
Global Risk Model Factor Exposures

Methodology

Morningstar Research

7 June 2016

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The Global Risk Model helps you identify and assess the amount of risk in your investments.

By tracking a stock's underlying economic exposure to 36 factors, including six unique to Morningstar, our model lets you quickly see how a variety of market conditions could affect a portfolio.

The factor exposures in our model root out underlying revenue drivers to find a stock's true sources of returns, and they include proprietary factors derived from the proven, forward-looking analysis of our research team. The risk model has four distinct types of exposure factors:

Style Exposures

A critical part of the Global Risk Model is the inclusion of proprietary style factors which we believe are superior drivers of returns. There are 11 style exposures included in the model as listed below. The Morningstar proprietary factors are bulleted in red:

Morningstar Proprietary Factors

- ▶ Economic Moat
- ▶ Financial Health
- ▶ Ownership Popularity
- ▶ Ownership Risk
- ▶ Valuation
- ▶ Valuation Uncertainty

Other Factors

- ▶ Liquidity
- ▶ Momentum
- ▶ Size
- ▶ Value-Growth
- ▶ Volatility

Economic Moat

The Economic Moat exposure is based on the Morningstar® Quantitative Economic Moat™ Rating designed to assess the strength of a firm's competitive position and by evaluating the sustainability of their profits. Higher scores indicate a firm will be able to keep competitors at bay for an extended period. Using the Economic Moat factor can help investors evaluate and adjust their portfolio exposure to firms with a stronger or weaker competitive position. We find that firms with strong moats tend to perform best relative to weaker moat companies during a crisis and when the economy recovers, the trend is reversed. As evidenced by the chart below, we see that a portfolio tilted towards strong moat companies would have generated stronger returns during 2008-2009 but as the economy recovers, the moat effect has a muted effect on returns. This pattern suggests that building portfolios tilted towards companies with strong moats can shield investors from extreme event risk.

Exhibit 1 Economic Moat Premia Through Time



Source: Morningstar.

To calculate the Morningstar® Quantitative Economic Moat™ Rating, we developed a statistical model to replicate the output of an analyst as faithfully as possible. The model calculates two probabilities: one to predict whether a company has a wide moat or not, and one to predict whether a company has no moat or not.

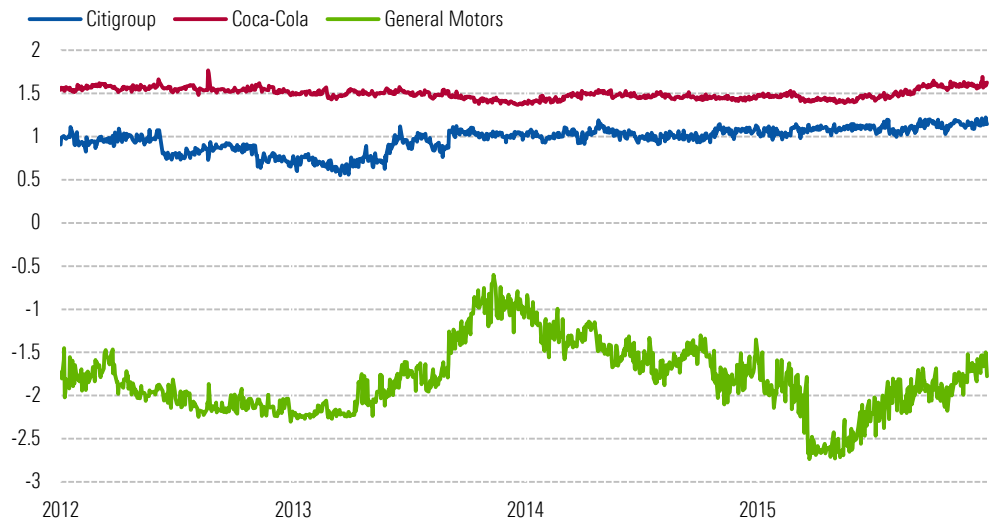
$$\text{Moat Score} = \frac{P(\text{Wide Moat Prediction}) + (1 - P(\text{No Moat Prediction}))}{2}$$

$$0 \leq P(\text{Wide Moat Prediction}) \leq 1$$

$$0 \leq P(\text{No Moat Prediction}) \leq 1$$

To calculate the Economic Moat exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean. Below, we see that Coca-Cola has consistently been considered a strong moat company while Citigroup has remained above average. Meanwhile, GM has been below average in terms of its moat over this time.

Exhibit 2 Economic Moat Factor Exposure over Time



Source: Morningstar.

Financial Health

The Financial Health factor is based on the Quantitative Financial Health metric designed to assess the strength of a firm's financial position and ranks companies on the likelihood that they will tumble into financial distress. Higher scores imply stronger financial health and therefore a lower risk of bankruptcy. Using the Financial Health factor exposure can help investors evaluate and adjust their portfolio exposure to more or less financially stable firms. We find that financially stable firms tend to perform best relative to financially unsound firms during a crisis as evidenced by the chart below. From 2008 through 2009, we see that a portfolio tilted towards financially sound companies would have generated stronger returns.

Exhibit 3 Financial Health Premia Through Time



Source: Morningstar.

