Understanding Multi-Asset Factor Models: Factor Exposure Interpretation

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In light of the weaknesses exposed during the financial crisis of 2008, the banking industry has been increasing focus on Risk Management issues.

Risk Management Division at BPI Gestão de Activos (GA)

- Strives to promote risk culture within the organization
- In an effort to increase awareness of portfolio managers to the risks being incurred
- With the purpose of increasing cooperation between portfolio managers and the risk management team

- Introduction of Bloomberg’s AIM software, through the Portfolio and Risk Analytics (PORT <GO>) tool
- Establishment of internal limits to constrain portfolio ex-ante volatility/tracking error
- Development of a risk monitoring system which accounts for the sources of risk

- PROBLEM: limits imposed fail to acknowledge where the risk is coming from (i.e. which factors contribute the most to portfolio risk)

- This software allows the decomposition of portfolio risk and return using factor models
- These models provide ex-ante volatility/TE and sources of risk (i.e. factors)
Risk Monitoring System

Previous work by NOVA students focused on the development of this risk monitoring system with the purpose of capturing the sources of BPI GA’s portfolios’ risk.

The system was set up roughly in the following manner:

- Several portfolios were analyzed
- “Types” of factors contributing the most to portfolio risk were determined
- Type of risk to be monitored – absolute or relative – was defined
- Historical analysis of top contributors to portfolio risk was performed
- Risk Management team checks on a monthly basis whether any limits have been reached
- Limits were defined for each type of factor based roughly on the 95% and 99% percentile of the statistical distribution of factor contributions
- For each of these limits, warnings were established:
  - Warning 1 (95% percentile) – whenever a factor of the considered types reaches this limit, an analysis of the causes that led to such contribution level is made and reported to the portfolio manager
  - Warning 2 (99% percentile) – in this case, the situation is reported to the Administration
The risk monitoring system currently in place accounts for the sources of portfolio risk, but there is a lack of understanding by portfolio and risk managers regarding the meaning of each factor exposure and contribution to risk. Without understanding its output, managers lose confidence in the model (i.e. in Bloomberg’s PORT tool output regarding portfolio risk).

Replicating Bloomberg’s procedure

The lack of understanding across the portfolio management division of Bloomberg’s procedure in calculating factor returns and exposures is the main focus of our work, as we find that it is the main issue holding back this risk monitoring system. In an effort to better understand the process through which Bloomberg calculates factor returns, we set out to replicate what is done in the model. Successfully replicating all the procedure will increase the confidence of managers in Bloomberg’s output.
BLOOMBERG’S FACTOR MODEL

Factor Models

Lay on the fundamental that assets with identical characteristics (industry, country, style, etc.) should have a similar performance.

Are based on the need of investors to understand the true sources of their risk.

Provide a detailed decomposition of portfolio risk and return into factors.

Factors are a set of common variables that drive and explain risk and return of a security.

Risk factors distinguish each security in the portfolio and help creating a specific risk profile for them, given by exposures to these factors.

\[ r_{n,t} = \sum_{k=1}^{K} X_{n,k,t} f_{k,t} + \varepsilon_{n,t} \]

- \( r_{n,t} \) is the local excess return of asset \( n \) in period \( t \)
- \( X_{n,k,t} \) is the exposure of asset \( n \) to factor \( k \)
- \( f_{k,t} \) is the return of factor \( k \) in period \( t \)
- \( \varepsilon_{n,t} \) is the residual of asset \( n \)’s return

Factor Returns Non-Factor Returns

A factor model discriminates returns and risk in two components, the asset-specific component – solely related to the asset itself – and the systematic component – determined by the risk factors.
There are three common types of factor models. These three differ in their approach to constructing exposures to risk factors and factor returns. They all have some specific advantages and disadvantages, related to the data intensity and interpretability.

<table>
<thead>
<tr>
<th>Factor Approach Type</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistical</td>
<td>• Easy to build</td>
<td>• Interpretability – there is no clear economic meaning associated to each principal component</td>
</tr>
<tr>
<td></td>
<td>• Require a relatively low amount of data</td>
<td></td>
</tr>
<tr>
<td>Statistical</td>
<td>Similar to what principal component analysis does(^1).</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Determines both factor returns and factor exposures from asset returns.</td>
<td></td>
</tr>
<tr>
<td>Explicit</td>
<td>• These models allow for an arbitrary number of factors, as long as we have sufficient factor data for the time-series interval used for estimation</td>
<td>• Relatively data intensive – security returns and factor returns are required to perform a regression analysis to determine factor exposures</td>
</tr>
<tr>
<td></td>
<td>• Exposures to factors can be non-intuitive</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Perform well out-of-sample (as they impose relatively more structure than other models)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Relatively data intensive – security returns and factor returns are required to perform a regression analysis to determine factor exposures</td>
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<tr>
<td></td>
<td>• Exposures are more intuitive</td>
<td></td>
</tr>
<tr>
<td>Implicit</td>
<td>Define security exposures to factors and use these to calculate factor returns through a regression of security returns on factor exposures.</td>
<td>• The most data intensive model – both security returns and security exposures are necessary</td>
</tr>
<tr>
<td></td>
<td>Also known as endogenous or cross-sectional models (as factor returns are determined from the model by cross-sectional regressions)</td>
<td></td>
</tr>
</tbody>
</table>

\(^1\) Similar to what principal component analysis does.
Bloomberg’s Models Equity and Fixed Income Factors

Bloomberg Factor Models are constructed with an *implicit factor approach*. This means that factor returns are calculated minimizing the sum of squared errors – $\epsilon_i^2$ – in the regression of securities’ returns on their exposures to the factors. The error component in this regression is the non-factor return of each security.

It is important to stress that securities’ returns and, most importantly, exposures are inputs of this process, which means that Bloomberg specifies them *a priori*. We will focus later on exposures: how they are calculated and how they should be interpreted.

**Equity**

In the equity models, there are five types of equity factors: *Market*, *Country*, *Industry*, *Currency* and *Style*.

### Equity Model Factors

<table>
<thead>
<tr>
<th>Market</th>
<th>Country</th>
<th>Currency</th>
<th>Industry</th>
<th>Style</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dummy variables: unit exposure to security’s market and zero to every other market. This factor is the main risk contributor for diversified long-only portfolios.</td>
<td>Dummy variables: unit exposure to security’s country of issue.</td>
<td>Dummy variables: unit exposure to trading currency.</td>
<td>Dummy variables: unit exposure to industry in which it operates. Industry factors are based on the GICS Industry Group membership (see Appendix 1 for a list of Industry factors).</td>
<td>These factors characterize securities using variables such as size, momentum, trading activity, leverage, etc. Each exposure is defined as the “amount” of each of these variables a security has.</td>
</tr>
</tbody>
</table>
BLOOMBERG’S FACTOR MODEL

Fixed Income

For the fixed income models, there are two types of factors: those whose returns are observable in the market, in which case the observed change is simply used directly (explicit factors), and those obtained by a cross-sectional regression (implicit factors). The explicit factors are currency, yield curve and volatility factors. The implicit factors are the spread factors.

