Morningstar Risk Model
Methodology

Introduction
Risk is inherent to investing. Developing a prospective view of risk allows investors to make investment decisions tailored to their individual risk preferences and ultimately increase the utility derived from their investment portfolios. A risk model forecasts the distribution of future asset returns. This distribution contains all the information needed to assess the riskiness of a portfolio. As the forecast distribution widens, that indicates more uncertainty about the future return potential of the portfolio. As tail probabilities increase, that indicates the portfolio has higher risk of experiencing an extreme loss. With this forecast, investors are empowered to evaluate the riskiness of assets or portfolios of assets.

In essence, the model seeks to identify a small number of independent, latent sources of return. Movements in these sources drive movement in a comparably small number of interpretable factors. An example of a factor is the exposure to particular industry currencies: For instance, how much does an increase in the euro/U.S. dollar exchange rate drive an increase in the value of a stock or bond?

Movements in the factors drive asset returns.

Several methodological choices must be made when building a risk model. Our choices were made with the goal of creating a unique, interpretable, responsive, and predictive model. We began with the following assumptions about asset returns, which shaped our methodological choices.

- A small number of independent sources of market movement drive the majority of variation in asset returns.
- Asset returns are not normally distributed.
- The distribution of asset returns changes through time.

These three concepts are well-recognized and not controversial, although some or all of them are often ignored for convenience by risk modeling practitioners.
Model Highlights
Several features make the Morningstar Risk Models unique:

1. We are holdings-based.
   Our risk models are entirely holdings-based. When looking at portfolios, holdings-based models will provide more accurate outputs for risk prediction, factor attribution, risk decomposition, and sensitivity analysis. Holdings-based models do not assume that the past equals the future as they allow for the fact that securities may change, managed products may change, and portfolios may change over time. They also enable new securities or funds to be covered immediately out-of-the-box.

2. We forecast the full probability distribution of future returns with non-normal distributions.
   Our risk models are agnostic to any particular risk metric a user wishes to employ. Volatility, conditional value at risk, downside deviation, interquartile range, skewness, kurtosis, and many other measures can be calculated directly from the probability distribution that is output from our models.

3. We use proprietary fundamentals-based factors that we believe are superior drivers of returns.
   Morningstar’s research group provides forward-looking ratings on assets, which have been successful in predicting the future distribution of returns. Factors based on these ratings also tend to be uncorrelated with traditional risk factors, making them a complementary addition to our risk factor model. Likewise, we have distilled Morningstar’s proprietary database of mutual fund holdings into factors, which are also uncorrelated predictors of the future distribution of returns.

4. We make no assumption that comovement of returns is exclusively linear.
   The common practice of building and analyzing only a covariance matrix misses the fact that stocks can experience tail events at the same time. Our model directly captures higher comovements of returns, enabling the construction of portfolios that can control tail risk.

5. We can customize each methodological decision at scale.
   Historically, risk model users are reliant on the decisions of the risk model providers. With Morningstar’s Risk Model technology platform, we can construct and build entire histories of new models within a matter of hours. We are in the process of deploying a suite of risk models specific to asset class, region, and currency. Descriptions for each risk model are found in Appendix A.

6. We offer robust risk analysis workflows.
   While risk models themselves offer exposures, premiums, and forecasts, these outputs are usually most valuable when placed within other workflows or modules. Morningstar offers users the ability to decompose risk or attribute returns to factors and holdings through time and across many instruments. Morningstar also offers a full complement of scenario analysis capabilities including historical scenarios, predefined macrofinancial scenarios, or market-driven scenarios.
Universe Construction

We define an estimation universe of investible companies with reliable data on which to build the model. Securities outside the estimation universe—generally illiquid assets with small market capitalizations—are relegated to the extended universe. We use only securities in the estimation universe to derive model parameters. This ensures the model parameters are not influenced by illiquid assets with unreliable data.

Exhibit 1 Estimation and Coverage Universe for the Morningstar Global Equity Risk Model

<table>
<thead>
<tr>
<th>Estimation Universe</th>
<th>Coverage Universe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approximately 7,000 stocks</td>
<td>Approximately 44,000 stocks</td>
</tr>
<tr>
<td>(Curated broad group of large, liquid stocks)</td>
<td>(Small, illiquid stocks)</td>
</tr>
</tbody>
</table>

Source: Morningstar.

We aim for a broad selection of companies across regions and sectors that are liquid enough to be investable for most investors and large enough to represent a large portion of the investable universe. Appendix B details the exact rules we use to filter our estimation universe for each model.

All market returns and factor inputs are converted into a denomination of the model currency when appropriate. For example, the outputs of the Morningstar United Kingdom Equity Risk Model measure risk with a British pound numeraire.

Factor Selection

There are many ways to estimate the comovement of asset returns. A naive approach might be to calculate a sample covariance matrix using historical returns. Unfortunately, this solution suffers from the curse of dimensionality, that is, the number of parameters in the covariance matrix is huge relative to the number of historical return observations. As a result, the covariance matrix will be dominated by noise and will poorly forecast future comovement.

To remedy this problem, we use a well-understood approach to reduce the number of dimensions: factor modeling. By finding common factors that drive asset returns, we no longer need to model each asset individually. We can instead model a much smaller number of factors. This reduces the dimension of our problem to reasonable levels and allows us to generate estimates of future comovement.

There are several key notions needed to understand the way this model works:

- An asset return is the return of an investible security over a period.
- A factor is an observable data point that appears to influence asset returns, like liquidity or sector.
- A factor exposure is a number that measures how much an asset's return is influenced by a factor. Exposures can be positive, negative, or zero. Exposures change through time.
- A factor premium is a number which represents how much a particular factor has influenced asset returns for a particular period.
We will later introduce sources. These are unobservable phenomena discovered through statistical inference that drive some collection of factor premiums.