To calculate the Quantitative Financial Health metric, we developed a linear model approximating the Distance to Default definition by measuring the interaction between the percentile of a firm's leverage and the percentile of a firm's equity volatility relative to the rest of the universe. Our model has the benefit of increased breadth of coverage, greater simplicity of calculation, and more predictive power while maintaining the timeliness of a market-driven metric.

$$\text{Financial Health Score} = 1 - \frac{(\text{EQVOLP} + \text{EVMVP} + \text{EQQLP} \times \text{EVMVP})}{3}$$

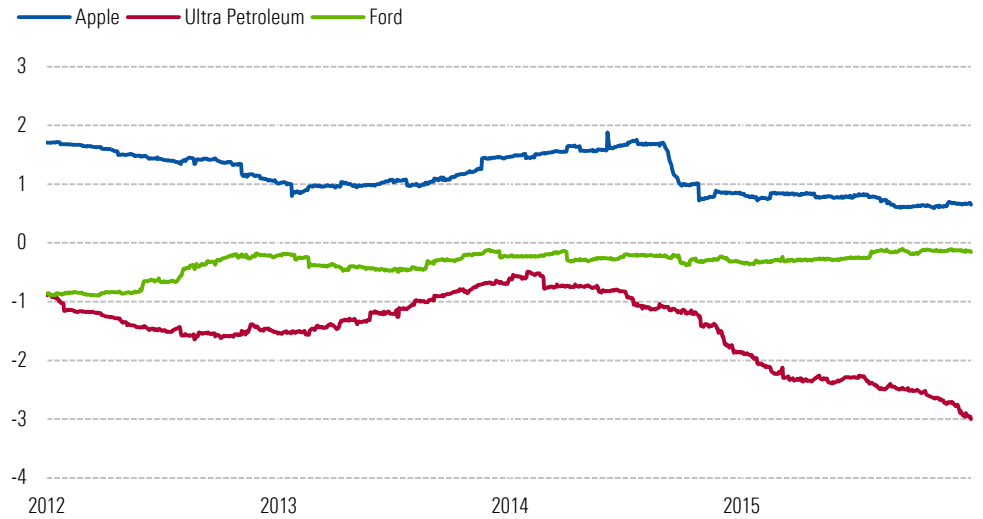
EQVOLP = Percentile of Annualized Trailing 300 Day Equity Total Volatility

$$\text{EVMVP} = \text{Percentile} \left(\frac{\text{Current Enterprise Value}}{\text{Market Cap Ratio}} \right)$$

To calculate the Financial Health exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation, so a score of zero can always be

interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean. Below, we see that Apple has consistently been considered a financially sound firm while Ultra Petroleum Corp’s financial positioning has weakened considerably over the past few years. Meanwhile, Ford has been about average in terms of its financial stability over this time.

Exhibit 4 Financial Health Factor Exposure over Time



Source: Morningstar.

Ownership Popularity

The Ownership Popularity factor represents the growth in the popularity of a particular stock from the perspective of fund manager ownership. The Ownership Popularity factor 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 3 months. We find that portfolios tilted towards stocks with high-levels of Ownership Popularity consistently perform poorly compared to unpopular stocks. However, the magnitude of this effect is not economically significant. Nonetheless, we find that differences in Ownership Popularity are quite meaningful for explaining the future variance of returns.

Exhibit 5 Ownership Popularity Premia Through Time



Source: Morningstar.

The Ownership Popularity factor 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/she holds in stock. If we observed that many managers are increasing their ownership of a specific stock, then the inference would be that this stock is gaining in popularity and we should expect its return to lower in the future.

The Ownership Popularity score is calculated in the following manner:

$$\text{Ownership Popularity}_n = \frac{1}{T} \sum_{t=1}^T \frac{O_{n,t} - O_{n,t-1}}{O_{n,t-1}}$$

$$O_{n,t} = \sum_{m=1}^M v_{m,n,t} \text{NetLong}_{m,t}$$

Where:

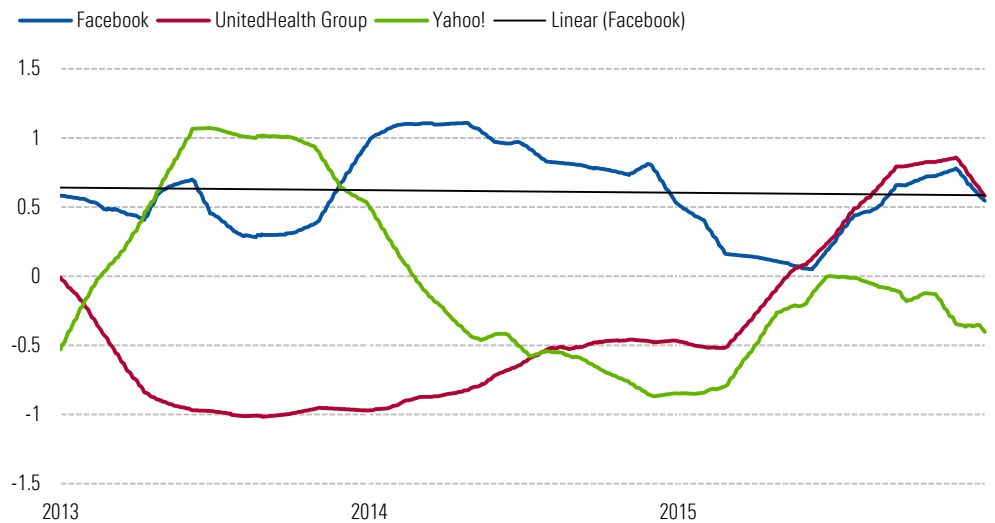
$$v_{m,n,t} = \frac{w_{m,n,t}}{\sum_{m=1}^M w_{m,n,t}}$$

$$NetLong_{m,t} = \begin{cases} -1 & \text{if } w_{m,n,t} < 0 \\ 0 & \text{if } w_{m,n,t} = 0 \\ 1 & \text{if } w_{m,n,t} > 0 \end{cases}$$

The raw scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation, so a score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

Stocks can fall into and out of favor very quickly. To smooth out these trends, we plot a six-month moving average of the Ownership Popularity exposures. Below, we see Facebook has been popular with equity fund managers since 2013. Yahoo, on the other hand, was quite popular in 2013 to early 2014, but has since fallen out of favor. United Health Group spent several years being out of favor until becoming more popular than Facebook in late 2015.

