Edouard Sénéchal joined Barra in 2000 as a consultant for the European Client Support Team, based in London. He then moved to New York where he took the position of senior consultant for Barra’s Applied Research department, where he is in charge of defining and implementing applications of Barra’s research and analytics into the investment process of our clients.

Edouard obtained a B.A. in Financial Economics from Dauphine University in Paris, he passed the Financial Risk Manager (FRM) certification and is a member of the Global Association of Risk Professionals (GARP) and successfully completed the CFA exams.
In September of 2002, Barra released the Barra Integrated Model (BIM), a new global risk model. The Barra Integrated Model is a major breakthrough in modeling international risk and return for both equity and fixed income securities. BIM introduces a revolutionary bottom-up approach to global risk modeling by integrating the accuracy of market-specific models in one global framework. This new methodology provides an unprecedented level of local depth and precision coupled with the breadth of a global model.

The benefits that BIM provides relative to alternative risk models are:

- Greater accuracy in predicting portfolio tracking error.
- Complete consistency of portfolio analysis for international, market-specific and multi-asset-class portfolios.
- Inclusion of local market idiosyncrasies in a global framework.
- Increased explanatory power from recognizing the importance of purely local factors.
- More effective hedging strategies due to the model’s ability to capture global and local influences.

In this series of papers, we will focus on the benefits from the equity portion of the model (called BIM equity or BIME). As stated, however, BIM integrates fixed income and equity risk and includes term structure risk, spread risk, and credit risk.

This series contains three papers:


The second paper, “The implications of The Barra Integrated Model for Portfolio Management,” reviews the business implications of this new model for investment managers.

Finally, “Analyzing Risk with the Barra Integrated Model” demonstrates how a global investment management firm can integrate the Barra Integrated Model into its investment process.
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1. Introduction

The Barra Integrated Model (BIM) uses an innovative bottom-up approach to modeling multinational equity risk and return. Instead of applying the same global framework to every market, it relies on local models specially calibrated for each market. This approach identifies the drivers of asset returns at the local level and then integrates those drivers to arrive at a framework for global risk analysis. Recognition of local factors in asset returns allows BIM to better capture both similarities in the behavior of securities within a market and differences in security returns across markets.¹

This contrasts with first-generation global equity and cross-asset-class risk models, such as Barra’s current global equity model (GEM), which assume that individual equity returns are driven by the same set of global factors. These factors include country market indices, global industries, and global style factors. Imposing a global industry and style structure to capture returns across markets ignores local influences in asset returns, resulting in poor portfolio decisions in today’s economy.

BIM’s local approach, and its reliance on the expertise that Barra research has developed in each local market, allows asset managers to integrate an unprecedented level of market-specific precision into a global framework. This paper discusses benefits of BIM relative to first-generation models. For simplicity, we focus on equity risk, but the same principles apply to fixed income and cross-asset-class analysis. In the next section, we further explicate BIM’s advantages with a more detailed discussion of BIM and first-generation global equity risk models. In section 3, we provide empirical evidence that BIM is able to capture more of the variation in global equity returns. In section 4, we show how BIM’s ability to capture more in common factor returns leads to better risk predictions. Section 5 summarizes and concludes.

2. Bottom-up Risk Modeling: The Ability to Capture Local Sources of Return

In a first-generation global equity model, Microsoft’s return is related to the US equity market, a global software industry factor, and a factor that is common to largecap firms globally. Moreover, the correlation between Microsoft and Toyota is driven by the correlation between a US market index and a Japan market index, the correlation between the global software industry and the global automobile industry once country effects have been removed, and the correlation between largecap stocks once country effects have been removed. Given the top-down, country-first approach to global investing, such a model provided both a reasonable and accurate approach to understanding the risk of global equity portfolios. Moreover, the technological constraints on computing memory and speed necessitated a simplified structure as well.