We set out with several criteria when selecting factors for our model:
► Our factors should have an economic basis and empirical relevance as predictors of the future distribution of asset returns.
► Our factors should be interpretable and lend insight to a risk attribution analysis.
► Our factor set should be parsimonious.
► Our factor exposures should be practical to calculate.

Each model has a specific list of factors tailored to the model’s asset class, region, and currency. For equity securities, the factors fall naturally into five distinct groups: style, sector, region, currency, and an equity market factor. The equity market factor results from our estimation methodology and captures the common equity market movement globally or for a specific region. For fixed-income securities, we currently group factors into duration and credit. A detailed treatment for each factor can be found in Appendix C.

**Factor Premium Estimation**

Given a collection of factor exposures $X_t$ for a set of $n$ stocks at time $t$, we perform a cross-sectional regression of those exposures on total returns from $t$ to $t+1$, $r_t$, to estimate the factor premium $f_t$.

$$r_t = X_t f_t + \varepsilon_t$$

Where

$r_t = (n \times 1)$ vector of returns between time $t$ and $t + 1$

$X_t = (n \times m)$ matrix of securities’ exposures to factors at time $t$

$f_t = (m \times 1)$ vector of factor premiums between time $t$ and $t + 1$

$\varepsilon_t = (n \times 1)$ vector of error terms between time $t$ and $t + 1$

To improve the statistical properties of the estimated factor premiums, the exposure table contains an intercept term and a column of 1, and certain conditions are imposed on premium estimates using a constrained regression. A detailed description of the methodology can be found in Appendix E.

By repeating this cross-sectional regression, we construct a historical time series of the factor premiums. We use this time series to analyze how each factor behaves in the context of the other factors by examining factor comovement in the history.
Exhibit 2 shows the cumulative return of the Morningstar Global Equity Risk Model style factor premiums in USD for the past five years.

Local-Currency Versions of Risk Models
Risk models must be interpretable by investors in their own local currencies. Morningstar approaches this problem straightforwardly by recalculating factor exposures and by re-estimating factor premiums using local currency returns in separate model runs. For example, momentum exposures may use EUR-based returns when an EUR model version is chosen and may use USD-based returns when a USD model version is chosen. These exposures are built from the ground up using the local currency returns. In the same vein, EUR-based returns are used in the factor premiums estimation when an EUR model version is chosen and USD-based returns are used in the factor premiums estimation when a USD model version is chosen.

While this implies that the factor exposures and factor premiums may differ between local currency versions of the same model, it does represent the most direct approach to building a risk model artifact that a local investor would desire.
Conclusion

The ability to model the risk of a portfolio is paramount to making investment decisions that maximize utility. Our fundamental factor-based methodology provides a way to forecast risk, but more importantly, it provides an intuitive interpretation of the mechanics behind the forecast. Monitoring factor exposures and making economically sound decisions about which exposures are prudent and which are worth avoiding is much easier when factor exposures are interpretable.

Some of our risk models include factors unique to Morningstar. These factors that spring from our analyst-driven research and our institutional portfolio holdings database are uncorrelated with more-traditional factors and are helpful tools for investors to use when tailoring their portfolio to suit their risk preferences. In addition, we also include some more-standard, academically backed factors in our risk models.

No risk model is perfect. Our aim has been to emphasize interpretability, responsiveness, and predictive accuracy, and in doing so, we believe we’ve developed a unique framework for building risk models. We recognize there are many decisions to make when constructing a risk model: from universe selection to individual factor calculations to forecasting methods. Our framework allows us to quickly spin up new models to better match the model with our users’ definition of risk.
References


Appendix A: Morningstar Risk Model Definitions

Morningstar Global Equity Risk Model
The Morningstar Global Equity Risk Model captures risk premiums across the global equity universe.

Factors
- The model is defined by 37 factors across style, sector, region, and currency.
  - **Style:** Economic Moat, Financial Health, Liquidity, Momentum, Ownership Risk, Ownership Popularity, Size, Valuation, Valuation Uncertainty, Value-Growth, Volatility
  - **Sector:** Basic Materials, Energy, Financial Services, Consumer Defensive, Consumer Cyclical, Technology, Industrials, Healthcare, Communication Services, Real Estate, Utilities
  - **Region:** Equity Market Factor, Developed Americas, Developed Europe, Developed Asia Pacific, Emerging Americas, Emerging Europe, Emerging Asia Pacific, Emerging Middle East
  - **Currency:** Australian dollar, British pound, Canadian dollar, euro, Japanese yen, New Zealand dollar, Swiss franc

Data Availability
- The model generates daily data from Jan. 1, 2003, to the present day.

Currency
- The model is available in five currencies: Australian dollars, British pounds, Canadian dollars, euros, and U.S. dollars.

Morningstar Global Multi-Asset Risk Model
The Morningstar Global Multi-Asset Risk Model captures risk premiums across global equity and fixed income.

Factors
- The model is defined by 49 factors across style, sector, region, currency, and duration.
  - **Style:** Economic Moat, Financial Health, Liquidity, Momentum, Ownership Risk, Ownership Popularity, Size, Valuation, Valuation Uncertainty, Value-Growth, Volatility
  - **Sector:** Basic Materials, Energy, Financial Services, Consumer Defensive, Consumer Cyclical, Technology, Industrials, Healthcare, Communication Services, Real Estate, Utilities
  - **Region:** Equity Market Factor, Developed Americas, Developed Europe, Developed Asia Pacific, Emerging Americas, Emerging Europe, Emerging Asia Pacific, Emerging Middle East
  - **Currency:** Australian dollar, British pound, Canadian dollar, euro, Japanese yen, New Zealand dollar, Swiss franc
  - **Yield Curve:** Shift (USD, EUR, GBP, and CHF), Twist (USD, EUR, GBP, and CHF), Curvature (USD, EUR, GBP, and CHF)
Data Availability
The model generates daily data from Jan. 1, 2003, to the present day.

