Spain	Spain
Currency			0	GLB Estonia	Estonia
Currency			0	GLB Finland	Finland
Currency			0	GLB France	France
Currency			1	GLB United Kingdom	United Kingdom
Currency			0	GLB Greece	Greece
Currency			1	GLB Hong Kong	Hong Kong
Currency			0	GLB Croatia	Croatia
Currency			1	GLB Hungary	Hungary
Currency			1	GLB Indonesia	Indonesia
Currency			1	GLB India	India
Currency			0	GLB Ireland	Ireland
Currency			0	GLB Iceland	Iceland

Table 35: Global Factors (continued)

ASSET CLASS	TYPE	SUB-TYPE	CORE	FACTOR NAME	COUNTRY/CURRENCY
Currency			1	GLB Israel	Israel
Currency			0	GLB Italy	Italy
Currency			0	GLB Jamaica	Jamaica
Currency			0	GLB Jordan	Jordan
Currency			1	GLB Japan	Japan
Currency			0	GLB Kazakhstan	Kazakhstan
Currency			0	GLB Kenya	Kenya
Currency			1	GLB Korea	Korea
Currency			0	GLB Kuwait	Kuwait
Currency			0	GLB Lebanon	Lebanon
Currency			0	GLB Sri Lanka	Sri Lanka
Currency			0	GLB Lithuania	Lithuania
Currency			0	GLB Latvia	Latvia
Currency			0	GLB Morocco	Morocco
Currency			1	GLB Mexico	Mexico
Currency			0	GLB Mauritius	Mauritius
Currency			1	GLB Malaysia	Malaysia
Currency			0	GLB Nigeria	Nigeria
Currency			0	GLB Netherlands	Netherlands
Currency			1	GLB Norway	Norway
Currency			1	GLB New Zealand	New Zealand
Currency			0	GLB Oman	Oman
Currency			0	GLB Pakistan	Pakistan
Currency			1	GLB Peru	Peru
Currency			1	GLB Philippines	Philippines
Currency			1	GLB Poland	Poland
Currency			0	GLB Portugal	Portugal
Currency			0	GLB Qatar	Qatar
Currency			0	GLB Romania	Romania
Currency			1	GLB Russia	Russia
Currency			0	GLB Saudi Arabia	Saudi Arabia
Currency			1	GLB Singapore	Singapore
Currency			0	GLB Serbia	Serbia
Currency			0	GLB Slovenia	Slovenia
Currency			1	GLB Sweden	Sweden
Currency			1	GLB Thailand	Thailand
Currency			0	GLB Tunisia	Tunisia
Currency			1	GLB Turkey	Turkey
Currency			1	GLB Taiwan	Taiwan
Currency			0	GLB Ukraine	Ukraine
Currency			1	GLB United States	United States
Currency			0	GLB Vietnam	Vietnam
Currency			1	GLB South Africa	South Africa

Table 36: Global Factors (continued)

ASSET CLASS	TYPE	SUB-TYPE	CORE	FACTOR NAME	COUNTRY/CURRENCY
Equity	Industry		0	GLB Airlines	
Equity	Industry		0	GLB Automobiles and Components	
Equity	Industry		0	GLB Banks	
Equity	Industry		0	GLB Biotechnology	
Equity	Industry		0	GLB Capital Goods	
Equity	Industry		0	GLB Chemicals	
Equity	Industry		0	GLB Commercial and Professional Services	
Equity	Industry		0	GLB Communications Equipment	
Equity	Industry		0	GLB Computers Electronics	
Equity	Industry		0	GLB Consumer Durables and Apparel	
Equity	Industry		0	GLB Construction Containers Paper	
Equity	Industry		0	GLB Hotels Restaurants and Leisure	
Equity	Industry		0	GLB Diversified Financials	
Equity	Industry		0	GLB Aluminum Diversified Metals	
Equity	Industry		0	GLB Energy Equipment and Services	
Equity	Industry		0	GLB Food Beverage and Tobacco	
Equity	Industry		0	GLB Food and Staples Retailing	
Equity	Industry		0	GLB Health Care Equipment and Services	
Equity	Industry		0	GLB Household and Personal Products	
Equity	Industry		0	GLB Insurance	
Equity	Industry		0	GLB Internet Software and Services	
Equity	Industry		0	GLB Media	
Equity	Industry		0	GLB Oil and Gas Exploration and Production	
Equity	Industry		0	GLB Oil Gas and Consumable Fuels	
Equity	Industry		0	GLB Pharmaceuticals and Life Sciences	
Equity	Industry		0	GLB Gold and Precious Metals	
Equity	Industry		0	GLB Real Estate	
Equity	Industry		0	GLB Retailing	
Equity	Industry		0	GLB Semiconductors	
Equity	Industry		0	GLB IT Services and Software	
Equity	Industry		0	GLB Steel	
Equity	Industry		0	GLB Telecommunication Services	
Equity	Industry		0	GLB Transportation Non-Airline	
Equity	Industry		0	GLB Utilities	

Table 37: Global Factors (continued)