Today, neither the computational constraints nor the top-down approach to global investing apply as they did in the last two decades. The recent increase in cross-border investments, the decline of trade barriers resulting from the implementation of the GATT, and the emergence of more integrated regions (as a result of the Monetary Union in Europe, NAFTA in North America, and ASEAN in Asia) has led global portfolio managers to a more bottom-up investment process based on firm, industry, and style characteristics.\(^2\)

Moreover, it is also increasingly clear that the factors that influence equity returns differ across countries. First, both the number of industries and the number of firms in any given industry differ substantially across developed and emerging markets and even within the sets of developed and emerging markets. For instance, it would be difficult to find a significant mining industry in Japan or Hong Kong. In contrast, due to the importance of the mining industry in the Australia model, the Global Industry Classification Scheme (GICS) sector Materials is divided into three separate industries\(^3\) that better reflect the diversity and the importance of the Australia Materials sector. Furthermore, the same industries often have a widely different composition across markets and, as a result, characteristics of companies included in the same global industry can be quite different across countries. For example, the type of companies that fall into the banking industry is fairly well defined, and the banking industry exists in every market. But what are the commonalities between a Geneva private bank and a Brazilian regional bank making loans to farmers and local businesses in the Mato Grosso State?

Similar differences exist in style-related factors. For example, equity returns in Thailand differ systematically depending on the amount of family control in the firm. This leads to a Family Control Factor in Thai equities, whereas such a factor need not exist in other markets. Another example of such local drivers of equity returns is the Redchip\(^4\) index in Hong Kong. Thus we clearly have local factors in each market that represent purely local influences and that we do not encounter at the global level.

Finally, the meaning of company fundamental data and its availability varies widely across markets because of different reporting requirements, accounting standards, and financing practices. For example, a measure of firm size is a common influence of equity returns across markets. The way in which this size exposure is computed, however, depends on local practices. In most markets, the size exposure is based on market capitalization, but for Japan one needs to adjust this measure for cross holdings. A local approach allows BIMe to capture and estimate the style factors that are relevant to each market and to take advantage of the specific insight of Barra’s research in each country.

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\(^2\) This change in the investment process is reflected in a decline in the dominance of country factors over industry or style factors. For a further discussion see Cavaglia, Stefano, C. Brightman, and M. Aked, “The Increasing Importance of Industry Factors”, *Financial Analysts Journal*, vol. 56, no. 5 (September/ October): 41–54.

\(^3\) The three industries are: Metals and Mining ex Gold, Gold, and Materials ex Metals and Mining. For more information on the Australian model see “The Australia Equity Model, AUE3 Research Notes,” in the Client Support Library at http://support.barra.com/

\(^4\) The Redchip factor distinguishes Hang Seng China affiliated corporations.
3. Capturing Local Factors: An Increase in Explanatory Power

Our discussion thus far clearly shows that BIM better captures a priori differences in local market structure by accounting for local factors in asset returns. BIM integrates these local factor models by imposing a global factor structure on these local factors, thus decomposing local factor returns into a global and a purely local component. This allows us to account for local and global common factors in a single framework5. In contrast, a classic global model is only able to capture global factors. As a result, the explanatory power of the common factors (local + global) is higher in BIMe than in a classic global model.

The higher explanatory power of the common factors of BIMe is especially relevant when investing in emerging markets. Emerging markets have a large number of specific characteristics and are less integrated in the “Global Economy”, and therefore are less sensitive to global industry and global style factors. In order to illustrate this we constructed a “heat map” of the historical correlations between MSCI indexes where each square’s color represents the intensity of the correlation between two markets6 (see Figure 1).

There are two kinds of factors that are important in capturing emerging markets specifics: country factors (the local stock market index) and local factors (that is, local industries and local style factors). Figure 1 tells us that global factors such as global industries or global styles will have a limited impact in emerging markets. A classic global model based on countries, such as the Barra Global Equity Model (GEM) will capture country factors well, but will not be able to capture the local common factors. On the other hand, the BIMe local approach will be able to capture both the country factor and the purely local factors.

Table 1 presents the predicted common factor variance as a percentage of the total predicted variance in Barra’s classic global model and in BIMe for the month of May 2003. Independent of the model used, we observe that common factors explain more variance in emerging markets than in developed markets, clearly showing the importance of country factors and purely local factors in emerging markets.