Currency
This model is available in the U.S. dollar currency.

Morningstar United Kingdom Equity Risk Model
The Morningstar United Kingdom Equity Risk Model captures equity risk premiums across the United Kingdom region.

The model is defined by 30 factors across style, sector, and currency.

- Equity market factor: Intercept
- Style: Valuation, Economic Moat, Financial Health, Momentum, Volatility, Size, Value Growth, Valuation Uncertainty, Liquidity, Ownership Popularity, Ownership Risk
- Currency: Australian dollar, Canadian dollar, euro, Japanese yen, New Zealand dollar, Swiss franc, U.S. dollar

Data Availability
The model generates daily data from Jan. 1, 2006, to the present day.

Currency
This model is available in the British pound currency.

Morningstar Eurozone Equity Risk Model
The Morningstar Eurozone Equity Risk Model captures equity risk premiums across the eurozone region.

The model is defined by 23 factors across style, sector, and currency.

- Equity market factor: Intercept
- Style: Economic Moat, Financial Health, Momentum, Size, Value-Growth, Volatility
- Currency: Australian dollar, British pound, Japanese yen, Swiss franc, U.S. dollar

Data Availability
The model generates daily data from Jan. 1, 2006, to the present day.

Currency
This model is available in the euro currency.
Morningstar North America Equity Risk Model

The Morningstar NA Regional Risk Model captures risk premiums across the North America equity universe.

Factors
The model is defined by 26 factors across style, sector, currency and equity market.

► Equity Market Factor: Intercept
► Style: Economic Moat, Financial Health, Liquidity, Momentum, Ownership Popularity, Size, Valuation, Valuation Uncertainty, Value-Growth, Volatility
► Sector: Basic Materials, Energy, Financial Services, Consumer Defensive, Consumer Cyclical, Technology, Industrials, Healthcare, Communication Services, Real Estate, Utilities
► Currency: Australian dollar, Euro, Canadian dollar and Japanese yen

Data Availability
The model generates daily data from Jan. 1, 2006, to the present day.

Currency
The model is available in one currency: USD.
Appendix B: Estimation Universe Construction Rules

We outline the estimation universe logic for each model and provide an illustration for the logic below.

**Morningstar Global Equity Risk Model**

Requirements:
- No ADRs

Filters:
- Market capitalization > USD 1 million
- Liquidity > USD 10,000
- Region-size rank ≤ 500
- Sector-size rank ≤ 250
- Sector-region-size rank ≤ 50
- Sector-country-size rank ≤ 10
- United States-size rank ≤ 2,000

**Morningstar Global Multi-Asset Risk Model**

Equity
The equity estimation universe follows the same logic as the Morningstar Global Equity Risk Model.

Fixed-Income
There is no estimation universe for the fixed-income portion of the risk model.

**Morningstar United Kingdom Equity Risk Model**

Requirements:
- Securities listed on London Stock Exchange and Alternative Investment Market
- Industry Classification is not Asset Management
- No ADRs

Filters:
- Market capitalization > GBP 1 million
- Liquidity > GBP 10,000
- Size rank ≤ 300
- Sector-size rank ≤ 30
- Sector-market capitalization coverage < 95%
Morningstar Eurozone Equity Risk Model

Requirements:
► Securities from the following countries: Austria, Belgium, Cyprus, Germany, Spain, Estonia, Finland, France, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal.
► Industry Classification is not Asset Management
► No ADRs

Filters:
► Market capitalization > EUR 1 million
► Liquidity > EUR 10,000
► Size rank ≤ 550
► Sector-size rank ≤ 30
► Country-size rank ≤ 75
Sector-country-size rank ≤ 2

Morningstar North America Regional Risk Model

Requirements:
► No ADRs

Filters:
► Market capitalization > USD 50 million
► Liquidity > USD 10,000
► Size rank ≤ 2500
- Sector-size rank ≤ 300
- SectorCountry-size rank ≤ 300
- Sector-marketcap % Canada (Exclude) ≤ 0.55
- Sector-marketcap % USA (Exclude) ≤ 0.70
An example of the estimation universe logic is depicted below:

\[ MvRank = \text{Rank of market capitalization} \]
\[ TvRank = \text{Rank of trading volume} \]
\[ SizeRank = MvRank + TvRank \]

**Exhibit 3 Estimation Universe Construction Logic**

Source: Morningstar.
Appendix C: Equity Factor Exposure Definitions

Interpretation

Style Factors

Our 11 style factors are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation, so a score of 0 can always be interpreted as the average score, and a nonzero score of n can be interpreted as being n standard deviations from the mean. In addition, we modify the sign of our exposures, so the premiums associated with them are generally positive.