ASSET CLASS	TYPE	SUB-TYPE	CORE	FACTOR NAME	COUNTRY/CURRENCY
Equity	Regional		1	GLB Asia Pacific Mkt	Asia Pacific
Equity	Regional		1	GLB EM FM Africa Mkt	EM FM Africa
Equity	Regional		1	GLB EM FM Asia Mkt	EM FM Asia
Equity	Regional		1	GLB EM FM Europe Mkt	EM FM Europe
Equity	Regional		1	GLB EM FM Latin America Mkt	EM FM Latin America
Equity	Regional		1	GLB EM FM Middle East Mkt	EM FM Middle East
Equity	Regional		1	GLB Emerging Markets Equity	Emerging Markets Equity
Equity	Regional		1	GLB Europe Mkt	Europe
Equity	Regional		1	GLB World Equity	World Equity
Equity	Style		0	GLB Beta	
Equity	Style		0	GLB Book-to-Price	
Equity	Style		0	GLB Dividend Yield	
Equity	Style		0	GLB Earnings Yield	
Equity	Style		0	GLB Growth	
Equity	Style		0	GLB Leverage	
Equity	Style		0	GLB Liquidity	
Equity	Style		0	GLB Momentum	
Equity	Style		0	GLB Residual Volatility	
Equity	Style		0	GLB Size	
Equity	Style		0	GLB Non-Linear Size	
Equity	Mkt	Devel	1	GLB Australia Mkt	Australia
Equity	Mkt	Devel	1	GLB Austria Mkt	Austria
Equity	Mkt	Devel	1	GLB Belgium Mkt	Belgium
Equity	Mkt	Devel	1	GLB Canada Mkt	Canada
Equity	Mkt	Devel	1	GLB Switzerland Mkt	Switzerland
Equity	Mkt	Devel	1	GLB Germany Mkt	Germany
Equity	Mkt	Devel	1	GLB Denmark Mkt	Denmark
Equity	Mkt	Devel	1	GLB Spain Mkt	Spain
Equity	Mkt	Devel	1	GLB Finland Mkt	Finland
Equity	Mkt	Devel	1	GLB France Mkt	France
Equity	Mkt	Devel	1	GLB United Kingdom Mkt	United Kingdom
Equity	Mkt	Devel	1	GLB Hong Kong Mkt	Hong Kong
Equity	Mkt	Devel	1	GLB Ireland Mkt	Ireland
Equity	Mkt	Devel	1	GLB Israel Mkt	Israel
Equity	Mkt	Devel	1	GLB Italy Mkt	Italy
Equity	Mkt	Devel	1	GLB Japan Mkt	Japan
Equity	Mkt	Devel	1	GLB Netherlands Mkt	Netherlands

Table 38: Global Factors (continued)

ASSET CLASS	TYPE	SUB-TYPE	CORE	FACTOR NAME	COUNTRY/CURRENCY
Equity	Mkt	Devel	1	GLB Norway Mkt	Norway
Equity	Mkt	Devel	1	GLB New Zealand Mkt	New Zealand
Equity	Mkt	Devel	1	GLB Portugal Mkt	Portugal
Equity	Mkt	Devel	1	GLB Singapore Mkt	Singapore
Equity	Mkt	Devel	1	GLB Sweden Mkt	Sweden
Equity	Mkt	Devel	1	GLB United States Mkt	United States
Equity	Mkt	Emerg	1	GLB Brazil Mkt	Brazil
Equity	Mkt	Emerg	1	GLB Chile Mkt	Chile
Equity	Mkt	Emerg	1	GLB China International Mkt	China International
Equity	Mkt	Emerg	1	GLB Colombia Mkt	Colombia
Equity	Mkt	Emerg	1	GLB Czech Republic Mkt	Czech Republic
Equity	Mkt	Emerg	1	GLB Egypt Mkt	Egypt
Equity	Mkt	Emerg	1	GLB Greece Mkt	Greece
Equity	Mkt	Emerg	1	GLB Hungary Mkt	Hungary
Equity	Mkt	Emerg	1	GLB Indonesia Mkt	Indonesia
Equity	Mkt	Emerg	1	GLB India Mkt	India
Equity	Mkt	Emerg	1	GLB Korea Mkt	Korea
Equity	Mkt	Emerg	1	GLB Mexico Mkt	Mexico
Equity	Mkt	Emerg	1	GLB Malaysia Mkt	Malaysia
Equity	Mkt	Emerg	1	GLB Peru Mkt	Peru
Equity	Mkt	Emerg	1	GLB Philippines Mkt	Philippines
Equity	Mkt	Emerg	1	GLB Poland Mkt	Poland
Equity	Mkt	Emerg	1	GLB Russia Mkt	Russia
Equity	Mkt	Emerg	1	GLB Thailand Mkt	Thailand
Equity	Mkt	Emerg	1	GLB Turkey Mkt	Turkey
Equity	Mkt	Emerg	1	GLB Taiwan Mkt	Taiwan
Equity	Mkt	Emerg	1	GLB South Africa Mkt	South Africa
Equity	Mkt	Frontier	1	GLB United Arab Emirates Mkt	United Arab Emirates
Equity	Mkt	Frontier	1	GLB Argentina Mkt	Argentina
Equity	Mkt	Frontier	1	GLB Bahrain Mkt	Bahrain
Equity	Mkt	Frontier	1	GLB China Domestic Mkt	China Domestic
Equity	Mkt	Frontier	1	GLB Jordan Mkt	Jordan
Equity	Mkt	Frontier	1	GLB Kuwait Mkt	Kuwait
Equity	Mkt	Frontier	1	GLB Sri Lanka Mkt	Sri Lanka
Equity	Mkt	Frontier	1	GLB Morocco Mkt	Morocco
Equity	Mkt	Frontier	1	GLB Nigeria Mkt	Nigeria
Equity	Mkt	Frontier	1	GLB Oman Mkt	Oman
Equity	Mkt	Frontier	1	GLB Pakistan Mkt	Pakistan
Equity	Mkt	Frontier	1	GLB Qatar Mkt	Qatar
Equity	Mkt	Frontier	1	GLB Saudi Arabia Mkt	Saudi Arabia