<table>
<thead>
<tr>
<th></th>
<th>Total (%)</th>
<th>Developed Markets (%)</th>
<th>Emerging Markets (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BIMe</strong></td>
<td>55.4</td>
<td>53.4</td>
<td>74.3</td>
</tr>
<tr>
<td><strong>GEM</strong></td>
<td>37.8</td>
<td>36.8</td>
<td>47.8</td>
</tr>
<tr>
<td>Difference (BIMe – GEM)</td>
<td>17.6</td>
<td>16.6</td>
<td>26.5</td>
</tr>
</tbody>
</table>

If we then compare percentages of common factor variance across models, we can measure the importance of local factors because BIMe common factor variance will include those local effects whereas a classic global model will not. In developed markets BIM explains an additional 16.6%, which represents an increase of 45% when compared to

5 A detailed discussion of the global structure is in the appendix.

6 Correlations were computed on MSCI country indexes fully hedged from a US dollar perspective. We used the last 100 monthly index returns ending April 2003.
GEM. The difference is even more significant for emerging markets: BIME captures 74.3% of common factor variance risk, which equals an increase of 55% over a classic global model. This represents a change of 26.5% for emerging markets, which shows that the BIME local approach is especially relevant for emerging markets investment managers.

The benefits of BIM over other current global equity models are very clear when examining actively managed portfolios in emerging markets. We implemented 12 active strategies based on industries and style tilts in 26 emerging markets. We then looked at the proportion of risk attributable to common factors in GEM and in BIME for each portfolio. On average, the GEM common factors explained 33.1% of the total active risk while the BIME common factors explained as much as 68.2%. The increase of 35% demonstrates the added value of BIM's local factors in an actively managed emerging market portfolio.

Figure 1
“Heat Map” of Historical Correlations Between MSCI Indexes

We see that there are many more commonalities among developed markets, where the average correlation between markets is 0.48, than among emerging markets (average correlation of 0.12) or among emerging and developed where the average correlation is 0.15.

<table>
<thead>
<tr>
<th></th>
<th>Developed Markets</th>
<th>Emerging Markets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asia Pacific Developed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>US, Canada</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Europe</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia Pacific Emerging</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eastern Europe</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle East, Africa</td>
<td></td>
<td></td>
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<tr>
<td>South America</td>
<td></td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Average Correlations</th>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Developed</td>
<td>Emerging</td>
</tr>
<tr>
<td>Developed</td>
<td>0.479 0.153</td>
</tr>
<tr>
<td>Emerging</td>
<td>0.153 0.118</td>
</tr>
</tbody>
</table>
In order to demonstrate the improvement of BIMe over a classic global model, we tested risk predictions for over 100 active strategies based on styles, industries, and random tilts. These strategies were implemented in 50 countries and 10 regions. Each of the resulting portfolios was benchmarked on its country or regional index. This represents a total of approximately 1,500 portfolios, for which we computed total risk, tracking error, active common factor risk, and active specific risk in each model. We then computed bias statistics for each portfolio in both models and looked at the number of times BIMe under- or outperformed our classic model in predicting risk. We performed the bias tests based on the following approach. We assume that every monthly return is a separate random variable with its own standard deviation, and for each of these random variables we have only one observation: the actual monthly return. The data we need to reconcile are the following:

- Time series of \( n \) predicted risk estimations: \( \sigma_1, \sigma_2, \sigma_3 \ldots \sigma_n \)
- Time series of \( n \) realized returns: \( r_1, r_2, r_3 \ldots r_n \)

\( \sigma_i \) is the predicted standard deviation of \( r_i \). If \( \sigma_i \) is an accurate prediction of the true standard deviation of \( r_i \), and if we divide \( r_i \) by \( \sigma_i \) we will effectively normalize the return. The standard deviation of a normalized return is one.