Exhibit 4 11 Style Factors

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valuation</td>
<td>The ratio of Morningstar’s quantitative fair value estimate for a company to its current market price. Higher scores indicate cheaper stocks.</td>
</tr>
<tr>
<td>Valuation Uncertainty</td>
<td>The level of uncertainty embedded in the quantitative fair value estimate for a company. Higher scores imply greater uncertainty.</td>
</tr>
<tr>
<td>Economic Moat</td>
<td>A quantitative measure of the strength and sustainability of a firm’s competitive advantages. Higher scores imply stronger competitive advantages.</td>
</tr>
<tr>
<td>Financial Health</td>
<td>A quantitative measure of the strength of a firm’s financial position. Higher scores imply stronger financial health.</td>
</tr>
<tr>
<td>Ownership Risk</td>
<td>A measure of the risk exhibited by the fund managers who own a company. Higher scores imply more risk exhibited by owners of the stock.</td>
</tr>
<tr>
<td>Ownership Popularity</td>
<td>A measure of recent accumulation of shares by fund managers. Higher scores indicate greater recent accumulation by fund managers.</td>
</tr>
<tr>
<td>Liquidity</td>
<td>Share turnover of a company. Higher scores imply more liquidity.</td>
</tr>
<tr>
<td>Size</td>
<td>Market capitalization of a company. Higher scores imply smaller companies.</td>
</tr>
<tr>
<td>Value-Growth</td>
<td>Situation in which a value stock has a low price relative to its book value, earnings, and yield. Higher scores imply firms that are more growth and less value oriented.</td>
</tr>
<tr>
<td>Momentum</td>
<td>Total return momentum over the horizon from negative 12 months through negative 2 months. Higher scores imply greater return momentum.</td>
</tr>
<tr>
<td>Volatility</td>
<td>Total return volatility as measured by largest minus smallest one-month returns in a trailing 12-month horizon. Higher scores imply greater return volatility.</td>
</tr>
</tbody>
</table>

Source: Morningstar.

Sector Factors

Our sector factors measure the economic exposure of a company to the Morningstar sectors. We perform a Bayesian time-series regression analysis to find the exposures of an individual company to the sector return with a prior based on the discrete sector classification of Morningstar’s data analysts. We enforce constraints that our sector exposures, including the intercept term, must sum to 1 and must individually be between 0 and 1.

Region Factors

Our region factors represent the economic exposure of a company to the Morningstar regions. We perform a Bayesian time-series regression analysis to find the exposures of an individual company to the
return of the portfolio of stocks in the region with a prior based on the discrete region classification of Morningstar’s data analysts.

**Currency Factors**
Our currency factors represent the economic exposure of a company to major currencies, excluding U.S. dollars. We perform a time-series regression analysis to find the exposures of an individual company’s return denominated in U.S. dollar currency to the following list of currency returns: Australian dollar, British pound, Canadian dollar, euro, Japanese yen, New Zealand dollar, and Swiss franc. We calculate the return of these currencies against the U.S. dollar.

**Style Factor Definitions**

**Valuation**
The valuation factor is the normalized ratio of Morningstar’s Quantitative Fair Value Estimate to the current market price of a security. It represents how cheap or expensive a stock is relative to its fair value. We arrive at a quantitative fair value estimate using an algorithm that extrapolates from the roughly 1,400 valuations our equity analyst staff assigns to stocks to a coverage universe of more than 45,000 stocks. For a detailed explanation of this methodology, please refer to the Morningstar Quantitative Equity Ratings methodology document cited in the References section.

The factor is unbounded, and higher scores indicate cheaper stocks. A score of 0 indicates an average valuation.

**Valuation Uncertainty**
The valuation uncertainty factor is the normalized value of Morningstar’s Quantitative Valuation Uncertainty Score. It represents the standard error of Morningstar’s quantitative valuation, in other words, how unsure we are of a particular valuation. For a detailed explanation of this methodology, please refer to the Morningstar Quantitative Equity Ratings methodology document cited in the References section.

The factor is unbounded, and higher scores indicate more-uncertain valuations. A score of 0 indicates an average level of uncertainty.

**Economic Moat**
The economic moat factor is the normalized value of Morningstar’s Quantitative Moat Score. It represents the strength and sustainability of a firm’s competitive advantages. We arrive at a moat score using an algorithm that extrapolates from the roughly 1,400 Morningstar Economic Moat Ratings our equity analyst staff assigns to stocks to a coverage universe of more than 45,000 stocks. For a detailed explanation of this methodology, please refer to the Morningstar Quantitative Equity Ratings methodology document cited in the References section.
The factor is unbounded, and higher scores indicate stronger and more-sustainable competitive advantages. A score of 0 indicates an average level of competitive advantages.

### Financial Health

The financial health factor is the normalized value of Morningstar’s Quantitative Financial Health Score. It represents the strength of a firm’s financial position. The financial health score is driven by market inputs, making it responsive to new information. It is calculated as follows.

\[
QFH = 1 - \frac{(EQVOLP + EVMVP + EQVOLP \times EVMVP)}{3}
\]

Where:
- \(EQVOLP = \text{percentile rank trailing 300 day equity return volatility}\)
- \(EVMVP = \text{percentile rank of } \frac{\text{Enterprise Value}}{\text{Market Capitalization}}\)

The factor is unbounded, and higher scores indicate stronger financial health. A score of 0 indicates an average level of financial health.

### Ownership Risk

The ownership risk factor represents, for a particular stock, the ownership preferences of fund managers with different levels of risk exposure. The factor relies on current portfolio holdings information and the raw Morningstar 36-month Risk score. High ownership risk scores signify that those stocks are currently owned and preferred by fund managers with high levels of Morningstar Risk. If high-risk managers are purchasing these stocks, then those stocks are likely to be high-risk. A stock’s characteristic is therefore defined by who owns it.

The ownership risk score is calculated in the following manner:

\[
Ownership Risk_n = \sum_{m=1}^{M} w_{m,n} MRISK36_m
\]

Where:

\[
v_{m,n} = \frac{w_{m,n}}{\sum_{m=1}^{M} w_{m,n}}
\]

\(MRISK36 = \text{Morningstar Risk Score 36-month}\)

The ownership risk score for stock \(n\) is the weighted average of each manager \(m\)'s Morningstar 36-month Risk score multiplied by the relative weight he or she holds in stock. After raw scores are calculated, ownership risk scores are cross-sectionally normalized.
The factor is unbounded, and higher scores indicate stronger ownership preference for risk. A score of 0 indicates an average level of ownership preference for risk.