Exhibit 6 Ownership Popularity Factor Exposure Through Time



Source: Morningstar.

Ownership Risk

The Ownership Risk factor represents, for a particular stock, the ownership preferences of fund managers with different levels of risk exposure. The Ownership Risk 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. We find that portfolios tilted towards stocks with high-levels of Ownership Risk perform very well during crises, like 2008-2009, when preference for risk-taking dissipates. During bull markets, however, the premium appears to dissipate.

Exhibit 7 Ownership Risk Premia Through Time



Source: Morningstar.

The Ownership Risk factor for stock n is calculated as the weighted average of each manager m 's Morningstar Risk 36-month score multiplied by the relative weight he/she holds in stock. If a manager exhibits extreme risk behavior over the past 36 months, then their Morningstar Risk 36-month score would be very high to reflect that. If we observed that every high risk manager owned a significant amount of a specific stock, then the inference would be that this stock is going to exhibit extreme risk behavior going forward.

$$\text{Ownership Risk}_n = \sum_{m=1}^M v_{m,n} \text{MRISK36}_m$$

Where:

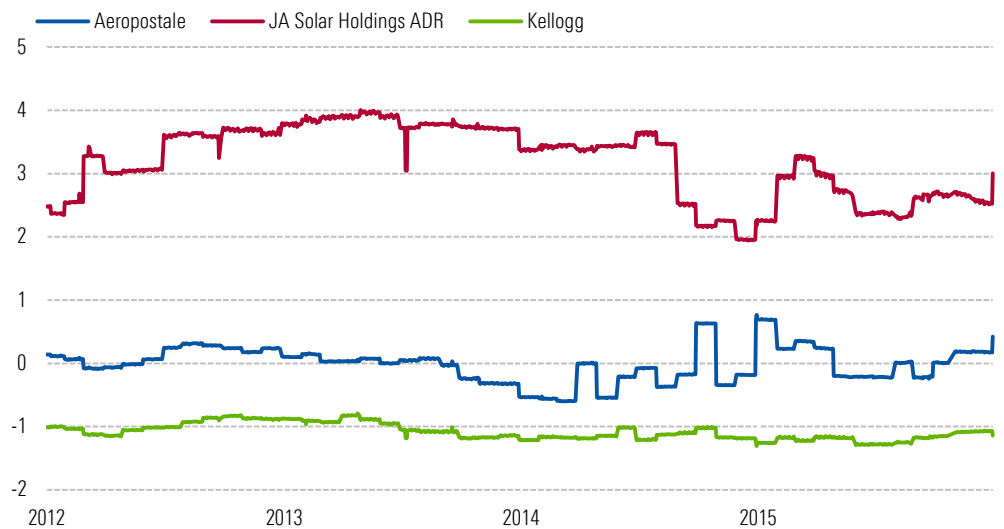
$$v_{m,n} = \frac{w_{m,n}}{\sum_{m=1}^M w_{m,n}}$$

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

The raw scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation, so a score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

Below, we see JA Solar has been highly preferred by very risky managers since 2008. Kellogg, on the other hand, has been preferred by relatively low risk managers for the entire period charted below. Aeropostale has been owned by managers with relatively average risk profiles.

Exhibit 8 Ownership Popularity Factor Exposure Through Time



Source: Morningstar.

Valuation

The Valuation factor is based on the Morningstar's Quantitative Valuation metric which compares the 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. Higher scores indicate we believe the company is undervalued and increases the likelihood the company will generate positive returns. Using the Morningstar Valuation factor can help investors adjust their portfolio exposure to their valuation preference. We find the Valuation factor is a significant indicator in future returns as evidenced by the chart Valuation Premia showing through time. A portfolio tilted towards undervalued companies would generate stronger returns, regardless of the market conditions.

Exhibit 9 Valuation Premia Through Time

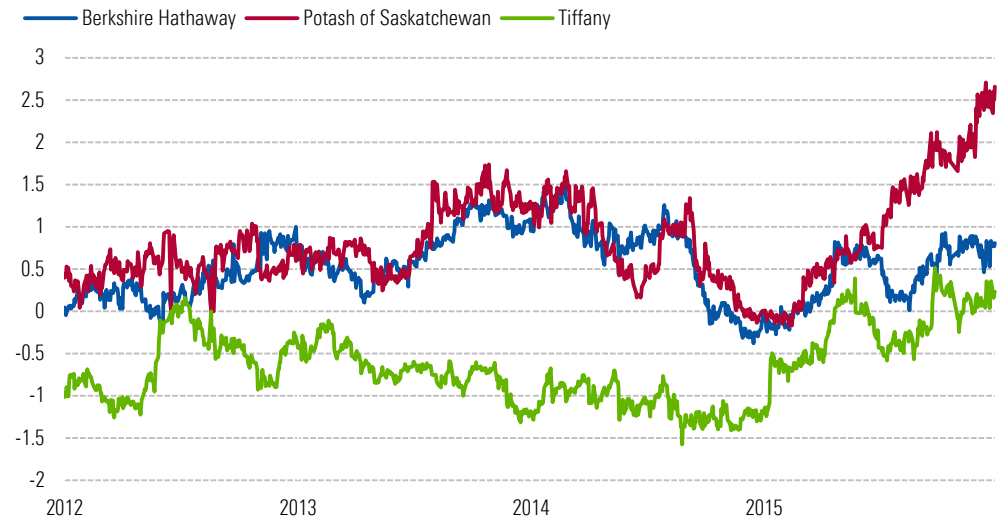


Source: Morningstar.