### Fixed Income Model Factors

<table>
<thead>
<tr>
<th>Curve</th>
<th>Volatility</th>
<th>Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>These factors are taken directly from the market, by looking at the changes along the yield curve nine tenor points - 6M, 1Y, 2Y, 3Y, 5Y, 7Y, 10Y, 20Y and 30Y – and the squared average curve change along those points. The exposures to these factors are the key rate duration and option-adjusted convexity.</td>
<td>The exposure of each security to the volatility factor is measured by its volatility duration, which is computed by the bond’s vega divided by its price.</td>
<td>The level of the spread in each bond reflects the additional amount of return investors require for taking additional risk. Changes in the spread reflect changes in the perceived risk of the security. These might come from forces common to all bonds with close characteristics, or from specific shocks to one issuer. Common forces are captured by these systematic spread factors, including sovereign, agency, corporate (Investment Graded and High Yield) and distressed.</td>
</tr>
</tbody>
</table>

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### Fixed Income Model Factors

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</tr>
</tbody>
</table>

\[
R_{yc} = - \sum_{i=1}^{9} KRD_i \cdot \Delta y_i + \frac{1}{2} OAC \cdot (\Delta y)^2
\]

- \(R_{yc}\) is the return due to changes in yields
- \(KRD_i\) is the Key Rate Duration at point \(i\)
- \(\Delta y_i\) is the yield change at point \(i\)
- \(OAC\) is the option-adjusted convexity
- \(\Delta y\) is the average change in the yield

### Volatility

\[
R_{vol} = \frac{vega}{P + AI} \cdot \Delta \sigma
\]

- \(R_{vol}\) is the return due to changes in volatility
- \(vega\) is the bond’s vega
- \(P\) is the bond’s clean price
- \(AI\) is the bond’s accrued interest
- \(\Delta \sigma\) is the average change in volatility
For the multi-asset model, Bloomberg uses a different approach in the construction of the factor covariance matrix. The difference lies in the way we look at the factors. The main goal is to obtain a covariance matrix that is dynamic, detailed and robust. To reach that goal, Bloomberg divides factors into three types to build a factor model of “successively coarser factors”.

This is the “three layer approach” that is used to distill the core relationships in the model.

As we go down in these layers, we look at a more parsimonious segment of the model. This procedure follows some steps:

1. Obtain returns for each group of factors. Detailed factor returns are obtained from individual models; core and core-of-core factor returns are obtained by distilling the detailed factors.
2. Build a covariance matrix for the core-of-core factors only – matrix $\Omega$.
4. Build covariance matrix for the core factors – matrix $\Lambda = \vartheta \Omega \vartheta' + J$.
5. Determine sensitivities of detailed factors to core factors – $\gamma$ – and residual risk – $H$ – from this relationship.
6. Use these values to construct factor-of-factor (F/F) covariance matrix of detailed factors – $\Sigma_{F/F} = \gamma \Lambda \gamma' + H$.
7. Convert to correlation matrix $W$, and twist this matrix in order to construct final correlation $C$, with the correlation of the individual models in the diagonal blocks.
8. Finally, convert correlation matrix $C$ to a covariance matrix – matrix $\Sigma_{factors}$ – by multiplying it by a diagonal matrix $V$, containing factor volatilities $\Sigma_{factors} = VCV$. 
Individual factor volatilities are estimated with the GARCH model, following an EWMA process:

\[ \sigma_{i+1}^2 = (1 - \lambda) \sigma_i^2 + \lambda f_{i+1}^2 \]

- \( \lambda = 1 - 2^{-\text{half-life}} \) is the decay factor
- \( f_i \) is the factor return in period \( t-1,t \)

Once we have the factor covariance matrix, we can calculate all measures of risk related to the securities in the portfolio, factors and the portfolio itself. The volatility of the portfolio can thus be determined together with the exposures of the portfolio to the factors.

\[ \Omega = X_t \times \Sigma_t \times X_t' \]

- \( \Omega \) is the portfolio volatility
- \( X_t \) is the exposures matrix of the portfolio to the factors
- \( \Sigma_t \) is the variance covariance matrix of the factors

Bloomberg’s Models: Coverage Universe

Each model covers a different universe of securities, with the exception of the Multi-Asset model, which uses exposures from both Equity and Fixed Income models.

- Equity
  - Region/country models
  - Global model
- Fixed Income
  - Regional
  - Global
- Multi-Asset
  - Uses exposures from Equity Region models
  - Uses exposures from Equity Global model
For a stock to be covered by any of Bloomberg’s Equity Models, i.e. for a stock to have an exposure to the factors of one model, there are a few data requirements:

- Stock price must be greater than 5% of one unit of the local currency;
- Price and market cap data on Bloomberg
- Industry and country membership information are available

Despite these general guidelines, common to all of the equity models, each model covers only securities listed on relevant exchanges (see Appendix 2 for further details on Coverage Universe). The ten equity models available are the following:

- Asia
- Australia
- Canada
- China A-Shares
- Emerging Europe, Middle-East & Africa (EMEA)
- European
- Japan
- Latin America
- US
- Global

The Global model takes a broader look into the risk of a given security, putting it into perspective in a global set of stocks.

IBM is covered by the US and Global Model

US Momentum compares IBM’s exposure to Momentum on a local level against American stocks, whereas the GL Momentum is attributed on a Global environment.

Moreover, when considering the Multi-Asset Model, choosing between the Region and Global model will be in fact choosing between which factors to use – the local or the global ones.
When it comes to bonds, coverage by the Fixed Income Model is defined in different terms. The model covers:

- **Sovereign Bonds**
- **Agency Bonds**
- **Corporate Bonds**
- **High Yield Graded**
- **Investment Graded**
- **Bonds denominated in 38 currencies**

Rather than splitting into several models covering securities from certain regions of the world, the model separates the world into two – the **developed markets**¹ and the **emerging markets** – and considers bonds based on the currency they are denominated in (developed or emerging currencies). There are four combinations considered in the model:

1. Bonds denominated in **hard currencies** (i.e. developed currencies) issued by **developed countries**
2. Bonds denominated in **hard currencies**, issued by **emerging countries**
3. Bonds denominated in **emerging currencies**, issued by **developed countries**
4. Bonds denominated in **emerging currencies**, issued by **emerging countries**.

The last two cases are grouped together since there is very few data for bonds denominated in emerging currencies issued by emerging countries. Hence, the Fixed Income model is separated into three models, one for each combination:

- **G6 Model**
- **EM Hard Currency Model**
- **EM Local Currency Model**

For a bond to be covered in any of these models, the following data needs to be available: single security prices, risk exposures and information on country, sector, industry, etc. so that each bond can be mapped to the correct model factors.