Ownership Popularity

The ownership popularity factor represents the growth in the popularity of a particular stock from the perspective of fund manager ownership. It relies on current and past portfolio holdings information. High ownership popularity scores signify that more funds have gone long the stock relative to those that have gone short the stock in the past three months.

The factor is calculated in the following manner:

\[
Ownership Popularity_n = \frac{1}{T} \sum_{t=1}^{T} \frac{O_{n,t} - O_{n,t-1}}{O_{n,t-1}}
\]

\[
O_{n,t} = \sum_{m=1}^{M} \frac{v_{m,n,t} Net Long_{m,t}}{w_{m,n,t}}
\]

Where:

\[
v_{m,n,t} = \frac{w_{m,n,t}}{\sum_{m=1}^{M} w_{m,n,t}}
\]

\[
Net Long_{m,t} = \begin{cases} 
-1 & \text{if } w_{m,n,t} < 0 \\
0 & \text{if } w_{m,n,t} = 0 \\
1 & \text{if } w_{m,n,t} > 0 
\end{cases}
\]

The ownership popularity score for stock n is the average growth in ownership over the past three months. Ownership is the weighted average of each manager m’s net long score multiplied by the relative weight he or she holds in stock. After raw scores are calculated, ownership popularity scores are cross-sectionally normalized.

The factor is unbounded, and higher scores indicate stronger ownership preference. A score of 0 indicates an average level of ownership preference.

Size

The size factor is the normalized value of the logarithm of a firm’s market capitalization:

\[
size_{ls} = -\ln(MV_{ls})
\]

The factor is unbounded, and higher scores indicate smaller market capitalization. A score of 0 indicates an average level of market capitalization.
Liquidity
The liquidity factor is the normalized value of the stock’s raw share turnover. The raw share turnover score is calculated as the logarithm of the average trading volume divided by shares outstanding over the past 30 days. It is essentially a churn rate for a stock and represents how frequently a stock’s shares get traded.

\[
\text{share turnover}_{t,t} = \ln \left( \frac{1}{T} \sum_{t=1}^{T} \frac{V_{t,t}}{SO_{t,t}} \right), \text{ where } T = 30
\]

The factor is unbounded, and higher scores indicate higher liquidity. A score of 0 indicates an average level of liquidity.

Value-Growth
Value-growth is a reflection of the aggregate expectations of market participants for the future growth and required rate of return for a stock. We infer these expectations from the relation between current market prices and future growth and cost-of-capital expectations under the assumption of rational market participants and a simple model of stock value.

The factor is unbounded, and higher scores indicate higher growth expectations and less value exposure. A score of 0 is average.

Momentum
The Momentum factor is the normalized value of the stock price’s raw momentum score. The raw momentum score is calculated as the cumulative return of a stock from 365 calendar days ago to 30 days ago. This is the classical 12-1 momentum formulation except using daily return data as opposed to monthly. To compute, U.S. dollar currency returns are used.

\[
\text{momentum}_{t,t} = \sum_{t=30}^{t=365} \left( \ln \left( 1 + r_{t,t} \right) - \ln \left( 1 + r_f \right) \right)
\]

The factor is unbounded, and higher scores indicate higher returns over the past year as well as a propensity for higher returns in the future. A score of 0 indicates an average level of momentum.

Volatility
The volatility factor is the normalized range of annual cumulative returns over the past year. Each day, we compute the trailing 12-month cumulative return. Then, we look over the past year and identify the maximum and minimum 12-month cumulative returns. We compute the range by taking the maximum minus the minimum 12-month cumulative returns.

\[
\text{range}_{t} = \left( \ln \left( 1 + r_{t,t} \right) - \ln \left( 1 + r_f \right) \right)_{\text{max}} - \left( \ln \left( 1 + r_{t,t} \right) - \ln \left( 1 + r_f \right) \right)_{\text{min}}
\]
The factor is unbounded, and higher scores indicate higher volatility. A score of 0 indicates an average level of volatility.

**Sector Factor Definitions**

Sector exposures are calculated based on a time-series regression of excess stock returns to a set of sector benchmarks.

\[
r_i - r_f = \alpha_i + \beta_1 (r_1 - r_f) + \cdots + \beta_k (r_k - r_f) + e_i
\]

- \(r_i\) = weekly return on the i-th stock
- \(r_f\) = weekly return on 3-mo US TBill
- \(r_k\) = weekly return on the kth sector benchmark (for example, Basic Materials)

constraints: 0 < \(\beta_k\) < 1; \(\sum_{k} \beta_k = 1\)

**Benchmark Construction**

Sector benchmark returns are calculated using a market-cap-weighting scheme using stocks from our estimation universe. Stocks are assigned to sectors on the basis of Global Sector ID. All returns are computed in U.S. dollars. Market capitalizations were also converted to dollars prior to benchmark constitution.

**Regression Setup**

Regressions are five years in length and are run on a rolling, weekly frequency. In the case where a stock does not have five years of history, we run the time-series regression back to the inception date. If a stock has less than one year of history, we do not run the regression and instead default to the stock’s Morningstar sector classification. We employ a Bayesian prior that presupposes companies should be entirely exposed to the sector to which they are assigned.

**Sectors**

Below is the complete list of sectors available to be included in the multivariate regression. Note, depending on the factor list of each model, only a subset could be used.

- Basic Materials
- Energy
- Financial Services
- Consumer Defensive
- Consumer Cyclical
- Technology
- Industrials
- Healthcare
Communication Services
Real Estate
Utilities

Interpretation
Sector exposures are bounded between 0 and 1. They must jointly (including the intercept) sum to 1. Higher scores indicate higher levels of sensitivity to individual sectors.