Table 39: Global Factors (continued)

ASSET CLASS	TYPE	SUB-TYPE	CORE	FACTOR NAME	COUNTRY/CURRENCY
Commodities			1	GLB COM Agriculture	
Commodities			1	GLB COM Energy	
Commodities			1	GLB COM Industrial Metals	
Commodities			1	GLB COM Livestock	
Commodities			1	GLB COM Precious Metals	
Equity Implied Vol			0	GLB AU Equity Variance Shift	Australia
Equity Implied Vol			0	GLB CH Equity Variance Shift	Switzerland
Equity Implied Vol			0	GLB DE Equity Variance Shift	Germany
Equity Implied Vol			0	GLB ES Equity Variance Shift	Spain
Equity Implied Vol			0	GLB EU Equity Variance Shift	Euro. Monetary Union
Equity Implied Vol			0	GLB GB Equity Variance Shift	United Kingdom
Equity Implied Vol			0	GLB HK Equity Variance Shift	Hong Kong
Equity Implied Vol			0	GLB JP Equity Variance Shift	Japan
Equity Implied Vol			0	GLB KR Equity Variance Shift	Korea
Equity Implied Vol			0	GLB US Equity Variance Shift	United States
Fixed Income	Spread	Country	1	GLB Average Australia Credit	Australia
Fixed Income	Spread	Country	1	GLB Average Canada Credit	Canada
Fixed Income	Spread	Country	1	GLB Average Switzerland Credit	Switzerland
Fixed Income	Spread	Country	1	GLB Average UK Credit	United Kingdom
Fixed Income	Spread	Country	1	GLB Average Japan Government Backed	Japan
Fixed Income	Spread	Country	1	GLB Average Sweden Credit	Sweden
Fixed Income	Spread	Country	1	GLB Average US Credit High Yield	US
Fixed Income	Spread	Country	1	GLB Average US Credit Investment Grade	US
Fixed Income	Spread	Country	0	GLB Average US Mortgages	US
Fixed Income	Spread	Country	1	GLB AR Spread	Argentina
Fixed Income	Spread	Country	0	GLB BG Spread	Bulgaria
Fixed Income	Spread	Country	1	GLB EG Spread	Egypt
Fixed Income	Spread	Country	0	GLB HR Spread	Croatia
Fixed Income	Spread	Country	1	GLB ID Spread	Indonesia
Fixed Income	Spread	Country	0	GLB RO Spread	Romania
Fixed Income	Spread	Country	1	GLB RU Spread	Russia
Fixed Income	Spread	Region	1	GLB Average Europe Credit	
Fixed Income	Spread	Region	0	GLB Africa Invest. Grade Sovereign	
Fixed Income	Spread	Region	0	GLB Asia Invest. Grade Sovereign	
Fixed Income	Spread	Region	0	GLB Eastern Europe Invest. Grade Sovereign	
Fixed Income	Spread	Region	0	GLB Latin America Invest. Grade Sovereign	
Fixed Income	Spread	Region	0	GLB Middle East Invest. Grade Sovereign	
Fixed Income	Spread	Sector	1	GLB Average Financial Credit	
Fixed Income	Spread	Sector	0	GLB Average Covered Bonds	
Fixed Income	Spread	Sector	1	GLB Average Government Implied Volatility	

Table 40: Global Factors (continued)