¹For the purpose of the Fixed Income risk model, the following countries are considered to be developed markets: Australia, Canada, US, Japan, Euro zone 17 nations, Denmark, New Zealand, Norway, Sweden and Switzerland
As previously mentioned, Bloomberg’s factor models are built using an implicit factor approach. Hence, it is necessary to determine factor exposures in order to calculate factor returns through a regression against securities returns.

Each model has an estimation universe, which is typically a subset of the coverage universe. Every security in the estimation universe has exposure to the model factors and is in turn used as an observation in the regression that will ultimately allow calculating factor returns.

In general, when considering equity models, to get to the Estimation Universe, one takes the Coverage Universe, sorts every stock by market cap and focuses on the companies that make up cumulatively 98% of the market cap within each country relevant for the models (see Appendix 2 for the list of countries covered in each model).

Some models, however, have further restrictions when it comes to including a stock in its estimation universe, even though some of those restrictions are not very detailed in Bloomberg’s papers (see Appendix 3 for more on details on these special situations).

The global model’s Estimation Universe focuses on companies that cumulatively make up 98% of the market cap within several different countries and country groups, which are detailed in Appendix 4.
BLOOMBERG’S FACTOR MODEL

Fixed Income Models

Disclosed information about Bloomberg’s models is much less specific regarding fixed income than it is for equity. It is known that the estimation universe for these models is constructed from a few different sources, such as:
- Bank of America Merrill Lynch indices
- Bloomberg security terms and conditions
- Bval pricing
- Bloomberg Analytics.

It is also known that, in general, bonds classify for inclusion in the estimation universe if they have at least one year to maturity remaining and also if they satisfy certain requirements for minimum amount outstanding, depending upon country of origination and type of bond. The example provided specifies that U.S. corporate bonds must meet a $250 million minimum amount outstanding requirement to be included. Further, these requirements are constantly being revised.

Rebalancing the Estimation Universe

<table>
<thead>
<tr>
<th></th>
<th>Before</th>
<th>Now</th>
</tr>
</thead>
<tbody>
<tr>
<td>Universe</td>
<td>Universe was updated only once a year, based on the market share of each stock.</td>
<td>It is rebalanced dynamically and weekly in order to keep the models up-to-date with market changes</td>
</tr>
</tbody>
</table>

Gatekeeping System

Imposed to keep the estimation universe smooth and to minimize its turnover: it is required that a certain stock meets the eligibility criteria for several consecutive weeks before it is included in the estimation universe, as it is required that a stock violates such criteria consecutively for a certain number of weeks in order to be excluded from it.
Before going through the reasoning behind the interpretation of each style factor exposure, we need first to analyze how these factors were chosen and why they were integrated in the Bloomberg’s Factor Model instead of others.

The roots of the Bloomberg’s Factor model lie on the MSCI BARRA factor models, and for that reason, both models are similar in the way they are constructed.

<table>
<thead>
<tr>
<th>Bloomberg European Equity Model</th>
<th>BARRA European Equity Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Market Factor</td>
<td>• Market Factor</td>
</tr>
<tr>
<td>• 17 country factors</td>
<td>• 29 country factors</td>
</tr>
<tr>
<td>• 24 industry factors</td>
<td>• 29 industry factors</td>
</tr>
<tr>
<td>• 10 style factors</td>
<td>• 9 style factors</td>
</tr>
</tbody>
</table>

However, the most important feature to address here is related to the style factors. Let us focus and describe the principles of this model, in order to understand the foundations of Bloomberg’s style factors.

MSCI BARRA Model

• The analysis it takes is based on a fundamental review of an asset.
• Its analysis consists conceptually in determining a security’s future value through macro and microeconomic events and the impact on the security.
• Differs from pure fundamental analysis in its focus (factor models forecast risk and fundamental analysis aim at forecasting returns)

BARRA risk factors are mainly microeconomic and fundamental characteristics that most firms share in common. In the environment of a well-diversified portfolio, company-specific events (idiosyncratic) won’t have much impact in portfolio’s risk. The systematic portion becomes increasingly larger as the portfolio gets larger.
The fundamental and microeconomic variables form the style factors in this model. The next table shows an example of a sample fundamental data used in Barra models: 5 variables and the descriptors used in their construction.

<table>
<thead>
<tr>
<th>Value</th>
<th>Growth</th>
<th>Earnings Variation</th>
<th>Leverage</th>
<th>Foreign Sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Book Value</td>
<td>- Five-year payout</td>
<td>- Variability in earnings</td>
<td>- Market leverage</td>
<td>- Exchange rate sensitivity</td>
</tr>
<tr>
<td>- Analyst predicted earnings</td>
<td>- Variability in capital structure</td>
<td>- Standard deviation of analyst predicted earnings</td>
<td>- Oil price sensitivity</td>
<td></td>
</tr>
<tr>
<td>- Trailing earnings</td>
<td>- Growth in assets</td>
<td>- Variability in cash flows</td>
<td>- Debt to assets</td>
<td>- Sensitivity to other market indices</td>
</tr>
<tr>
<td>- Forecast operating income</td>
<td>- Growth in sales</td>
<td>- Extraordinary items in earnings</td>
<td>- Senior debt ratio</td>
<td>- Export revenues as percentage of total</td>
</tr>
<tr>
<td>- Sales</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Forecast sales</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Once identified the factors, the model links each stock to each factors. For this, a set of microeconomic characteristics – descriptors – that relate to each factor are used are identified.

Having identified them, descriptors are standardized across a universe of stocks. This is done by subtracting the estimation universe average and dividing by the standard deviation of the coverage universe of stocks. Finally, this model performs a weighting scheme of the descriptors, according to their importance in explaining the factor.

Besides these style factors, security’s risk and return are also function of its industry, currency and country. These exposures are calculated in a simpler way: a certain stock has unit exposure to its industry, currency and country and no exposure to all the others.

Interpretation is the same as in the CAPM, despite the differences in both models. Exposures measure sensitivities to percentage variations in the factors. For instance, if a stock has an exposure of 0.5 to the size factor, and the size factor increases by 20%, the stock’s return is expected to be 10%, all else equal.
We will briefly explain how these exposures are exactly calculated and which effects they are supposed to capture in the behavior of a stock, as well as how the descriptors help doing that for each characteristic.

The way style factors are calculated will be further addressed later on, along with the description of the replication process. In this section, the focus will be on understanding style factor exposures.
We begin by looking at the momentum factor. This is supposed to capture the effect of momentum in the return of a stock, distinguishing between stocks that have risen over the past year from stocks that have fallen. Stocks that raised the most over the past year are said to have high exposure to this factor. To avoid the price reversal effect in this exposure, the two most recent weekly returns are excluded of the calculation.