To calculate the Quantitative Valuation metric, we developed an algorithm which attempts to divine the characteristics of stocks that most differentiate the overvalued stocks from the undervalued stocks as originally valued by our team of human equity analysts. Once these characteristics have been found, and their impact on our analyst-driven valuations has been estimated, we can apply our model beyond the universe of analyst-covered stocks. To be more precise, we use a machine learning algorithm known as a random forest to fit a relationship between the variable we are trying to predict (an analyst's estimate of the over- or under-valuation of the stock) and our fundamental and market-based input variables.

To calculate the Valuation exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation, so a score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean. Below, we see Potash has been historically undervalued since 2008 but has now reached deep value. Berkshire Hathaway has been slightly undervalued historically as well. Tiffany, on the other hand, has recently become fairly valued after a period of overvaluation. Since the Valuation factor is a significant indicator of future returns, we expect the returns to be correlated to their valuation.

Exhibit 10 Valuation Factor Exposure Through Time



Source: Morningstar.

Valuation Uncertainty

The Valuation Uncertainty factor is based on the Quantitative Uncertainty Rating and measures the level of uncertainty embedded in a company's Quantitative Fair Value Estimate. Higher scores imply greater uncertainty so we expect to see a greater range of outcomes. Using the Quantitative Uncertainty Rating can help investors evaluate and adjust their portfolio exposure to firms with more certain equity valuations. Overall, we see the premia for the Valuation Uncertainty factor is not an economically strong indicator of mean returns though it is consistent as shown by the chart below. This means that we find only small benefit to be derived from investing in low uncertainty stocks vs. high uncertainty stocks. The Valuation Uncertainty Factor, however, does have strong, marginal explanatory power in helping to describe the future variance of returns.

Exhibit 11 Valuation Uncertainty Premia Through Time



Source: Morningstar.

To calculate the Quantitative Valuation Uncertainty metric, we use the outputs from the statistical model calculating the Quantitative Valuation Estimate. For each Quantitative Valuation Estimate, the model generates 500 predictions before averaging them at the final prediction. The dispersion (or more specifically, the interquartile range) of these 500 tree predictions is our raw Valuation Uncertainty Score. The higher the score, the higher the disagreement among the 500 tree models, and the more uncertainty is embedded in our quantitative valuation estimate.

$$\text{Quantitative Valuation Uncertainty} = Q_3(\{x_i \mid 1 < i < n\}) - Q_1(\{x_i \mid 1 < i < n\})$$

x_i = Valuation Estimate

n = number of estimates produced by model

Q_3 = Third Quartile

Q_1 = First Quartile

To calculate the Valuation Uncertainty exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero can always be interpreted as the average score, and a non-zero score of n can be interpreted as being n standard deviations from the mean. In the chart below, we can see that Energy Transfer Equity has had significantly higher Valuation Uncertainty from 2008 to 2015 compared to Wal-Mart, which has been rated Low Uncertainty by Morningstar's analysts. We also see that Energy Transfer Equity's Valuation Uncertainty score has increased substantially going into the last 6 months of 2015 indicating that this company is becoming increasingly difficult to value. At the end of 2015, we would expect Wal-Mart to exhibit lower variance of returns and a somewhat lower mean return compared to Energy Transfer Equity based on this information.

Exhibit 12 Valuation Uncertainty Exposure Through Time



Source: Morningstar.

Liquidity

Liquidity in stocks has been written about since Demsetz (1968), but the first paper to identify a relationship between future returns and liquidity probably falls to Amihud and Mendelson (1986) but many authors have written extensively on this topic. Liquidity can be proxied in a number of different ways and there is much similarity amongst the measures. Our measure probably fits closest to the measure used in Datar, Naik, and Radcliffe (1998) as we define liquidity as share turnover. Over time, we have found that the premia to liquidity is economically small, but does seem to be counter-cyclical as it pays off strongest in recession periods. Overall, however, portfolios tilted in favor of liquid stocks would not see a big change to their expected return.

Exhibit 13 Liquidity Premia Through Time



Source: Morningstar.

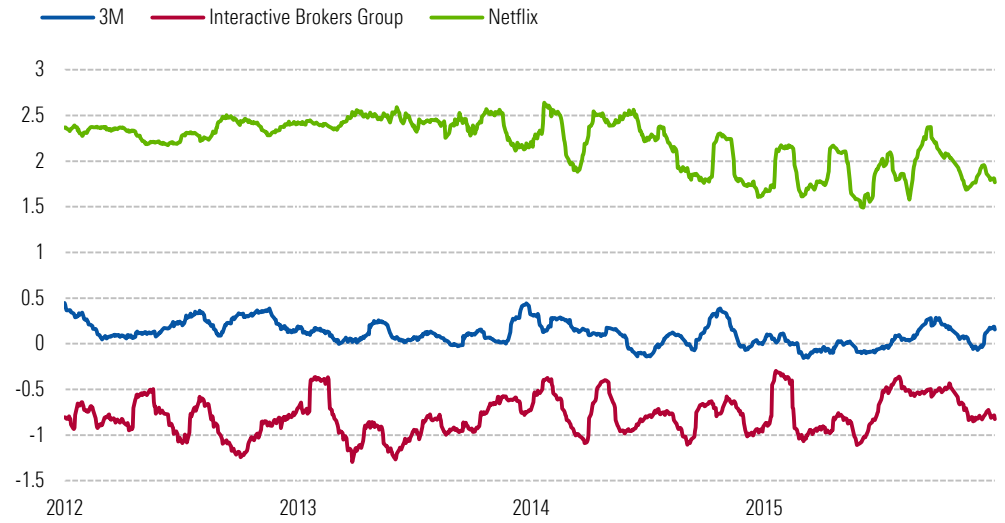
We calculate the Liquidity factor as the normalized value of the stock's raw share turnover. The raw share turnover score is calculated as the logarithm of the average trading volume divided by shares outstanding over the past 30 days. It is essentially a churn-rate for a stock and represents how frequently a stock's shares exchange hands.

$$shareturnover_{i,t} = \ln \left(\frac{1}{T} \sum_{t=1}^T \frac{V_{i,t}}{SO_{i,t}} \right), \text{ where } T = 30$$

To calculate the final Liquidity exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of liquidity, and a non-zero score of n can be interpreted as being n standard deviations from the mean. Below, we see Netflix can be considered a stock with lots of liquidity as its shares frequently change hands. 3M sits about average through this time period. Interactive Brokers Group, however, has

considerably less trading velocity than these two previous examples, though it is far from being the least liquid stock.