ASSET CLASS	TYPE	SUB-TYPE	CORE	FACTOR NAME	COUNTRY/CURRENCY
Fixed Income	Term	shift	1	GLB AU Shift	Australia
Fixed Income	Term	shift	1	GLB BR Shift	Brazil
Fixed Income	Term	shift	1	GLB CA Shift	Canada
Fixed Income	Term	shift	1	GLB CH Shift	Switzerland
Fixed Income	Term	shift	1	GLB CL Shift	Chile
Fixed Income	Term	shift	1	GLB CX Shift	China
Fixed Income	Term	shift	1	GLB CN Shift	China
Fixed Income	Term	shift	1	GLB CO Shift	Colombia
Fixed Income	Term	shift	1	GLB CZ Shift	Czech Republic
Fixed Income	Term	shift	1	GLB DK Shift	Denmark
Fixed Income	Term	shift	1	GLB ES Shift	Spain
Fixed Income	Term	shift	1	GLB EU Shift	Euro. Monetary Union
Fixed Income	Term	shift	1	GLB GR Shift	Greece
Fixed Income	Term	shift	1	GLB IE Shift	Ireland
Fixed Income	Term	shift	1	GLB IT Shift	Italy
Fixed Income	Term	shift	1	GLB PT Shift	Portugal
Fixed Income	Term	shift	1	GLB GB Shift	United Kingdom
Fixed Income	Term	shift	1	GLB HK Shift	Hong Kong
Fixed Income	Term	shift	1	GLB HU Shift	Hungary
Fixed Income	Term	shift	1	GLB IL Shift	Israel
Fixed Income	Term	shift	1	GLB IN Shift	India
Fixed Income	Term	shift	1	GLB JP Shift	Japan
Fixed Income	Term	shift	1	GLB KR Shift	Korea
Fixed Income	Term	shift	1	GLB MX Shift	Mexico
Fixed Income	Term	shift	1	GLB MY Shift	Malaysia
Fixed Income	Term	shift	1	GLB NG Shift	Nigeria
Fixed Income	Term	shift	1	GLB NO Shift	Norway
Fixed Income	Term	shift	1	GLB NZ Shift	New Zealand
Fixed Income	Term	shift	1	GLB PE Shift	Peru
Fixed Income	Term	shift	1	GLB PH Shift	Philippines
Fixed Income	Term	shift	1	GLB PL Shift	Poland
Fixed Income	Term	shift	1	GLB SE Shift	Sweden
Fixed Income	Term	shift	1	GLB SG Shift	Singapore
Fixed Income	Term	shift	1	GLB SK Shift	Slovakia
Fixed Income	Term	shift	1	GLB TH Shift	Thailand
Fixed Income	Term	shift	1	GLB TR Shift	Turkey
Fixed Income	Term	shift	1	GLB TW Shift	Taiwan
Fixed Income	Term	shift	1	GLB US Shift	United States
Fixed Income	Term	shift	0	GLB US Municipal Shift	United States
Fixed Income	Term	shift	1	GLB ZA Shift	South Africa

Table 41: Global Factors (continued)

ASSET CLASS	TYPE	SUB-TYPE	CORE	FACTOR NAME	COUNTRY/CURRENCY
Fixed Income	Term	IPB	0	GLB AU Inflation-protected Shift	Australia
Fixed Income	Term	IPB	0	GLB BR Inflation-protected Shift	Brazil
Fixed Income	Term	IPB	0	GLB CA Inflation-protected Shift	Canada
Fixed Income	Term	IPB	0	GLB EU Inflation-protected Shift	Euro. Monetary Union
Fixed Income	Term	IPB	0	GLB GB Inflation-protected Shift	United Kingdom
Fixed Income	Term	IPB	0	GLB JP Inflation-protected Shift	Japan
Fixed Income	Term	IPB	0	GLB US Inflation-protected Shift	United States
Fixed Income	Term	swap	0	GLB AU Swap Shift	Australia
Fixed Income	Term	swap	0	GLB Average Swap Twist	
Fixed Income	Term	swap	0	GLB BR Swap Shift	Brazil
Fixed Income	Term	swap	0	GLB CA Swap Shift	Canada
Fixed Income	Term	swap	0	GLB CH Swap Shift	Switzerland
Fixed Income	Term	swap	0	GLB CN Swap Shift	China
Fixed Income	Term	swap	0	GLB EU Swap Shift	Euro. Monetary Union
Fixed Income	Term	swap	0	GLB GB Swap Shift	United Kingdom
Fixed Income	Term	swap	0	GLB HK Swap Shift	Hong Kong
Fixed Income	Term	swap	0	GLB IN Swap Shift	India
Fixed Income	Term	swap	0	GLB JP Swap Shift	Japan
Fixed Income	Term	swap	0	GLB KR Swap Shift	Korea
Fixed Income	Term	swap	0	GLB MX Swap Shift	Mexico
Fixed Income	Term	swap	0	GLB SE Swap Shift	Sweden
Fixed Income	Term	swap	0	GLB US Swap Shift	United States
Fixed Income	Term	twist	0	GLB AU Twist	Australia
Fixed Income	Term	twist	0	GLB Average Twist	
Fixed Income	Term	twist	0	GLB BR Twist	Brazil
Fixed Income	Term	twist	0	GLB CA Twist	Canada
Fixed Income	Term	twist	0	GLB CH Twist	Switzerland
Fixed Income	Term	twist	0	GLB CN Twist	China
Fixed Income	Term	twist	0	GLB EU Twist	Euro. Monetary Union
Fixed Income	Term	twist	0	GLB GB Twist	United Kingdom
Fixed Income	Term	twist	0	GLB IN Twist	India
Fixed Income	Term	twist	0	GLB JP Twist	Japan
Fixed Income	Term	twist	0	GLB KR Twist	Korea
Fixed Income	Term	twist	0	GLB TW Twist	Taiwan
Fixed Income	Term	twist	0	GLB US Twist	United States

B.4 How Single Country Equity Models are integrated in BIM

The Barra Integrated Model is built from the same Barra equity factor models used on a standalone basis by single-country and regional investors, but with two modifications.

First, BIM303 is built with a consistent set of half-life parameters across all component models. While the standalone models employ a wider range of parameters, integrated models require a consistent level of responsiveness to avoid distortions during periods of change in the markets. For example, forecasts of Beta are easily distorted if the volatilities of the portfolio and the market respond differently to changes in volatility. Typically, correlations are slowly varying, while volatility levels can change quickly with the market environment. Since

$$\beta = \frac{\sigma_{portfolio}}{\sigma_{market}} cor(portfolio, market),$$

distortions arise if the volatilities in the numerator and denominator change with different speeds. To avoid such distortions, BIM303 estimates new model variants with parameters consistent across all components in each of the S, L, and XL model horizons, as discussed in Section 2.2.1.