The value factor differentiates value stocks from growth stocks. This factor is also included in the Fama-French three-factor model – as the HML (high-minus-low) – and is based in the finding that value stocks (high book-to-market, or low market-to-book ratios) have higher returns than growth stocks. The descriptors for this factor are ratios, which intended to classify stocks according to this perspective. These are the B/P, CF/P, E/P, EBITDA/EV, Forecasted E/P and Sales/EV. All of these descriptors show in the numerator a book measure and in the denominator a market measure. This means that a value stock, with high values for these ratios, will have a high exposure to this factor.

This factor represents another feature of the value factor, being sufficiently relevant to be a standalone factor. The exposure to this factor is just the most recently announced annual net dividends divided by the market price. The reasoning is identical to the previous factor. Stocks with high dividend yields have high exposures to this factor.
This is another factor that is present in the FF three-factor model, as the SMB (small-minus-big) factor, based in the perception that small caps have had consistently higher returns than big caps. The composition for this factor is the Market Capitalization of the stock, Sales and Total Assets. These were the stock variables chosen to represent the size of a stock: how much does the stock cost, how much does it sell, and on how much capital does it operate.

A stock is said to have a high exposure to this factor when it has a big market cap, sales and/or total assets.

The trading activity factor tries to uncover the effect that liquidity and trading frequency have in the stocks returns. In order to capture this feature in stocks’ behavior, Bloomberg uses a formula on turnover rather than trading volume, in order to avoid correlation with the size factor. This would be damaging, as we would be hiding a relation between two variables in the cross-sectional regression, which could potentially lead to wrong results.

This factor tries to capture the difference in returns between stocks that have had different levels of growth in the last years – distinguishing between high and low growers in terms of returns. The historic indicators Bloomberg looks at to calculate the exposure to the growth factor are the growth in Total Assets (TAG), Sales (SG) and Earnings (EG). Bloomberg looks also to near-term forecasts of earnings (EFG) and sales (SFG) from the analyst estimates database.

The composition of the formula used to calculate exposure to growth should be interpreted as the way Bloomberg uses to define it. In this case, it weighs between historical and forward looking fundamental data from analysts.
Leverage

This variable represents the level of leverage of a company given by an average between three indicators. This should differentiate stocks with different levels of indebtedness in terms of returns. The measures of leverage used to calculate the level of debt of each stock are the book leverage (Debt over Book Value of the company), market leverage (Debt over Market Value of the company) and debt to total assets, which are approximately equal weighted.

Profitability

This factor uses profit margins to measure the performance of each company and differentiate between moneymakers and money losers. The measures of profitability used are: return on equity (book measure), return on capital employed, return on assets and EBITDA margin.

Volatility

Bloomberg includes this factor in order to account for the effect of volatility in the return of each security. This isn’t just to account for the volatility of the stocks’ returns, but to reach a value that captures a broader concept of volatility. This factor is constructed to differentiate more and less volatile stocks through a measurement of volatility that comes from several distinct perspectives. These are: return volatility over the last year, CAPM beta, volatility of the CAPM residuals and a cumulative range given by the ratio between the maximum and minimum price over the last 5 years.

Earnings Variability

This factor represents another feature of volatility of a company, including other measures related to the operating activities of the company. These are the volatility of earnings, cash flows and sales, for the past 5 years.
Bloomberg’s PORT tool omits a great amount of information when it comes to details on exposures calculations, i.e.:
• which data fields are used
• what is the time span of the data used
• how certain descriptors are calculated
• how exactly are the estimation universes composed

Issue becomes even more evident when it comes to fixed income factors, of which no information is displayed on PORT.

Replicating process becomes highly restrained without such detailed information regarding exposures calculations. The decision to replicate an equity model imposed itself due to the mentioned restrictions.

After carefully analyzing all of the available models, it was decided that it would be best to replicate the European Equity Fundamental Factor Model.

Picking this model was based on the following criteria:
• Firstly, it would be best to pick a model whose estimation universe is made up of securities that would likely have a lot of data available on Bloomberg (necessary to calculate exposures);
• Secondly, choosing a model that aggregates more than one country would allow us to replicate the model more completely, as we would be able to include several country factors.
Below, a list of all the restrictions and filters imposed to reach the sample estimation universe is presented:
1. Trading status of security – Active
2. Exchanges where the security is traded – Western Europe
3. Price greater than 0.05 (local currency)
4. Security has market cap data
5. Security has GICS industry group data
6. Security has country data
7. Security has price data since 01/01/2007 (this filter allowed the exclusion of securities that were not quoted through the entire time span necessary to calculate some factor exposures)
8. Security has Total Assets, Revenue, Net Income and Cash data available since the first quarter of 2007

Criteria restricted the universe of securities to a sample of around 1000 equities, as was the objective.

Even though several filters were applied, it was still necessary to deal with some missing data, in which cases we simply filled the inexistent data points for each security with the average value across the sample for a certain date.
## Binary Factor Exposures

We first focus on the binary factors: **country**, **currency** and **industry factors**.

<table>
<thead>
<tr>
<th><strong>Country</strong></th>
<th>The matrix of country factor exposures is a set of binary values. Each security in this universe will have a unit exposure to its own country, and 0 exposure to all other countries in the European Model.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Countries present in the European Model are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and Emerging Europe.</td>
</tr>
<tr>
<td></td>
<td>Relatively to the remaining countries, we aggregated them in three geographical groups: Northern Europe (NE), Central Europe (CE) and Southern Europe (SE). Information on how we aggregated countries in these three groups can be found in Appendix 5.</td>
</tr>
<tr>
<td></td>
<td>Since our estimation universe is considerably smaller than the one we’re trying to replicate, we shortened also the number of factors, so that the factor returns we have to estimate remain equally robust and significant.</td>
</tr>
<tr>
<td><strong>Currency</strong></td>
<td>The currency exposures of each security are also binary variables, which equal to one if the share is denominated in that currency and zero if it’s not.</td>
</tr>
<tr>
<td></td>
<td>We also decreased the number of currency exposures relative to Bloomberg, as securities from some Eastern Europe countries were not included. See annex xxx</td>
</tr>
<tr>
<td><strong>Industry</strong></td>
<td>If a security belongs to a certain industry – or an industry group, or sector, depending on how industry factors are constructed – then it is assigned an exposure value of 1 to this industry, and 0 to all other industries.</td>
</tr>
<tr>
<td></td>
<td>Industry factors are constructed based on the GICS membership. It divides industries in 24 industry groups and 10 sectors. When the GICS data isn’t available, Bloomberg infers the industry group of a security on the basis of the BICS.</td>
</tr>
<tr>
<td></td>
<td>Due to the same reason we pointed in the case of the country factors, we reduced the number of industry factors from 24 to 10.</td>
</tr>
</tbody>
</table>
In order to promote a better comprehension of the model and its output by the portfolio managers at BPI GA, we aim to discriminate the procedure by steps and thoroughly explain each one of them. We now set to explain the most technical part of the replication, the style factor exposures:

- How Bloomberg constructs each one of them
- How we replicated it
- It will not always be feasible to completely mimic the way Bloomberg constructs the exposures

Style factors differ from these binary factors as they characterize stocks in a more elaborate way than just zeros and ones. Besides reporting the country of the stock, the currency and the industry in which it operates, in order to decompose the whole profile of that stock, we have to look to more stylized and descriptive information of a company which might be significant in influence its performance in terms of risk and return. Of course, this requires more than just binary variables: it takes continuous variables.