Exhibit 14 Liquidity Factor Exposure Through

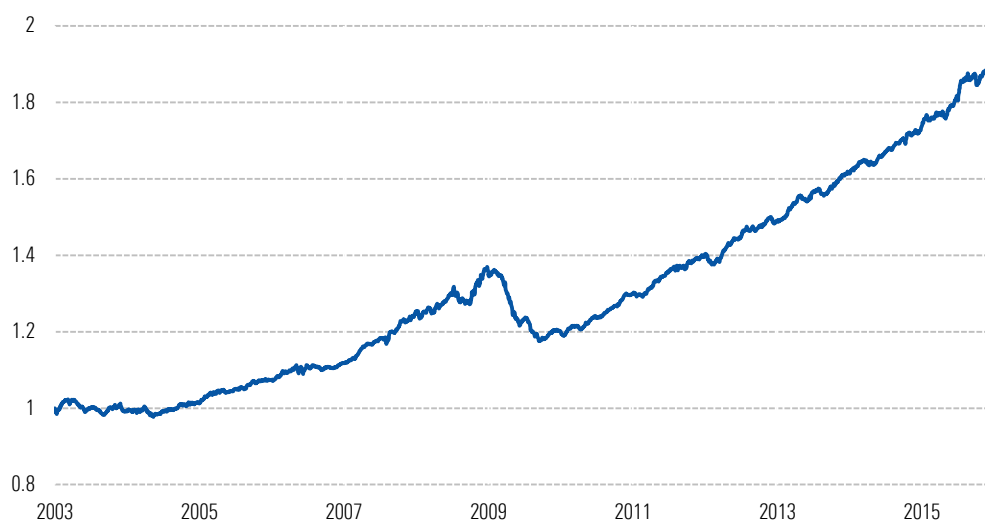


Source: Morningstar.

Momentum

A critical part of the Risk Model is the inclusion of the momentum style factor which measures how much a stock has risen in price over the past year relative to other stocks. Controversial since its discovery, momentum refers to the finding that stocks that have recently performed well continue to perform well even after accounting for other return drivers. Momentum was first written about by Jegadeesh and Titman (1993) but has been the focus of numerous studies since as researchers have sought to explain why the phenomenon exists at all. The Risk Model work we have done suggest that Momentum remains a critical element to forecasting returns even after accounting for other factors. We find that investments tilted toward Momentum perform well in almost all economic environments except during the financial crises of 2008 and subsequent recovery in 2009.

Exhibit 15 Momentum Premia Through Time



Source: Morningstar.

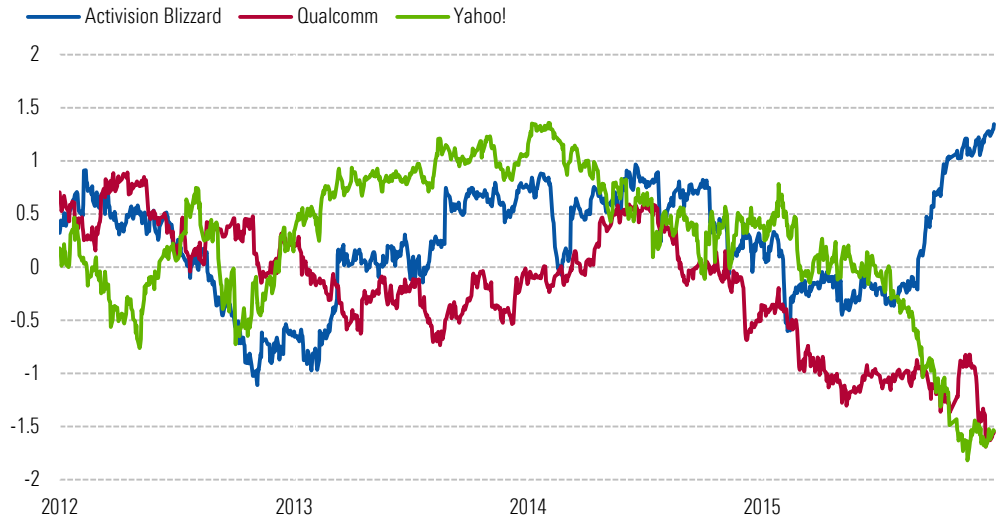
We calculate a raw Momentum score as the cumulative return of a stock from 365 calendar days ago to 30 days ago. This is the classical 12-1 momentum formulation except using daily return data as opposed to monthly. To compute, US dollar currency returns are used.

$$momentum_{i,t} = \sum_{t-365}^{t-30} (\ln(1 + r_{i,t}) - \ln(1 + r_{f,t}))$$

To calculate the final Momentum exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of momentum, and a non-zero score of n can be interpreted as being n standard deviations from the mean. Below, we see that three stocks began 2012 with approximately the same Momentum exposure but over the course of four years their exposure to Momentum shifted significantly. By the end of 2015, we find that Activision Blizzard was positively exposed to Momentum while Qualcomm and

Yahoo! were negatively exposed suggesting that Activision Blizzard was poised to outperform going forward.