A second modification is used in BarraOne to put similar sources of risk on the same footing across markets, applying the technique described in Shepard (2011) Appendix B: European Equity. Many newer equity models have adopted an overall Country factor to capture the overall return of each market, rather than embedding the market return in net-long industry factors as before. This change provides the important benefit of making it possible to quickly and robustly detect marketwide increases in correlation, which register as a shock to the volatility of the country factor. However, as a result of this change, the interpretation of the Industry factors changes to represent the return of each industry net of the overall market. When such market-neutral industries are combined with the net-long industry factors in other models, the risk forecasts cannot be sensibly compared side-by-side. One industry factor represents a market-hedged industry effect, while the other represents the total industry effect. To reconcile these two types of factors, BarraOne rotates all industry factors back to the “net-long” form. The Country factor is used to estimate the full covariance matrix, preserving the advantages of greater responsiveness to correlation shocks. However, BarraOne displays the country factor risk as rolled into the corresponding net-long industry factors.

B.5 Multiple Horizon Models

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 using the Newey-West estimator, and it uses an Expectation Maximization algorithm 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 S and L 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 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.

The half-life parameters of BIM303 are very homogenous. This is especially important in a global model measuring the relationships between different parts of the market. To achieve uniform responsiveness, BIM303S and BIM303L 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.

The greater responsiveness of the short horizon model enables it to react more quickly to changes in the markets, but it 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.

A stable, long-horizon variant to BIM, called BIM303XL, complements the BIM303L variant of the Barra Integrated Model. The XL variant of the Barra Integrated Model is built with an 8-year half-life parameter used to calculate both the factor volatilities and correlations using an exponentially weighted moving average over an expanding window of all available return history. In this variant, the component covariance matrix blocks, global factor covariance matrix, and local-global exposures are re-estimated with equal weights from the same factor returns as BIM303L. (The block for hedge funds is not fully re-estimated.) Most of the factors have a return history spanning the full 10-year history. BIM303XL is useful for Solvency II requirements and for asset owners who are interested in a long-horizon model.

Appendix C: Complete List of Portfolios Tested

C.1 Equity

Table 42: Country / Regional Models included in R-Squared Tests

COUNTRY	REGION	301	303
Australia	Developed	AUE3	AUE4
Canada	Developed	CNE4	CAE5
Europe excl. UK	Developed	EUE3DUK	EUE4DUK
Japan	Developed	JPE3	JPE4
United States	Developed	USE3	USE4
China	Emerging	CHE2	CNE5
Korea	Emerging	KRE2	KRE3
South Africa	Emerging	SAE3	ZAE4

Table 43: 54 MSCI Country Indexes included in Bias Tests

Developed Markets	Emerging Markets	Frontier Markets
Australia	Brazil	Argentina
Austria	Chile	Bahrain
Belgium	China International	Jordan
Canada	Colombia	Kuwait
Denmark	Czech Republic	Oman
Finland	Egypt	Pakistan
France	Greece	Qatar
Germany	Hungary	Saudi Arabia
Hong Kong	India	UAE
Ireland	Indonesia	
Israel	Korea	
Italy	Malaysia	
Japan	Mexico	
Netherlands	Morocco	
New Zealand	Peru	
Norway	Philippines	
Portugal	Poland	
Singapore	Russia	
Spain	South Africa	
Sweden	Taiwan	
Switzerland	Thailand	
United Kingdom	Turkey	
United States		

Table 44: 50 (of 77) GEM3 Country Factor Portfolios included in Bias Tests

Developed Markets	Emerging Markets	Frontier Markets
Australia	Brazil	Argentina
Austria	Chile	Jordon
Belgium	China International	Pakistan
Canada	Colombia	Qatar
Denmark	Czech Republic	United Arab Emirates
Finland	Egypt	
France	Greece	
Germany	Hungary	
Hong Kong	India	
Ireland	Indonesia	
Israel	Korea	
Italy	Malaysia	
Japan	Mexico	
Netherlands	Morocco	
New Zealand	Peru	
Norway	Philippines	
Portugal	Poland	
Singapore	Russia	
Spain	South Africa	
Sweden	Taiwan	
Switzerland	Thailand	
United Kingdom	Turkey	
United States		

Table 45: 34 GEM3 Industry Factor Portfolios included in Bias Tests

GEM3 INDUSTRY FACTORS			
Airlines	Computers Electronics	Hotels Restaurants and Leisure	Real Estate
Aluminum Diversified Metals	Construction Containers Paper	Household and Personal Products	Retailing
Automobiles and Components	Consumer Durables and Apparel	Insurance	Semiconductors
Banks	Diversified Financials	Internet Software and Services	Steel
Biotechnology	Energy Equipment and Services	IT Services and Software	Telecommunication Services
Capital Goods	Food and Staples Retailing	Media	Transportation Non-Airline
Chemicals	Food Beverage and Tobacco	Oil and Gas Exploration and Production	Utilities
Commercial and Professional Services	Gold and Precious Metals	Oil Gas and Consumable Fuels	
Communications Equipment	Health Care Equipment and Services	Pharmaceuticals and Life Sciences	