Region Factor Definitions
Regional exposures are calculated based on a time-series regression of excess stock returns to a set of region benchmarks.

\[ r_i^t - r_f^t = \alpha_i + \beta_1^i (r_1^t - r_f^t) + \cdots + \beta_k^i (r_k^t - r_f^t) + \epsilon_i^t \]

\( r_i^t = \text{weekly return on the } i\text{th stock} \)
\( r_f^t = \text{weekly return on } 3 - \text{mo US TBill} \)
\( r_k^t = \text{weekly return on the } k\text{th region benchmark (for example, Developed North America)} \)

constraints: \( 0 < \beta_k^i < 1; \sum_k \beta_k^i = 1 \)

Benchmark Construction
Region benchmark returns are calculated using a market-cap-weighting scheme using stocks from our estimation universe. Stocks are assigned to regions on the basis of company-level Country ID. All returns are computed in U.S. dollars. Market capitalizations were also converted to dollars prior to benchmark construction.

Regression Setup
Regressions are five years in length and are run on a rolling, weekly frequency. In the case where a stock does not have five years of history, we run the time-series regression back to the inception date. If a stock has less than one year of history, we do not run the regression and instead default to the stock's Morningstar region classification based on country of domicile. We employ a Bayesian prior that presupposes that companies should be entirely exposed to the region in which their company-level Country ID belongs.

Regions
Below is the complete list of regions available to be included in the multivariate regression. Note, depending on the factor list of each model, only a subset could be used.

- Developed North America
- Developed Europe
► Developed Asia Pacific
► Emerging Latin America
► Emerging Europe
► Emerging Asia Pacific
► Emerging Middle East & Africa

Exhibit 5 Map of Countries to Regions

<table>
<thead>
<tr>
<th>Region</th>
<th>Country List</th>
</tr>
</thead>
<tbody>
<tr>
<td>Developed Asia Pacific</td>
<td>Australia</td>
</tr>
<tr>
<td></td>
<td>Hong Kong</td>
</tr>
<tr>
<td></td>
<td>Japan</td>
</tr>
<tr>
<td></td>
<td>New Zealand</td>
</tr>
<tr>
<td></td>
<td>Singapore</td>
</tr>
<tr>
<td>Developed Europe</td>
<td>Belgium</td>
</tr>
<tr>
<td></td>
<td>Switzerland</td>
</tr>
<tr>
<td></td>
<td>Germany</td>
</tr>
<tr>
<td></td>
<td>Denmark</td>
</tr>
<tr>
<td></td>
<td>Spain</td>
</tr>
<tr>
<td>Developed North America</td>
<td>United States</td>
</tr>
<tr>
<td></td>
<td>Canada</td>
</tr>
<tr>
<td>Emerging Europe</td>
<td>Czech Republic</td>
</tr>
<tr>
<td></td>
<td>Hungary</td>
</tr>
<tr>
<td>Emerging Europe</td>
<td>Poland</td>
</tr>
<tr>
<td></td>
<td>Russian Federation</td>
</tr>
<tr>
<td>Emerging Latin America</td>
<td>Brazil</td>
</tr>
<tr>
<td></td>
<td>Chile</td>
</tr>
<tr>
<td></td>
<td>Colombia</td>
</tr>
<tr>
<td>Emerging Middle East &amp; Africa</td>
<td>Egypt</td>
</tr>
<tr>
<td></td>
<td>Israel</td>
</tr>
<tr>
<td></td>
<td>Morocco</td>
</tr>
<tr>
<td></td>
<td>South Africa</td>
</tr>
</tbody>
</table>

Source: Morningstar.

Interpretation
Region exposures are bounded between 0 and 1. They must jointly (including the intercept) sum to 1. Higher scores indicate higher levels of sensitivity to individual regions.

Currency Factor Definitions
Currency exposures are calculated based on a time-series quantile regression of excess stock returns to a set of exchange rates.

\[ r_i^t - r_t^f = \alpha^i + \beta_1^i (r_1^t) + \cdots + \beta_k^i (r_k^t) + \epsilon_i^t \]

- \( r_i^t \) = weekly return on the ith stock
- \( r_t^f \) = weekly return on 3-month US TBill
- \( r_k^e \) = weekly return on the kth exchange rate return (for example, % change in EUR USD)

Regression Setup
Regressions are five years in length and are run on a rolling, weekly frequency. In the case where a stock does not have five years of history, we run the time-series regression back to the inception date. Stock returns are calculated in U.S. dollars.
Currencies
Below is the complete list of currencies available to be included in the multivariate regression. Note, depending on the factor list of each model, only a subset could be used. For example, the Morningstar U.K. Equity Risk Model includes the U.S. dollar but not the British pound.

- euro
- Japanese yen
- British pound
- Swiss franc
- Canadian dollar
- Australian dollar
- New Zealand dollar
- U.S. dollar

Interpretation
Currency exposures are unbounded but generally fall between negative 1 and 1. Higher scores indicate higher levels of sensitivity to individual exchange-rate fluctuations.
Appendix D: Fixed-Income Factor Exposures

The factors driving fixed-income returns can be best understood by examining the basic bond valuation formula. The simplest arbitrage-free model of security valuation, applicable to bonds with fixed cash flows, serves as a valuable starting point for understanding fixed-income modeling. The present value of a bond is simply the sum of the present values of the cash flows, with discount rates given by the term structure of interest rates:

\[ PV_{Bond} = \sum_{t=1}^{T} CF_t \ast e^{-r_t} \]

The valuation formula states that the present value \( PV_{Bond} \) of a bond is the sum of cash flows \( CF_t \) at times \( t \) discounted by the time \( t \) interest rates \( r_t \). The valuation formula makes clear that changes in bond prices, or bond returns, are driven by changes in the expected cash flows and/or changes in the appropriate discount rates. For a risk-free fixed-coupon bond, the cash flows are the coupon and the principal payments, and the interest rates are the prevailing risk-free rates. The valuation formula becomes more complex when we leave the realm of risk-free fixed-coupon bonds because the cash flows may be state- or even history-dependent, and the discount rates include a spread to compensate investors for the additional risks. We plan to tackle these risks in future releases of the multi-asset model.