Exhibit 16 Momentum Factor Exposure Through

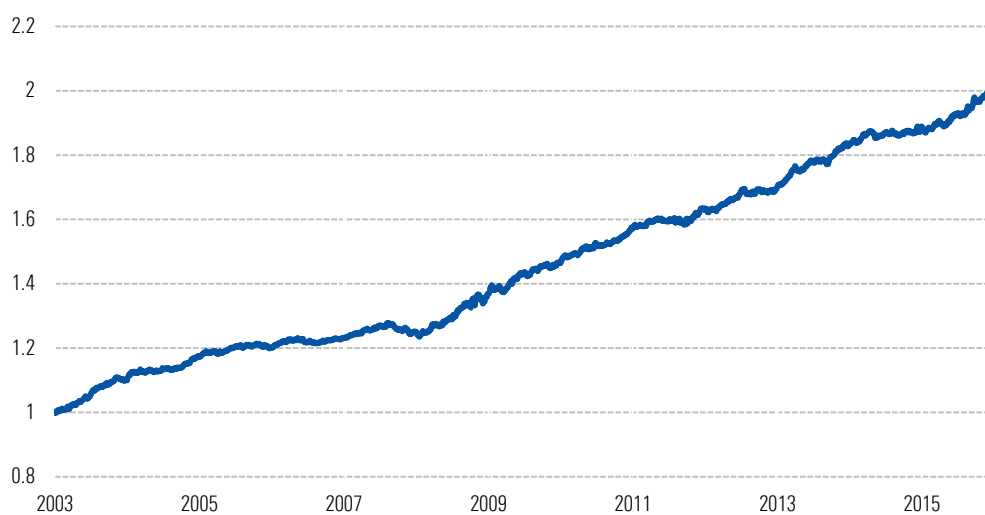


Source: Morningstar.

Size

A critical part of the Risk Model is the inclusion of the size style factor which measures the market capitalization of a company relative to other stocks in the universe. Fama and French (1992) were one of the first to study the relationship between market cap and returns even after accounting for market beta. In their paper and many others subsequently, a premia associated with investing in small cap stocks relative to large cap stocks has been observed. The Morningstar Global Risk Model generates a similar result. We use a historical time series of factor premia to analyze how each factor behaves in the context of the other factors by examining historical factor co-movement. We find that small cap firms tend to outperform larger cap firms after controlling for other return drivers as evidenced by the chart below.

Exhibit 17 Size Premia Through Time



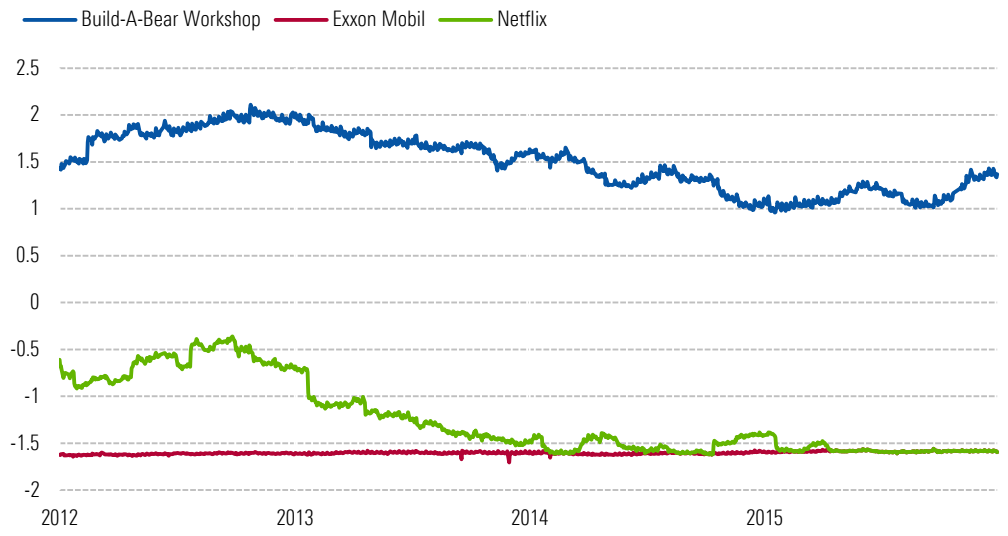
Source: Morningstar.

To calculate the Size factor, we normalized value of the logarithm of a firm's market capitalization.

$$Size_{i,t} = -\ln(MV_{i,t})$$

To calculate the Size exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of market capitalization, and a non-zero score of n can be interpreted as being n standard deviations from the mean. Below, we see Netflix was considered a mid-cap stock in 2008 but now is a large-cap stock. During that same time period, Exxon Mobile remained one of the largest companies by market cap. Build-A-Bear, however, has been considered a small over even micro-cap stock during this time period.

Exhibit 18 Size Factor Exposure Through



Source: Morningstar.

Value-Growth

Our Risk Model includes the value-growth style factor which measures 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. We find that, at different points in time, a stock's performance can depend significantly on its tilt toward Value or Growth. However, over the long-run, we found that portfolios tilted in favor of Value or Growth do not always outperform. Instead, we find that the Value-type return pattern observed in many studies to be more associated with our Valuation metric, which compares current prices to estimated Fair Value, rather than market-wide definitions of Value or Growth.

Exhibit 19 Value-Growth Premia Through Time



Source: Morningstar.

The Dividend Discount Model relates the present value of a company's equity to its future dividends, the growth rate of those dividends, and the discount rate of the dividend cash flow stream.

$$P_0 = \frac{D_0 \times (1 + g_1)}{r - g}$$

Rather than model this formula directly, we perform a regression analysis to make a prediction about the market value of a firm's equity today using only knowledge of that firm's current fundamentals (proxies for the Dividends in the Dividend Discount Model). We deliberately exclude any information that might inform the required rate of return or the growth rate.