Table 46: 11 GEM3 Style Factor Portfolios included in Bias Tests

GEM3 STYLE FACTORS			
Beta	Earnings Yield	Liquidity	Residual Volatility
Book-to-Price	Growth	Momentum	Size
Dividend Yield	Leverage	Non-linear Size	

Table 47: Summary of 831 concentrated equity portfolios included in Bias Tests

Country	Country x bottom style portfolios	Country x top style portfolios	Country x industry portfolios	Country	Country x bottom style portfolios	Country x top style portfolios	Country x industry portfolios
AUSTRALIA	11	11	1	MALAYSIA	11	11	3
AUSTRIA	3	1		MEXICO	6	11	
BELGIUM	10	4		NETHERLANDS	9	8	
BRAZIL	11	11	3	NEW ZEALAND	2	7	
CANADA	11	11	8	NORWAY	9	1	1
CHILE	3	3		PAKISTAN	2	9	
CHINA	10	11	15	PHILIPPINES	2	2	
DENMARK	7	5		POLAND	8	4	
EGYPT	4	3		PORTUGAL	1	9	
FINLAND	7	7		RUSSIA	1	2	
FRANCE	11	11	2	SINGAPORE	11	11	2
GERMANY	11	11	1	SOUTH AFRICA	11	10	2
GREECE	9	6		SPAIN	11	10	1
HONG KONG	11	11	2	SWEDEN	10	10	1
INDIA	10	11	12	SWITZERLAND	11	9	2
INDONESIA	5		1	TAIWAN	11	11	10
IRELAND	3	11		THAILAND	11	11	1
ISRAEL	9	1	1	TURKEY	9	11	
ITALY	11	10	3	UAE		2	
JAPAN	11	10	25	UNITED KINGDOM	11	11	13
JORDAN	2	11		USA	10	11	32
KOREA	11	1	11	TOTAL	181	161	85

C.2 Fixed Income

Table 48: Term Structure Factors for 41 bond markets included in R^2 and Bias Tests

COUNTRY TERM STRUCTURE MODELS					
COUNTRY	REGION	MODEL	COUNTRY	REGION	MODEL
AUSTRALIA	Developed	AUF3	HUNGARY	Emerging	HUF2
CANADA	Developed	CAF3	INDIA	Emerging	INF4
DENMARK	Developed	DKF2	INDONESIA	Emerging	IDF2
EMU	Developed	EUF3	KOREA	Emerging	KRF3
HONG KONG	Developed	HKF4	MALAYSIA	Emerging	MYF4
ISRAEL	Developed	ILF1	MEXICO	Emerging	MXF3
JAPAN	Developed	JPF4	PERU	Emerging	PEF1
NEW ZEALAND	Developed	NZF2	PHILIPPINES	Emerging	PHF4
NORWAY	Developed	NOF2	POLAND	Emerging	PLF2
SINGAPORE	Developed	SGF4	RUSSIA	Emerging	RUF2
SWEDEN	Developed	SEF2	SOUTH AFRICA	Emerging	ZAF2
SWITZERLAND	Developed	CHF3	TAIWAN	Emerging	TWF3
UNITED KINGDOM	Developed	GBF3	THAILAND	Emerging	THF4
USA	Developed	USF4	TURKEY	Emerging	TRF3
BRAZIL	Emerging	BRF1	ARGENTINA	Frontier	ARF1
CHILE	Emerging	CLF2	BULGARIA	Frontier	BGF2
CHINA	Emerging	CNF4	CROATIA	Frontier	HRF2
CHINA INTER	Emerging	CXF1	LITHUANIA	Frontier	LTF2
COLOMBIA	Emerging	COF1	NIGERIA	Frontier	NGF1
CZECH REPUBLIC	Emerging	CZF2	ROMANIA	Frontier	ROF2
EGYPT	Emerging	EGF1			

Table 49: Fixed Income Indexes (Government and Credit) included in R^2 and Bias Tests

CODE	BofA Merrill Lynch Indexes	CODE	BofA Merrill Lynch Indexes
G0T0	Australian Governments	G0RU	Russia Government Index
G0H0	Austrian Governments	G0TR	Turkey Government Index
G0G0	Belgian Governments	G0SA	South Africa Governments G0SA
G0C0	Canadian Governments		
G0M0	Danish Governments		
G0K0	Finnish Governments	C0D0	US Domestic Industrial C0D0
G0F0	French Governments	C0Z0	US Domestic Yankee Master (incl CAN) C0Z0
G0D0	German Federal Governments	C0A0	ML US Investment Grade Corporate bonds
G0HK	Hong Kong Government Index	C0J0	The BofA Merrill Lynch US Insurance & Financial Services Index
G0R0	Irish Governments	C0R0	The BofA Merrill Lynch US Telecommunications Index
G0IS	Israel Government Bond Index	C0Q0	US Domestic Utilities C0Q0
G0I0	Italian Governments	H0HB	US High Yield Homebuilders/Real Estate H0HB
G0Y0	Japanese Governments		
G0N0	Dutch Governments	EJ00	EMU Corporates Industrials Index EJ00
G0Z0	New Zealand Governments	EP00	EMU Pfandbrief Index EP00
G0U0	Portuguese Governments	EB00	The BofA Merrill Lynch Euro Financial Index
G0SP	Singapore Government Index	HPC0	Euro High Yield Constrained Index
G0E0	Spanish Governments	HE30	The BofA Merrill Lynch CCC & Lower Euro High Yield Index
G0W0	Swedish Governments	HEFA	The BofA Merrill Lynch Euro Fallen Angel High Yield Index
G0S0	Swiss Governments		
G0L0	UK Gilts	UC00	Sterling Corporate Index UC00
G0Q0	US Treasury Master		
G0CL	Chile Government Index	G0BC	ML Global Investment Grade Corporate bonds
G0CN	China Government Index	IC00	The BofA Merrill Lynch Global Emerging Markets Credit Index
G0ID	Indonesia Government Index	IP00	The BofA Merrill Lynch Global Emerging Markets Sovereign Plus Index
G0IN	India Government Bond Index	UKL0	The BofA Merrill Lynch Sterling Large Cap Index
G0MY	Malaysian Government Index		
G0SK	South Korean Government Index	W0G1	ML Global Government Index
G0PL	Polish Governments	W0GI	ML Global Inflation-linked Sovereign bonds