Now we have time series \( \{ r_1 / \sigma_1, r_2 / \sigma_2, r_3 / \sigma_3 \ldots r_n / \sigma_n \} \) that should have a constant volatility equal to one. The standard deviation of this time series is our bias statistic. Because of sampling error the bias statistic will rarely equal one, but it is a good measure of model performance. The closer the bias test statistic is to one, the better the model’s performance. If it is significantly below one, we are over-predicting risk, and if it is significantly above one we are under-predicting risk.

The following bias statistics analysis in Tables 2 and 3 is focused on the tracking error, the active common factor risk and active specific risk, realizing that BIMe and the classic model perform very similarly at the total risk level. When looking at total risk predictions, market risk is by far the most important component. Therefore a classic global model, which accurately captures few broad factors, is able to perform just as well as BIMe.

On the other hand, when it comes to predicting tracking error, the risk coming from active bets and security-specific returns will play a significant role. Therefore we expect BIMe to thrive and outperform for tracking error predictions compared to our classic global model. In Tables 2 and 3 we can observe that BIMe indeed adds significant value and precision for active risk predictions and strongly outperforms the classic model on a consistent basis.

Table 2 shows the percentage of portfolios where BIMe bias statistics are superior than the ones for GEM; that is, it shows the number of portfolios expressed in percent for which the risk forecast for BIMe was more accurate than the risk forecast of our classic
global model. For example, looking at the tracking error bias statistics on emerging market portfolios, the percentage of times BIMe outperforms GEM is 75%; in other words, in three out of four times the BIMe tracking error prediction is more accurate.

Table 2

<table>
<thead>
<tr>
<th></th>
<th>Emerging Markets (%)</th>
<th>All Countries (%)</th>
<th>Regional</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking Error</td>
<td>75</td>
<td>79</td>
<td>61</td>
</tr>
<tr>
<td>Active Common Factor Risk</td>
<td>86</td>
<td>66</td>
<td>59</td>
</tr>
<tr>
<td>Active Specific Risk</td>
<td>92</td>
<td>94</td>
<td>91</td>
</tr>
</tbody>
</table>

Table 3

<table>
<thead>
<tr>
<th></th>
<th>Emerging Markets</th>
<th>All Countries</th>
<th>Regional</th>
<th>All Portfolios</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking Error</td>
<td>0.38</td>
<td>0.28</td>
<td>0.17</td>
<td>0.27</td>
</tr>
<tr>
<td>Active Common Factor Risk</td>
<td>0.22</td>
<td>0.18</td>
<td>0.20</td>
<td>0.18</td>
</tr>
<tr>
<td>Active Specific Risk</td>
<td>0.70</td>
<td>0.59</td>
<td>0.58</td>
<td>0.59</td>
</tr>
</tbody>
</table>

Table 3 indicates the magnitude of the difference between the bias statistics when BIMe outperformed GEM and vice versa. To illustrate the numbers let us assume that BIMe's average tracking error bias statistic for emerging markets in cases where it outperformed GEM was 0.90, a minor over-prediction of the predicted tracking error versus the realized one. Based on the absolute difference of 0.38 in the bias statistic for emerging markets tracking error prediction (see Table 2, first cell under Emerging Markets) we can compute an average bias statistic of 0.90 + 0.38 = 1.28 for GEM, a significant under-prediction of the realized tracking error.

Looking at the active common factor and active specific risk we can see another manifestation of the consistent outperformance of BIMe. For the 86% of the portfolios where BIMe performed better than GEM in predicting active common factor risk, the improvement is significantly larger than in the 14% of the analyzed portfolios where GEM outperforms BIMe (0.22 vs. 0.12).

BIMe’s local approach also has a large positive impact predicting specific risk. BIM takes advantage of Barra’s locally estimated structural specific risk models. Again, a local approach coupled with the experience of the Barra research department in developing tailored specific risk models for each market noticeably improves BIMe’s specific risk predictions. The improvements in specific risk accuracy between the classic model and BIMe are extremely impressive: more than 90% of the time BIMe outperformed the classic model in predicting active stock specific risk.