We then compare a prediction from this model to the actual observable market capitalization of the firm's common equity. The error in our prediction is attributable to the inputs to the dividend discount

model which were excluded in our regression model, namely the required rate of return and the growth rate. This error represents the raw form of our new Value-Growth Score.

Data Requirements

We require all of the following inputs to be present for a company before calculating its Value-Growth Score.

- ▶ Most Recent Trailing 12 Months Net Income in USD (E)
- ▶ Most Recent Trailing 12 Months Dividends Paid in USD (D)
- ▶ Most Recent Book Value of Common Equity in USD (B)
- ▶ Most Recent Market Capitalization in USD (M)
- ▶ Morningstar Sector Classification (S)
- ▶ Morningstar Region Classification (R)

Data Preprocessing

Winsorize E and B at the 99th and 1st percentile to dampen the impact of severe outlier data points.

$$E_i = \begin{cases} E^{(99)} & \text{if } E_i > E^{(99)} \\ E^{(1)} & \text{if } E_i < E^{(1)} \\ E_i & \text{otherwise} \end{cases}$$

Where:

E_i is the i th observation of E in the cross – sectional data set

$E^{(1)}$ is the 1st percentile E in the cross – sectional data set

$E^{(99)}$ is the 99th percentile of E in the cross – sectional data set

$$B_i = \begin{cases} B^{(99)} & \text{if } B_i > B^{(99)} \\ B^{(1)} & \text{if } B_i < B^{(1)} \\ B_i & \text{otherwise} \end{cases}$$

Where:

B_i is the i th observation of B in the cross – sectional data set

$B^{(1)}$ is the 1st percentile of B in the cross – sectional data set

$B^{(99)}$ is the 99th percentile of B in the cross – sectional data set

Create dummy variables to signify the sign of earnings, book value and dividends.

$$DE_i = \begin{cases} 1 & \text{if } E_i > 0 \\ 0 & \text{if } E_i \leq 0 \end{cases}$$

$$DB_i = \begin{cases} 1 & \text{if } B_i > 0 \\ 0 & \text{if } B_i \leq 0 \end{cases}$$

$$DD_i = \begin{cases} 1 & \text{if } D_i > 0 \\ 0 & \text{if } D_i = 0 \end{cases}$$

Create dummy variable vectors signifying Morningstar's Sector classification. Then combine them into a single vector. For example, the dummy variable for the Consumer Defensive sector is determined as follows.

$$DConsumerDefensive_i = \begin{cases} 1 & \text{if } Sector_i = \text{Consumer Defensive} \\ 0 & \text{if } Sector_i \neq \text{Consumer Defensive} \end{cases}$$

$$\overrightarrow{DS}_i = \begin{bmatrix} DConsumerDefensive_i, DConsumerCyclical_i, DCommunicationservices_i \\ DUtilities_i, DEnergy_i, DFinancialServices_i, DBasicMaterials_i, \\ DIndustrials_i, DTechnology_i, DRealEstate_i, DHealthcare_i \end{bmatrix}$$

Create dummy variable vectors signifying Morningstar's Region classification. Then combine them into a single vector. For example, the dummy variable for the United States Region is determined as follows.

$$DUnitedStates_i = \begin{cases} 1 & \text{if } Region_i = \text{United States} \\ 0 & \text{if } Region_i \neq \text{United States} \end{cases}$$

$$\overrightarrow{DR}_i = \begin{bmatrix} DUnitedStates_i, DCanada_i, DLatinAmerica_i, DEurope_i, \\ DAsiaExJapan_i, DJapan_i \end{bmatrix}$$

Use logarithmic transformations to reduce tails and enhance distributional properties of regression inputs.

$$TE_i = \ln(1 + |E_i|) \times \text{sign}(E_i)$$

$$TB_i = \ln(1 + |B_i|) \times \text{sign}(B_i)$$

$$TD_i = \ln(1 + D_i)$$

$$TM_i = \ln(M_i)$$

Perform Regression

Using all companies with the requisite data at a point in time, we can estimate the beta coefficients from the equation below using Ordinary Least Squares (OLS) regression. Finding these betas allows us to make a prediction about where a particular market cap should be given only knowledge of our input data points.

$$\widehat{TM}_i = \beta_1 DE_i + \beta_2 DB_i + \beta_3 DD_i + \beta_4 \overrightarrow{DR}_i + \overrightarrow{DS}_i \times (\beta_5 DE_i TE_i + \beta_6 DB_i TB_i + \beta_7 TD_i)$$

We fit different intercepts depending on:

- ▶ Morningstar Region Classification
- ▶ Sign of Earnings
- ▶ Sign of Book Value
- ▶ Zero or non-zero Dividends

We fit different slopes depending on:

- ▶ Morningstar Sector Classification
- ▶ Sign of Earnings
- ▶ Sign of Book Value
- ▶ Zero or non-zero Dividends

Calculate the Raw Value-Growth Score

Our raw Value-Growth Score represents the error in our regression model. Since the regression model only incorporates information about current fundamentals, sector and region, this error term can be largely attributed to the market's opinion of growth and value. Any variables that might foretell growth and value characteristics were intentionally left out of our regression equation for this purpose.

$$RawVG_i = Ti - \widehat{TM}_i$$

A high raw Value-Growth score indicates that the stock is trading at a higher market capitalization than we would anticipate given the inputs to our regression model. This indicates that market participants put a large value on the future growth of the company, and thus, we should treat it as a growth stock. Conversely, a low raw Value-Growth score would indicate that market participants do not value growth of the company highly, and thus we should treat it as a value stock. The raw Value-Growth score is unbounded.