The most important return drivers for most fixed-income securities, with exception of high-yield instruments, are the changes in the government yield curves in the respective markets. These changes affect the value of all fixed-income instruments because of the changes in the marketwide risk-free discount rates. While there are many ways to describe government yield-curve movements, one commonly used technique involves using principal component analysis. Many academic studies and commercial fixed-income attribution systems use PCA to analyze and attribute yield-curve movements. PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This transformation is defined in such a way that the first principal component accounts for as much of the variability in the data as possible, and each succeeding component, in turn, accounts for as much of the variability in the data as possible under the constraint that it is orthogonal to the preceding components. The resulting vectors, each being a linear combination of the original variables, are an uncorrelated orthogonal basis set.

We find, consistent with most published PCA studies of yield curves, that the first three principal components, commonly known as the shift, twist, and curvature (or butterfly), can explain between 90% and 99% of interest-rate variation. The explanatory power of shift, twist, and curvature persists across markets and time periods. Because PCA generally attributes at least 85% of curve changes to the first principal component, the general expectation is that the bulk of yield-curve returns should be attributed to shift, with only a small fraction from twist and an even smaller fraction from curvature. A rule of
thumb is that twist volatilities are usually about half of shift volatilities, while curvature volatilities are in turn half of the twist volatilities.

Morningstar’s Multi-Asset Risk Model captures the interest-rate component of USD-, EUR-, GBP-, and CHF-denominated bonds in terms of the respective shift, twist, and curvature factors of the U.S., German, British, and Swiss government yield curves.

Shift
Defined as the first principal component, or PC, of absolute daily changes in the par government yield curve, this factor can be interpreted as a parallel movement of the curve across all maturities.

Twist
Defined as the second principal component of absolute daily changes in the par government yield curve, this factor can be interpreted as a steepening or flattening of the curve.

Curvature
Defined as the third principal component of absolute daily changes in the par government yield curve, this factor can be interpreted as a change in the curvature of the curve, when yields at intermediate maturities change with respect to those at short and long maturities.

We model the interest-rate return of each bond as its exposures to the currency-matched shift, twist, and curvature factors multiplied by the currency-matched factor premiums:

\[ R_t = I_{Rate,t} \times (X_{Shift,t} \times Shift_t + X_{Twist,t} \times Twist_t + X_{Curvature,t} \times Curvature_t) + s_t \]

Where:
- \( R_t \): The daily price return (total return - income return) of the bond
- \( I_{Rate,t} \): The dummy variable categorizing the currency of the security (USD/EUR/GBP/CHF)
- \( X_{Shift,t} \): The bond’s daily exposure to the shift factor of each currency \( Shift_t \), defined as the sensitivity of the bond's price return to a unit change in the shift factor:
  \[ \frac{1}{P \delta Shift_t} \]
- \( X_{Twist,t} \): The bond’s daily exposure to the twist factor of each currency \( Twist_t \), defined as the sensitivity of the bond's price return to a unit change in the twist factor:
  \[ \frac{1}{P \delta Twist_t} \]
- \( X_{Curvature,t} \): The bond’s daily exposure to the curvature factor of each currency \( Curvature_t \), defined as the sensitivity of the bond's price return to a unit change in the curvature factor:
  \[ \frac{1}{P \delta Curvature_t} \]
- \( Shift_t \): The shift factor premium of each currency (first PC of government curve changes)
- \( Twist_t \): The twist factor premium of each currency (second PC of government curve changes)
- \( Curvature_t \): The curvature factor premium of each currency (third PC of government curve changes)
- \( s_t \): vector of idiosyncratic returns (residual returns)
Appendix E: Cross-Sectional Regression

After deciding on the universe of securities to include in the model and gathering quality input data, the next important step in risk model construction is to run the cross-sectional regression. There are numerous techniques and specifications we can employ in the regression; the following method has been chosen to provide accurate, meaningful, and stable estimates of factor premiums. Special care has been given to deal with the common multicollinearity issue associated with sector and region factors; as the sum of all sectors and regions are both the entire universe of securities, it is difficult to estimate the pure sector and region effects that are uncorrelated with each other. We apply a constrained regression to disentangle the sector and region effects from each other, as well as from the overall market movement.

The Constrained Regression

The return of a security \( r_i \) in the cross section can be explained as

\[
 r_i = \alpha + \sum_{m=1}^{M} X_{i,m} f_m^{Style} + \sum_{s=1}^{S} X_{i,s} f_s^{Sector} + \sum_{r=1}^{R} X_{i,r} f_r^{Region} + \sum_{c=1}^{C} X_{i,c} f_c^{Currency} + \varepsilon_i \tag{E1}
\]

where \( X_{i,m}, X_{i,s}, X_{i,r}, X_{i,c} \) are security \( i \)'s exposure to style factor \( m \), sector \( s \), region \( r \), and currency \( c \); \( f_m^{Style}, f_s^{Sector}, f_r^{Region}, f_c^{Currency} \) are factor premiums for style \( m \), sector \( s \), region \( r \), and currency \( c \); \( M, S, R, C \) are the total number of style, sector, region, and currency factors in a particular model; \( \alpha \) is the intercept; and \( \varepsilon_i \) is the residual term, representing a stock’s specific return.