More complex data will require more care in dealing with these factors. We have to make it robust and homogeneous. To do so, we apply the same reasoning and the same procedure to the construction of all style exposures. As we have explained when describing more broadly the Bloomberg’s Factor Model, each style factor consists of several “atomic” descriptors, which refers to a particular security feature that is part of.
In order to combine the features into style factors, we first standardize the descriptors. This standardization has its own particularities.

To the original value of descriptor, subtract country relative mean (i.e. average across same-country securities)

Divide by the global standard deviation (i.e. across all securities in the Estimation Universe)

Iterate this process until the mean is equal to 0 and standard deviation is equal to 1

Set extreme values below -3 and above 3 to -3 and 3, respectively

For instance, when standardizing an exposure of EDP, a Portuguese stock, one subtracts that exposure by the average exposure on that same day across all the Portuguese stocks in the universe, and divide by the standard deviation of the exposures across all the stocks (and not only the Portuguese).

The standardization process applies both to the descriptors and to the final value of the exposure. After weighting all the descriptors to form the exposures to each style factors, those values will also be standardized the same way the descriptors were.

The European model covers around 45 000 securities. Its estimation universe contains an equally (but lower) great number of securities. Our standardization process is based on a much lower universe. Hence, the average and the standard deviation are computed relatively to the stocks and countries present in this estimation universe.
Factor Weighting

We have seen that style factor exposures are constructed based on:
1. Choosing descriptors
2. Standardizing descriptors
3. Weighting descriptors in order to reach the exposure to a factor
4. Standardizing the descriptors weighted average to get to the final exposure value

Having explained the standardization process and the rationale behind the chosen descriptors for each factor, we now focus on the weighting of the descriptors.

To merge the descriptors into style factors, Bloomberg has come up with an algorithm to determine the weight of each one of them. The logic behind this algorithm is to find a common dimension among descriptors within a given style factor. Equal weighting would be the simplest way to combine the descriptors, but Bloomberg developed another way that is robust, intuitive and describes more accurately the style characteristic, by capturing the most common information contained in the descriptors.

The method consists in calculating a cross-sectional Spearman rank correlation matrix of descriptors. Then, Bloomberg extracts the first principal component from the principal component analysis, which explains descriptor variability. The loadings of the first principal component are normalized to sum up to 100% and these are the percentage values chosen to weight the descriptors. The logic is that, if a descriptor has the highest correlation with the rest of the descriptors that compose that style factor, then that descriptor should be attributed the highest weight, since it points more closely than other descriptors to the combined style characteristic.

Exposures Calibration

In Bloomberg’s equity models, exposures of each stock to any of the style factors are updated each week, along with the estimation universe. Every Wednesday the models are calibrated and exposures are recalculated using the latest data available.
Having covered the characteristics that are common among all of the style factors – atomic descriptors, standardization process and factor weighting – we now go into greater detail on each of the style factors.

When replicating the process, exposures were calculated for each week since the beginning of September 2012 until September 2015.

**Momentum**

\[
\text{Momentum} = \sum_{t=-54 \text{ weeks}}^{t=-2 \text{ weeks}} \log (1 + r_{n,t})
\]

Where \( r_{n,t} \) is the return of asset \( n \) at time \( t \)

The exposures to this factor are constructed differently from the other factors, as they are not calculated with the weighting of some indicators. The formula includes last year weekly returns for the stocks, but skips the two most recent weeks with the purpose of avoiding the price reversal effect.

**Dividend Yield**

\[
\text{DivYield} = \frac{\text{Last Dividend paid}}{\text{Price}}
\]

It is important to notice that a non-dividend paying stock also has exposure to this factor: it is considered that the dividend yield is simply zero and through the standardization process the exposure eventually deviates from zero.
Calculating Factor Exposures (II)

**Value**

\[
Value = 0.13 \times \frac{B}{P} + 0.18 \times \frac{CF}{P} + 0.18 \times \frac{E}{P} + 0.21 \times \frac{EBITDA}{EV} + 0.16 \times \frac{For.E}{P} + 0.13 \times \frac{Sales/EV}{P}
\]

Where \( CF/P \) is the Cash Flow to Price ratio, \( E/P \) is the Earnings to Price ratio, \( EBITDA/EV \) is the EBITDA to Enterprise Value ratio, \( For.E/P \) is the Forecasted Earnings to Price ratio and \( Sales/EV \) is the Sales to Enterprise Value ratio and Enterprise Value was calculated as:

\[
EV = Market\ Cap + LT\ Debt + \max(St\ Debt - Cash, 0)
\]

The Forecasted Earnings to Price ratio takes into account both the 1-year and 2-year forward Bloomberg earnings estimates. On PORT, it can be seen that a weight is attributed to each of the estimates, but it is not clear how such weight is determined. We verify, however, that this weight is the same across all the securities covered by the model. Over time, Bloomberg quants have been decreasing the weight applied to the 1-year forward-looking estimates, shifting it towards the 2-year forward-looking earnings estimates. For the sake of simplicity we have equally weighted the two estimates, thus using the following formula:

\[
For.\ E = \frac{w \times EF1 + (1 - w) \times EF2}{P}
\]

Most of the data extracted from Bloomberg to get to this exposure is reported on a quarterly basis, but not necessarily on the exact same dates. To simplify the process, we considered that quarterly data was always reported on the last Friday of March, June, September and December each year. Thus, the only variable causing value exposures to change on a weekly basis is market cap.
The size formula, just like with the value factor, is rather simple to apply: taking the weights given to each descriptor as seen on Bloomberg and multiplying them by the log of Market Cap, Sales and Total Assets. Again, since both Sales and Total Assets are only updated on a quarterly basis, exposures change weekly due to the variability of Market Cap.