BIMe improvements are not limited to emerging markets. In all markets, the ability of BIMe to capture local factors adds significant value, and in nearly 80% of all the country portfolios BIMe outperformed the classic model. In the cases where the classic model outperformed BIMe the improvement in the risk prediction is small compared to the improvements brought by BIMe, when BIMe outperformed the classic model.
The difference between the classic model and BiMe is less important for regional portfolios. This is simply due to the diversification of country-specific risk and asset-specific risk in portfolios invested across several countries. For well-balanced international portfolios, the local-factor and asset-specific risk will be diversified. In those cases, the classic model will be able to provide an accurate risk prediction. BiMe still outperforms in predicting the specific risk of these regional portfolios but this has a limited impact given the smaller importance of specific risk in such portfolios.

5. Conclusion

The key to BiMe superior risk forecasting performance is its bottom-up approach that uses local models tailored to each market. This approach takes advantage of the market-specific knowledge and expertise that the Barra research department has developed in more than 40 equity markets for nearly 30 years.

BiMe uses a structural model to integrate an unprecedented level of market-specific information into a global framework. As a result, BiMe brings a new dimension to global equity modeling: local factors. These local factors, which cannot be captured by a classic global model, significantly increase the explanatory power and therefore the accuracy of the risk prediction. In particular, BiM adds significant value for forecasting tracking error, active common factor risk, and stock-specific risk. The additional predictive power for specific and common factor risk makes BiM an invaluable tool for risk management and portfolio construction decisions.
Appendix: Linking Local Market Factors with a Structural Model

The Barra research department has developed unprecedented experience during the last three decades in developing single-market models. BIME now provides a robust and rigorous way to link those local models in order to obtain a global covariance matrix that offers the precision of a local model.

The approach that first comes to mind when trying to link the single-market models is to simply calculate the historical correlation between all the local factors.

Although this approach is very simple to understand, it requires capturing a large number of correlations from history: the current version of BIME contains 507,031 cross-model correlations. By computing so many historical correlations we are bound to capture spurious relationships; that is, correlations that are due to circumstances but not driven by a fundamental relationship. In other words, we want to be able to distinguish a fundamental relationship, which is useful in managing risk, from a circumstantial one that is

\[
\text{Cov}(\text{Size}_{\text{Europe}}, \text{Financials}_{\text{US}}) = \sigma_{\text{Size}_{\text{Europe}}} \sigma_{\text{Financials}_{\text{US}}} \rho_{\text{Size}_{\text{Europe}}, \text{Financials}_{\text{US}}}
\]

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The covariance between two factors can be derived from the historical correlation between the two factors and the local model volatility of each factor. \(\text{Cov}(\text{Size}_{\text{Europe}}, \text{Financials}_{\text{US}}) = \sigma_{\text{Size}_{\text{Europe}}} \sigma_{\text{Financials}_{\text{US}}} \rho_{\text{Size}_{\text{Europe}}, \text{Financials}_{\text{US}}}
\)
due to chance, and therefore likely to disappear. It is important to realize that spurious correlations can have very negative consequences when it comes to managing portfolios. An historical correlation of -0.2 between the Australia Building Material and US Size local factors, for example, would lead us to buy largecap stocks in the United States in order to cover an overexposure to the Building Materials industry in Australia, which does not make sense intuitively or economically. BIM with its global factors framework is able to predict a much more economically sensible correlation of 0.18.

Instead of relying on past correlations, BIMe uses a structural model based on global factors to link local market factors[^1]. Similarly to Barra single-market models, which use common factors to estimate correlations between assets, BIMe uses global factors to estimate correlations between local factors in different markets. By computing correlations arising from global factors (such as the global industries or country stock market performance), we largely eliminate the occurrence of spurious correlations.

Using the structural approach to capture the relationship between the different local markets, we keep the accuracy of the local market risk predictions, eliminate spurious correlations between markets, and capture the significant global factor correlations relevant to accurately calculate the global portfolio risk.

[^1]: Correlation observed in March 2003 BIMe correlation matrix.