In the estimation, the market-cap-weighted average sector premiums and region premiums are both constrained to zero:

\[
 \sum_{s=1}^{S} u_s f_s^{Sector} = \sum_{r=1}^{R} v_r f_r^{Region} = 0 \tag{E2}
\]

where \( u_s \) and \( v_r \) are the market-cap weights of sector \( s \) and region \( r \), respectively. This means certain sectors and regions earn positive returns and others earn negative, but the market-cap-weighted average sector and region returns are zero.

To understand the logic of these constraints, imagine an investor who has a portfolio that has the same sector and region composition as the entire market; the region and sector average return from this portfolio should not contribute extra return to the market because the sum of sectors and regions are both the market. But what captures the market return in this setting? It turns out that under certain conditions, the estimated \( \alpha \) is a good proxy for the market.
The Equity Market Factor
The intercept is represented by a column of 1 in the exposure table, and it can be viewed as stocks’ exposure to a factor. What factor does every stock have the same level of exposure to? It should be a factor that represents the equity market universe, and an exposure of 1 indicates membership in this universe. For this reason, the estimated $\alpha$ can approximate the overall equity market return; we name it the "equity market factor." The approximation becomes accurate with some additional conditions.

In addition to the constraints on sector and region premiums, all style factor exposures are standardized cross-sectionally to have a market-cap-weighted mean of zero:

$$\tilde{X}_m = \sum_{i=1}^{N} w_i X_{i,m} = 0 \quad (E3)$$

where

- $\tilde{X}_m$ = market-cap weighted average exposure of the estimation universe to factor $m$,
- $w_i$ = market-cap weight of security $i$,
- $X_{i,m}$ = security $i$'s exposure to style factor $m$.

This standardization ensures the overall market is style neutral. Now, consider aggregating the market-cap-weighted estimation universe as

$$r_E = \alpha + \sum_{m=1}^{M} \tilde{X}_m f_m^{Style} + \sum_{s=1}^{S} u_s f_s^{Sector} + \sum_{r=1}^{R} v_r f_r^{Region} + \sum_{c=1}^{C} \tilde{X}_c f_c^{Currency} + \sum_{i=1}^{N} w_i e_i \quad (E4)$$

where $r_E$ is the market-cap-weighted average return. Note, by equations (E2) and (E3), the second to the fourth items on the right-hand side become zero. The last term of weighted residuals equals zero because in a least-squares estimation the residual term is orthogonal to the independent variables including the intercept of 1s. Although we do not standardize the currency exposures, the impact of currency return is limited. Therefore, the estimated $\alpha$ can approximate closely the market-cap-weighted average return of the estimation universe.

Note that the regression has been weighted using the square root of the market-cap weight of each stock in the estimation universe. This is to reduce the uneven variability of the specific returns among stocks, which improves the statistical properties of premium estimates. In this case, the weighted sum of residuals in equation (E4) is only approximately zero.

To sum up, with the constrained regression, the sector and region premiums measure the pure and uncorrelated sector and region returns relative to the overall market return, captured by $\alpha$. $\alpha + f_s^{Sector}$ approximates the return of a geographically diversified portfolio of companies in sector $s$. "Geographically diversified" means the portfolio has the same market-cap-weighted region composition as the equity market universe and is free from any additional region effects. Similarly, $\alpha + f_r^{Region}$ gives the return of a portfolio of stocks that is sector diversified as the equity market universe.
Appendix F: Frequently Asked Questions

What is the portfolio coverage threshold for calculating forecasts?
We calculate risk exposures for all equity portfolios, but we make forecasts only if we can generate risk forecasts for at least 80% of the portfolio. We can calculate roughly 10,000 equity funds. Note, this excludes money market funds and funds-of-funds but includes exchange-traded funds and any equity separately managed accounts with holdings information.

I see stock-level exposures are centered around mean 0 with a standard deviation of 1, but this does not appear to be the case for portfolio exposures. Why is that?
Portfolios are specific subsets of stocks. These subsets are often not equally weighted. Also, the subsets are usually tilted toward large-cap and more-liquid stocks. Furthermore, some stocks are never held by portfolios or indexes for which we have portfolio information. All these factors would contribute to the fact we would never expect portfolios to be centered around mean 0 with a standard deviation of 1.

What is the calculation date of the factor exposure data points?
The risk factors are recalculated daily. For portfolios, we use the most recent portfolio holdings information and assume the portfolio weightings do not change.

Why do region and sector exposures not sum to 1?
Region and sector exposures sum to 1 when we include the intercept term of the Bayesian regression. However, we do not display the intercept currently.

Why do some premiums that I observe differ across the risk model options?
Premiums depend on what sets of controls are used in the model and the universe over which the model is applied. For example, in some risk models, value shows up with a large premium and in others, the size premium may be small. In the Morningstar Global Equity Risk Model, value generates a high mean return. This is not the case in the Morningstar U.K. Equity Risk Model.

Do you model equity and fixed-income securities independently?
Yes, we model equity and fixed-income securities independently, capturing the common risks in equities with the equity risk factors and introducing a set of new yield curve factors to capture the impact of interest-rate movements on bonds.

What types of fixed-income bonds do you cover?
Currently, we cover noncallable corporate, sovereign, and muni bonds denominated in four major currencies (USD, EUR, GBP, CHF). In future releases, we plan to improve the coverage by adding bonds denominated in more currencies, callable bonds, mortgage-backed securities, and interest derivatives, as well as improve the explanatory power of our model by introducing new risk factors to capture the effects of credit, liquidity, prepayment, and interest volatility risks.
About Morningstar® Quantitative Research™
Morningstar Quantitative Research is dedicated to developing innovative statistical models and data points, including the Quantitative Equity Ratings and the Morningstar Risk Model.

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