Size

\[ Size = 0.28 \times \log(\text{Market Cap}) + 0.36 \times \log(\text{Sales}) + 0.36 \times \log(\text{Total Assets}) \]

Trading Activity

\[ Trading Activity = \sum_{t=-500 \text{ days}}^{t=-1 \text{ day}} \exp\left( t \times \frac{\log(2)}{180} \right) \times \frac{\text{Volume}}{\text{Shares Outstanding}} \]

This is the ratio of shares traded over shares outstanding daily, using exponential weighting of each observation in the past 2 years (500 trading days), with a half-life of 180 days. Although this exposure would change every day, for the purpose of the model it is only updated on a weekly basis.
Calculating Factor Exposures (IV)

**Growth**

\[ \text{Growth} = 0.23 \times \text{TAG} + 0.26 \times \text{SG} + 0.15 \times \text{EG} + 0.16 \times \text{EFG} + 0.20 \times \text{SFG} \]

Where TAG is the Total Asset growth over the last 5 years, SG is the Sales growth over the last 5 years, EG is the Earnings growth over the last five years, EFG is the near-term forecasted earnings and SFG is the near-term forecasted Sales according to Bloomberg’s estimates. \textit{EFG is calculated as } EFG=EF2/EF1 \text{ and } \text{SFG is calculated as } SFG=SFG2/SFG1

The growth factor was one of the most complex to replicate. This is so due to uncleanness by Bloomberg on how the growth rate of each descriptor is achieved. When replicating this factor exposure, we calculated each growth rate based on quarterly observations, as the average growth rate between same quarters over 5 years (i.e. average between growth rates, for instance, of Total Assets from 1Q 2007 to 1Q 2008, from 1Q 2008 to 1Q 2009, etc.).
Calculating Factor Exposures (V)

Leverage

\[
Leverage = 0.34 \times BLev + 0.33 \times MLev + 0.33 \times D2TA
\]

Where BLev is the Book Value of Leverage, MLev is the Market Value of Leverage and D2TA is the Debt to Total Assets ratio.

BLev is calculated as:

\[
\frac{LTDebt + \max (STDebt - Cash, 0)}{Book \ Value + LTDebt + \max (STDebt - Cash, 0)}
\]

MLev is calculated as:

\[
\frac{LTDebt + \max (STDebt - Cash, 0)}{Market \ Cap + LTDebt + \max (STDebt - Cash, 0)}
\]

D2TA is calculated as:

\[
\frac{LTDebt + \max (STDebt - Cash, 0)}{Total \ Assets}
\]

Similarly to the Value and Size factors, the Leverage factor only changes on a weekly basis due to the MLev descriptor, since it includes market cap data in its calculation. In these cases, the replication naturally deviates from Bloomberg’s procedure, potentially leading to different results.
The descriptors that make up the profitability factor use exclusively data only reported quarterly. It is thus one of the cases in which the replicated exposures only change from quarter to quarter and we have simply extended such calculations to a weekly basis. This, again, deviates from Bloomberg procedure, it is so because not every company reports their financials at the same time (which we have considered so), thus causing the profitability factor exposure to change at different times. Companies exposures are overall affected by this fact every week, not because their individual exposure changes this regularly, but due to the fact that the mean exposure across the estimation universe changes and affects every security through the standardization process.

\[
\text{Profitability} = 0,26 \times \text{ROE} + 0,28 \times \text{ROCE} + 0,28 \times \text{ROA} + 0,18 \times \text{EBITDA Margin}
\]

Similarly to the Profitability factor, this exposure only changes on a quarterly basis. Hence, the same issues and characteristics apply.
Calculating Factor Exposures (VII)

Volatility

\[ Volatility = 0.30 \times VLRT + 0.14 \times \beta + 0.29 \times \sigma + 0.26 \times CRNG \]

Where:

- **VLRT** is the return volatility over the last year
- **\( \beta \)** is the CAPM beta
- **\( \sigma \)** is the volatility of the CAPM residuals
- **CRNG** is a cumulative range calculated as the ration between max and min price of security over the last year

After calculating the exposures, a modification is made in the exposures to the volatility factor. This change is made to ensure that the explanatory variables of the cross-sectional regression are not correlated to each other. The modification consists in regressing the volatility exposures to the exposures of the other factors. The residual of this regression is the exposure to the factor used in the cross-sectional regression to calculate factor returns, after applying the standardization process, like it is done for all the other exposures.

---

1Calculated through a time-series regression of security returns on excess-market returns. A German 10Y Govt Bond was used as proxy for the risk free rate and the S&P500 as market, even though the European model was being replicated (since it is Bloomberg’s market proxy as well).
Calculating Factor Returns

**Replication Process Steps**

- 1. Attribution of binary exposures: country, currency, industry and market factors
- 2. Calculation of style factors
- 3. Modification to the volatility factor
- 4. Calculation of factor returns

**Cross Sectional Regressions**

- To get to factor returns
- Of security returns on security exposures to factors
- One for each period $t$
- For every week from 09/2012 to 09/2015

$$r_{n,t} = \sum_{k=1}^{K} X_{n,k,t} f_{k,t} + \varepsilon_{n,t}$$

- $r_{n,t}$ is the local excess return of asset $n$ in period $t$
- $X_{n,k,t}$ is the exposure of asset $n$ to factor $k$
- $f_{k,t}$ is the return of factor $k$ in period $t$
- $\varepsilon_{n,t}$ is the residual of asset $n$’s return
Next Step: Portfolio Analysis

After generating and constructing a model, the next step will always be about how it can be applied.

*How can this model help managing the risk of a portfolio?*

In this case, we have replicated the model by generating an output of weekly factor returns for the past 3 years. The reason we chose to calculate these returns for this time period was to enable us to compute the correlation which would help us evaluating the quality of our model, but most importantly, to calculate factor volatilities. This involves a time-series of observations since the factor volatilities are calculated with a rolling-window of one year. Hence, with three years of weekly factor returns, we will be able to calculate weekly factor volatilities for a period of two years. The next thing PORT does is to compute these factor volatilities, and the risk analysis metrics that might be calculated within the context of a portfolio. The most important is the factors’ contributions to risk. Currently at BPI GA, a set of limits is defined based on the historical distribution of factors contributions to risk. Those limits, as we have described earlier, are set close to the 95% and 99% percentiles of historical values, but might be adjusted with the help of portfolio managers.

Factor contribution to risk is calculated according to the formula:

\[
\text{Factor } k \text{ % Contribution to Risk} = \frac{X_k \times \sigma_k \times \rho_{k,p}}{\sigma_p}
\]

- \( \sigma_p \) is volatility of the portfolio
- \( X_k \) is the portfolio exposure to factor k
- \( \sigma_k \) is the volatility of factor k
- \( \rho_{k,p} \) is the portfolio correlation with factor k
Our primary objective for this project was to help promoting a better risk culture in BPI GA through a better understanding of Bloomberg’s Factor Model. Hence, the goal of the replication the model is to discriminate the process by steps and exploring each step instead of contesting Bloomberg’s values.

This means that our most important result will always be the way we were able to do this, instead of the values we computed, i.e., the results are less important than the process.

However, in order to control for the process, we have to analyze the resulting output and compare it somehow to Bloomberg’s, so that we are able to validate what we did with significant confidence. The most efficient way to do this is to compute the correlations between our style exposures and the ones from Bloomberg, for each day.

Comparing the exposures for the whole estimation universe, however, by looking at the cross-sectional correlations with Bloomberg will underrate the quality of the model, since the estimation universe is different in some ways from Bloomberg’s universe. More specifically, the proportion of each country’s equities in the estimation universe we created does not correspond to the one from Bloomberg.