Table 50: Credit Portfolios for these eight hard currency markets included in R^2 and Bias Tests

CURRENCY	
AUD	Australian Dollar
CAD	Canadian Dollar
EUR	Euro
JPY	JapaneseYen
CHF	Swiss Franc
SEK	Swedish Kroner
GBP	Great Britain Pound
USD	United States Dollar

See https://support.msci.com/docs/DOC-3631 for detail on all credit spread factors except JPY and SEK

See https://support.msci.com/docs/DOC-3651 for detail on JPY credit spread factors

See https://support.msci.com/docs/DOC-3233 for detail on SEK credit spread factors

C.3 Multi-Asset Class

Table 51: Target Date Funds (“Lifecycle”) from TIAA-CREF included in Bias Tests

TIAA-CREF Target Date Fund Glidepath					
Years to Retirement	U.S. Equity	Int’l Equity	Fixed Income	Short-Term Fixed Income	Inflation-Protected Assets
45 to 25	63%	27%	10%	0%	0%
20	57%	25%	18%	0%	0%
15	52%	22%	26%	0%	0%
10	46%	20%	30%	2%	2%
5	41%	17%	34%	4%	4%
0	35%	15%	38%	6%	6%
-5	31%	14%	39%	8%	8%
-10 to -30	28%	12%	40%	10%	10%

See: https://www.tiaa-cref.org/public/pdf/Methodology_And_Design.pdf

For the Risk Balanced Equity/Bond long-only country portfolios, we used the same countries as in Table 48. For each of these countries we use: 20% x the MSCI Country Equity Index+ 80% x the country’s aggregate bond portfolio. So, in Japan for example, we use the securities in the MSCI Japan IMI Index (for equity), and we use all the bonds in the Barra Japan bond estimation universe (for bonds).

C.4 Alternatives

Table 52: Components of Commodity Portfolios included in Bias Tests

Commodity Long / Short Portfolios		
Long Commodity	**Long Commodity**	**Short Equity Index**
Aluminum	Minnesota Wheat	MSCI ACWI
Brent Crude	Natural Gas	Airlines
Cocoa	Nickel	Australia_IMI
Coffee	NY Copper	Diversified Financials
Copper	Orange Juice	Gold_Precious Metals
Corn	Palladium	Oil Gas Exploration Production
Cotton	Platinum	
Crude Oil	Robusta Coffee	
Feeder Cattle	Silver	
Gas Oil	Soybean Meal	
Gasoline	Soybean Oil	
Gold	Soybeans	
Heating Oil	Sugar	
Kansas Wheat	Tin	
Lead	Wheat	
Lean Hogs	White Sugar	
Live Cattle	Zinc	

Appendix D: The Integrated Model: A Brief Methodological Summary

This section contains a very brief summary of the methodological innovations in the Barra Integrated Model. Readers looking for a more complete exposition are directed to Shepard (2011).

Our chief goal is to provide a single model that best forecasts the risk of a wide range of portfolios, from those concentrated in a single market to large, international multi-asset-class portfolios. To do this, the model must offer both broad coverage and in-depth analysis. It should be detailed enough to enable a manager to drill down to his or her assets in a local market and obtain an insightful and accurate analysis, and yet broad enough to cover a large investment universe. Unfortunately, these objectives are conflicting. As new markets are added to a global model, the complexity needed to maintain a fine level of detail increases, posing a serious econometric challenge.

In the Barra Integrated Model, we employ a novel methodology to address this issue. First, to provide the needed level of detail, we build factor models for all of the local equity and bond markets covered by BIM. These factor models attribute the explainable portion of an asset's return to the local factors at work in each market. These factors include styles and industries for equities, and term structure movements and credit spreads for bonds. They may differ significantly from market to market. By modeling each market individually, BIM enables institutional investors to see their exposures to various factors of each particular market and also provides more accurate forecasts of local market risk.

Next, we build two asset class models, one for equities and one for bonds, by combining the local models in each class, ignoring currencies for the moment. This requires an understanding of what links the behavior of assets across markets. Since asset returns are driven, in part, by local factors, the key to developing each model is to determine the covariance between these factors across different markets. There are far too many factors to reliably estimate their covariances directly on the basis of available data. Fortunately, within each asset class, a much smaller set of intermarket or "global" factors accounts for much of the cross-market correlation. By building structural models of how these global factors link local factors across markets, we are able to obtain estimates that are more accurate.