Two main issues:
- Replicating the model with a much smaller sample of stocks
- Replicating each country’s proportion of stocks in the sample. This is not possible to execute because:
  1. there is no clear information on these proportion;
  2. it is dynamic, changing through time.

Hence, we chose to compare the exposures we calculated for the Portuguese stocks on our sample estimation universe and verify the correlations with Bloomberg’s exposures.
We calculated these cross-sectional correlations between both exposures for every month from September of 2012 to September of 2015 – 37 observations. Then, we computed the average correlation through the 37 months for each style exposure and some additional statistics, as shown later.

Our results show:

- 4 factors whose exposures average correlation is very strong (Dividend Yield, Leverage, Size and Trade Activity)
- 3 whose correlation is acceptable (Volatility, Momentum and Earnings Variability). The explanation for these medium correlations is related with the natural difference between the original and the replication model, such as differences in the available data and in the standardization process, which will originate different values with the use of different estimation universes.
- 3 factors whose results are not so strong (Growth, Value and Profit).

We have strong confidence, from this information, that the exposure calibration process was done correctly. Most exposures have consistent results, and for the ones with worse results, there are some features that can explain the weak correlations and the statistically non-significant averages.
RESULTS

Issues Replicating Growth Exposures

It is unclear how Bloomberg calculates annual growth rates of each descriptor from quarter to quarter. From the available information through PORT, on Bloomberg, one can assume the following formula:

\[
T \Delta G_q = \left( \sum_{q=1}^{4} \frac{T A_q - T A_{q-4}}{T A_{q-4}} \right) / T
\]

However, different ways of calculating growth rates were experimented in an effort to get a better correlation between the model’s exposures and the replicated ones, but no success was achieved for this factor in particular factor.

Issues Replicating Profit Exposures

- Descriptors used in the calculation of this exposure are only reported quarterly.
- For the Profit factor, as well as to the Growth factor, this problem is even more evident, since none of the descriptors contains an input that changes more frequently.
Issues Replicating Value Exposures

- One of its descriptors (forecasted earnings-to-price ratio) includes in its calculation a weight applied to the one and the two-year forward-looking earnings estimates - for simplicity, it was assumed equal-weight to both but this naturally differs from what is done in the model.
- With the exception of market cap, all other inputs are only updated quarterly. This poses an issue because we have assumed that every company reports this information at the same time but this does not necessarily verify. Thus differentiating the replicated exposures to the ones provided on PORT, in particular through the standardization process.

<table>
<thead>
<tr>
<th>Correlation</th>
<th>average</th>
<th>min</th>
<th>max</th>
<th>stdev</th>
<th>lower</th>
<th>upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>EU DivYld</td>
<td>0.86</td>
<td>0.45</td>
<td>0.99</td>
<td>0.16</td>
<td>0.54</td>
<td>1.17</td>
</tr>
<tr>
<td>EU EarnVariab</td>
<td>0.38</td>
<td>0.25</td>
<td>0.54</td>
<td>0.10</td>
<td>0.19</td>
<td>0.57</td>
</tr>
<tr>
<td>EU Growth</td>
<td>-0.05</td>
<td>-0.26</td>
<td>0.23</td>
<td>0.15</td>
<td>-0.33</td>
<td>0.24</td>
</tr>
<tr>
<td>EU Leverage</td>
<td>0.92</td>
<td>0.76</td>
<td>0.98</td>
<td>0.06</td>
<td>0.80</td>
<td>1.03</td>
</tr>
<tr>
<td>EU Momentum</td>
<td>0.66</td>
<td>0.43</td>
<td>0.89</td>
<td>0.13</td>
<td>0.40</td>
<td>0.92</td>
</tr>
<tr>
<td>EU Profit</td>
<td>0.19</td>
<td>-0.26</td>
<td>0.68</td>
<td>0.31</td>
<td>-0.42</td>
<td>0.80</td>
</tr>
<tr>
<td>EU Size</td>
<td>0.99</td>
<td>0.98</td>
<td>1.00</td>
<td>0.01</td>
<td>0.98</td>
<td>1.00</td>
</tr>
<tr>
<td>EU TradeAct</td>
<td>0.99</td>
<td>0.97</td>
<td>0.99</td>
<td>0.00</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td>EU Value</td>
<td>0.17</td>
<td>-0.49</td>
<td>0.68</td>
<td>0.28</td>
<td>-0.39</td>
<td>0.73</td>
</tr>
<tr>
<td>EU Volatility</td>
<td>0.65</td>
<td>0.51</td>
<td>0.76</td>
<td>0.08</td>
<td>0.49</td>
<td>0.80</td>
</tr>
</tbody>
</table>
Having set out to replicate Bloomberg’s procedure in calculating factor returns, the main objective of our work was to promote a better understanding of Bloomberg’s Factor Model and its portfolio analysis tool, PORT, to ultimately aid the Risk Management team in their effort to promote a risk culture at BPI Gestão de Activos.

The decision to focus our work on the replication process of Bloomberg’s factor exposures calculations through the investigation of PORT helped us get a much deeper perception of the functionalities of this tool but also of some issues in terms of data transparency on PORT as well.

Nevertheless, it is clear now that having gone through the replicating process, we have been able to document our findings in detail to pass on to both portfolio and risk management teams.

With a clearer understanding of how exposures and factor returns are calculated, we expect to increase the impact of PORT as a risk tool to be used by asset managers at BPI GA.
APPENDIX 1

GICS Industry Groups

Energy  
Materials  
Capital Goods  
Commercial & Professional Services  
Transportation  
Automobiles & Components  
Consumer Durables & Apparel  
Consumer Services  
Media  
Retailing  
Food & Staples Retailing  
Food, Beverage & Tobacco  
Household & Personal Products  
Health Care Equipment & Services  
Pharmaceuticals, Biotechnology & Life Sciences  
Banks  
Diversified Financials  
Insurance  
Real Estate  
Software & Services  
Technology Hardware & Equipment  
Semiconductors & Semiconductor Equipment  
Telecommunication Services  
Utilities
## Coverage Universe for Equity Fundamental Factor Models