Our use of structural models provides a new framework for global analysis. These models decompose local factor returns into a part due to global factors (that is shared across markets) and a part that is purely local (that only affects the securities within each market). This explains, for example, why the industry risk of a US bank is better hedged with another US bank than with a Japanese bank.

We complete the single-asset-class models by adding currency, commodity, and hedge fund models. Our final step is then to combine all models together to form the complete Barra Integrated Model. Leveraging our earlier work, we use the global factors to estimate the correlation structure across asset classes.

Our approach to modeling global equities and bonds consists of building a set of local risk models and establishing links between them. It is based on the view that an asset's return is strongly influenced by local market factors. These factors may differ in number, character, and behavior across markets. However, relationships across markets are better described by a smaller set of global factors.

The local models are the building blocks of our global model. Each local model decomposes an asset's local excess return into a part due to local factors and a part that is unique to the underlying asset, the specific return. Thus, the risk of a portfolio arises from its exposure to factors in the market as well as from the idiosyncratic behavior of the individual securities it contains.

Just as a local factor model can be written (in matrix notation) as **r = Xf + u**

> **r** is a vector of asset returns
>
> **X** is an exposure matrix relating asset exposures to local factors
>
> **f** is a vector of local factor returns
>
> **u** is a vector of idiosyncratic asset returns (not explained by factors **f**)

The matrix equation for asset covariance as a function of local factor covariance is

$$\mathbf{COV(r,r)} = \mathbf{X\ F\ X^T} + \mathbf{COV(u,u)}, \text{ where } \mathbf{F} = \mathbf{COV(r,r)}$$

To compute the risk of a portfolio of international equities (or international bonds), we need a global equity (or bond) risk model that gives the covariance between returns to equities (or bonds) in different markets. We form such a model by aggregating our local models. The factors of this new model are simply all the local market factors. Further, each asset is exposed only to its own market's factors. Continuing our global equity example, we now need to more fully specify the factor covariance matrix. The diagonal blocks of this matrix contain covariances between the local factors within each market; the local models have already provided these. What remains to be specified is the covariance between local factors in different markets. This involves estimating a significant number of covariances, since there are a large number of local equity factors. The underlying data are available at monthly intervals and in many cases go back fewer than 15 years. Trying to compute these covariances directly would almost certainly result in numerous spurious relationships.

Our solution to this problem is to use a structural model for each asset class that establishes a sensible relationship between factors in different markets. The idea is that the behavior of local factors may be accounted for, in part, by a much smaller set of global factors. For example, part of the return to the local US and UK oil factors is due to an underlying global oil factor, which captures global oil prices, cartel activity, etc. In similar fashion, spreads on corporate bonds of different credit qualities in the US and UK are partly driven by corporate spread factors for these countries. These global factors link local factors across markets, accounting for any correlation between them. To estimate the covariance between local market factors, we need only to determine a much smaller set of global factor covariances, improving the reliability of our estimates.

For any asset class covered by BIM, the structural model has the following form:

An integrated factor models will decompose the local factors into global factors and purely local contributions:

f = Bg + p

> **f** is a vector of *local* factor returns
>
> **B** is an exposure matrix relating local factor exposures to global factors

g is a vector of *global* factor returns

p is a vector of purely local factor returns (not explained by global factors g)

The matrix equation for local factor covariance as a function of global factor covariance is

$$\mathbf{COV(f,f) = B\ G\ B^T + COV(p,p)}, \text{ where } \mathbf{G} = \mathbf{COV(f,f)}$$

The structural models not only overcome the econometric problem, but they also provide a new framework for global analysis. They decompose each local factor return into a part due to global factors and a part that is purely local. These purely local returns are not correlated across markets but may be correlated within each market. This construction enables the factors in different markets to be correlated but not identical. From the structural models, we obtain an estimate of the factor covariance matrix consisting of two parts:

Due to purely local factors: **COV(p,p)**

Due to global factors: $\mathbf{B\ G\ B^T}$.

Methodological enhancements of BIM303 (and earlier versions) eliminate the need to choose between global factors and local detail, with a methodology[25] that brings together GEM3 and the local models. One particular enhancement is a refinement of the local-global exposures. The empirically observed relationships among factors demonstrate that local-global equity exposures can take values other than zero and one. Instead of taking these exposures as a fixed input, BIM303 takes the global equity returns as an input and estimates the local-global exposures from time-series regression:

Define B to ensure that the local residuals p are uncorrelated with the global factor returns g: $\text{cov}(p,g) \equiv 0$

We get the standard time series regression:

$$B = \text{cov}(f,g)\ \text{cov}(g,g)^{-1}$$

which is analogous to familiar "market beta":

$$\beta = \text{cov}(r, R_M)\ \text{cov}\ (R_M, R_M)^{-1}$$

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

[25] See Shepard (2007)

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See complete list of factors at https://support.msci.com/docs/DOC-9770

Equity Model Details (BarraOne, BIMe Models Direct): https://support.msci.com/docs/DOC-3074

Fixed Income Model Details (BarraOne, FIAT): https://support.msci.com/docs/DOC-3077

Countries Covered — Barra Integrated Model (BIM) Equities: https://support.msci.com/docs/DOC-2487

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