<table>
<thead>
<tr>
<th>Fundamental Factor Equity Model</th>
<th>Coverage Universe</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Asia</strong></td>
<td>All equities listed on major exchanges in the following countries: China (B and offshore shares), Hong Kong (and China H-shares), Indonesia, India, Pakistan, Sri Lanka, Bangladesh, Mauritius, Korea, Malaysia, Philippines, Singapore, Thailand, Taiwan and Vietnam.</td>
</tr>
</tbody>
</table>
| **Australia** | All equities with country of risk defined as Australia or New Zealand on Bloomberg (field: COUNTRY_RISK_ISO_CODE).  
**Note:** it is not required that a stock is priced over 5 local cents to be covered by this model. |
| **Canada** | All equities listed in Canada or which have Canada defined as the country of risk on Bloomberg (field: COUNTRY_RISK_ISO_CODE). |
| **China A-Shares** | All equity China-A shares. |
| **Emerging Europe, Middle-East & Africa (EMEA)** | All equities listed on major exchanges in the following countries: United Arab Emirates, Botswana, Ghana, Kenya, Nigeria, Senegal, Bahrain, Cyprus, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Serbia, Slovakia, Slovenia, Egypt, Israel, Jordan, Kuwait, Morocco, Oman, Qatar, Russia, Ukraine, Kazakhstan, Saudi Arabia, Tunisia, Turkey and South Africa. |
| **European** | All equities listed on European exchanges, including GDRs. |
| **Japan** | All equities listed on Japanese exchanges. |
| **Latin America** | All equities listed on major exchanges in the following countries: Argentina, Brazil, Chile, Mexico, Colombia, Jamaica, Panama, Peru, Trinidad & Tobago and Venezuela. |
| **US** | All equities listed on the United States exchanges, including ADRs. |
| **Global** | All equities listed on major exchanges. |
Emerging Markets Factor Country Groupings

United Arab Emirates [AE]
Botswana, Ghana, Kenya, Nigeria, Senegal [AFG]
Bahrain [BH]
Cyprus [CY]
Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Serbia, Slovakia, Slovenia [EEG]
Egypt [EG]
Israel [IL]
Jordan [JO]
Kuwait [KW]
Morocco [MA]
Oman [OM]
Qatar [QA]
Russia, Ukraine, Kazakhstan [RUG]
Saudi Arabia [SA]
Tunisia [TN]
Turkey [TR]
South Africa [ZA]
Latin America Factor Country Groupings

Argentina [AR]
Brazil [BR]
Chile [CL]
Mexico [MX]
Latin America Group [LAG]: Colombia, Jamaica, Panama, Peru, Trinidad & Tobago, Venezuela

Asia Factor Country Groupings

China (B-shares and offshore shares) [CN]
Hong Kong (and China H-shares) [HKG]
Indonesia [ID]
India, Pakistan, Sri Lanka, Bangladesh, Mauritius [ING]
Korea [KR]
Malaysia [MY]
Philippines [PH]
Singapore [SG]
Thailand [TH]
Taiwan [TW]
Vietnam [VN]
## Global Model Factor Country Groupings

<table>
<thead>
<tr>
<th>Argentina (AR)</th>
<th>Latvia (LV)</th>
<th>Lebanon (LB)</th>
<th>Japan (JP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia (AU)</td>
<td>Lithuania (LT)</td>
<td>Oman (OM)</td>
<td>Korea (KR)</td>
</tr>
<tr>
<td>Austria (AT)</td>
<td>Macedonia (MK)</td>
<td>Qatar (QA)</td>
<td>Malaysia (MY)</td>
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<tr>
<td>Brazil (BR)</td>
<td>Romania (RO)</td>
<td>Saudi Arabia (SA)</td>
<td>Mexico (MX)</td>
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<tr>
<td>Belgium (BE)</td>
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<td>Canada (CA)</td>
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<td>Czech Republic (CZ)</td>
<td>Ecuador (EC)</td>
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<td>USA (US) +Bermuda,</td>
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<td>Jamaica (JM)</td>
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<td>Bahamas, Cayman</td>
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<td>Peru (PE)</td>
<td></td>
<td>Islands</td>
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<tr>
<td>Eastern Europe Frontier:</td>
<td>Trinidad and Tobago (TT)</td>
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<tr>
<td>Albania (AL)</td>
<td>Emerging Middle East:</td>
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<td>Belarus (BY)</td>
<td>Egypt [EG]</td>
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<td>Bosnia Herzegovina (BA)</td>
<td>Jordan (JO)</td>
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<td>Morocco (MA)</td>
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<td>Tunisia (TN)</td>
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<td>Estonia (EE)</td>
<td>Kuwait (KW)</td>
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<td>Results</td>
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<td>Appendix</td>
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<td>Motivation and Objectives</td>
<td>Bloomberg’s Factor Model</td>
<td>Interpreting Exposures</td>
<td>Replication Process</td>
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<td>Appendix</td>
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</tbody>
</table>
### Estimation Universe Special Situations

<table>
<thead>
<tr>
<th>Model</th>
<th>Estimation Universe</th>
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<tbody>
<tr>
<td>Australia</td>
<td>Starting from the Coverage Universe, which includes all equities with country of risk defined as Australia or New Zealand (field: COUNTRY_RISK_ISO_CODE), Bloomberg considers only those stocks with country of risk Australia and further imposes requirements on liquidity, price and minimum size.</td>
</tr>
<tr>
<td>European</td>
<td>The Coverage Universe includes all equities traded on European exchanges, however, when it comes to the Estimation Universe, Bloomberg excludes all companies incorporated outside of Europe and focuses on companies that account for 98% of the market cap in these countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and UK. Also, a company is also included if it is member of a major European equity index.</td>
</tr>
<tr>
<td>Japan</td>
<td>This model covers all equities listed on Japanese exchanges, but excludes on its Estimation Universe companies incorporated outside of Japan. Also, if a company is a member of the TOPIX index, it is automatically included in the universe.</td>
</tr>
<tr>
<td>US</td>
<td>Companies incorporated outside of the US are excluded from the Estimation Universe of this model, but if a company is a member of the S&amp;P500, it is included in the universe regardless.</td>
</tr>
</tbody>
</table>
Country Factor Aggregation in Replication Model

The reasoning behind the aggregation in these three groups is mainly geographic, but it also relates to the economic characteristics of each country and the country risks they face (that’s why we included Ireland in the SE factor).

<table>
<thead>
<tr>
<th>Northern Europe</th>
<th>Central Europe</th>
<th>Southern Europe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Denmark</td>
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<td>Greece</td>
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<td>Ireland</td>
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<td>Switzerland</td>
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<td></td>
<td>United Kingdom</td>
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<tr>
<td>Currency Factors in Replication Model</td>
<td>Industry Factors in Replication Model</td>
<td></td>
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<tr>
<td>----------------------------------------</td>
<td>---------------------------------------</td>
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<tr>
<td>Euro</td>
<td>Basic Materials</td>
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<td>Great British Pound</td>
<td>Communications</td>
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<tr>
<td>Norwegian Krone</td>
<td>Consumer (Cyclical)</td>
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<tr>
<td>Swiss Franc</td>
<td>Consumer (Non-cyclical)</td>
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<tr>
<td>Icelandic Krone</td>
<td>Diversified</td>
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<td>Swedish Krone</td>
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<td>Utilities</td>
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</tbody>
</table>

Relatively to Bloomberg’s model, some currencies (Eastern Europe) were not included.

Instead of using the 24 sectors as industry factors, we used the 10 industry groups in the replication model.
BIBLIOGRAPHY

- Menchero, J. (2010). *Characteristics of Factor Portfolios*