Rescale the Value-Growth Score

In order to smooth our Value-Growth Score in such a way that it is uniformly distributed across our Style Box, we evaluate the cumulative density function of RawVG conditional upon the company's Size Score and its Morningstar Region assignment. We estimate this conditional cumulative density function using a technique known as kernel density estimation with a Gaussian kernel. For more information on finding the cumulative density function, F , using kernel density estimation, please refer to Appendix A.

$$RescaledVG_i = 500 \times F(RawVG_i | RescaledSize_i, \overline{DR}_i) - 100$$

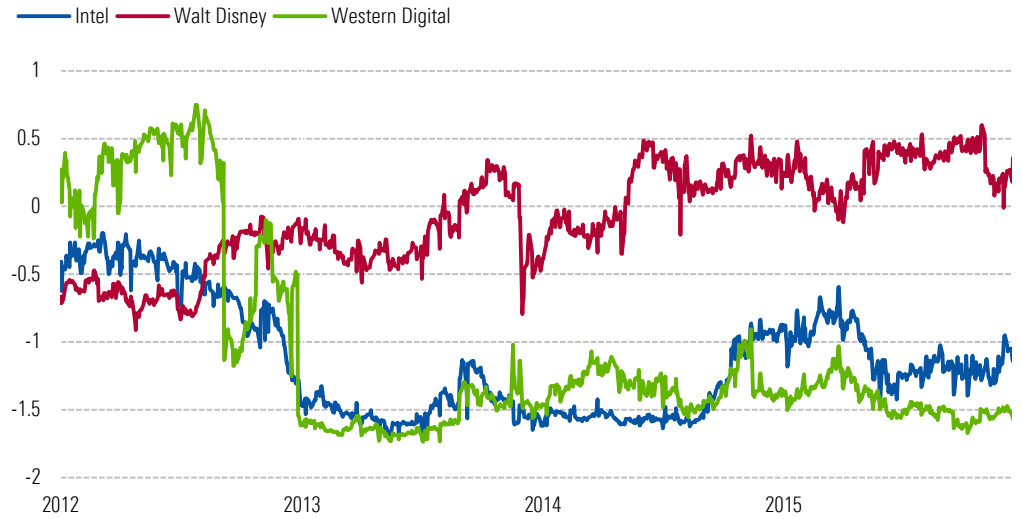
Like the raw Value-Growth score, a higher rescaled Value-Growth score is indicative of Growth, while a lower score is indicative of Value. Unlike the raw score, the rescaled score is bounded on the interval [-100,400].

To calculate the final Value-Growth exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of value-growth, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

Below, we show typical Value-Growth exposures over time for three stock examples. We see that Walt Disney has slowly trended towards Growth during this period though remains a Blend stock.

Furthermore, we see that Western Digital and Intel began as blend but have since developed into Value stocks.

Exhibit 20 Value-Growth Factor Exposure Through



Source: Morningstar.

Volatility

A critical part of the Risk Model is the inclusion of the volatility style factor which measures the maximum observed spread in long-term returns. Volatility can be measured in a variety of ways, including the well-known historical standard deviation of returns. For the purposes of our Risk Model, we chose to employ a different construction of for volatility that doesn't focus on the daily or monthly variance of returns, but rather on the range of possible long-term returns. Measured in this manner, we find that our Volatility factor plays an economically important and statistically significant role in the explanation of future returns. We find that investments tilted toward Volatility perform well in almost all economic environments, especially during the 2009 recovery.

Exhibit 21 Volatility Premia Through Time



Source: Morningstar.

We calculate the Volatility factor as 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.

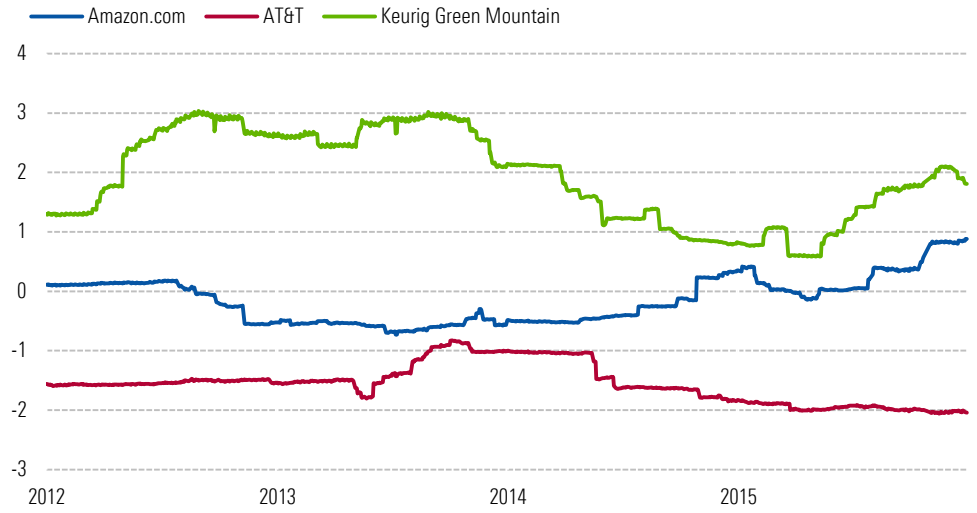
$$range_i = \left(\ln(1 + r_{i,t}) - \ln(1 + r_{f,t}) \right)^{max} - \left(\ln(1 + r_{i,t}) - \ln(1 + r_{f,t}) \right)^{min}$$

To calculate the final Volatility exposure, the scores are normalized by subtracting the cross-sectional mean and then dividing by the cross-sectional standard deviation. A score of zero indicates an average level of volatility, and a non-zero score of n can be interpreted as being n standard deviations from the mean.

Below, we see that Keurig Green Mountain is considered a stock with high Volatility exposure suggesting that there is a large variation in long-run outcomes. Amazon has historically been an average

company when considered through the lens of Volatility, but towards the end of 2015, we see that this exposure is rising. AT&T has consistently been a low Volatility stock.

Exhibit 22 Volatility Factor Exposure Through



Source: Morningstar.

Sector Exposures

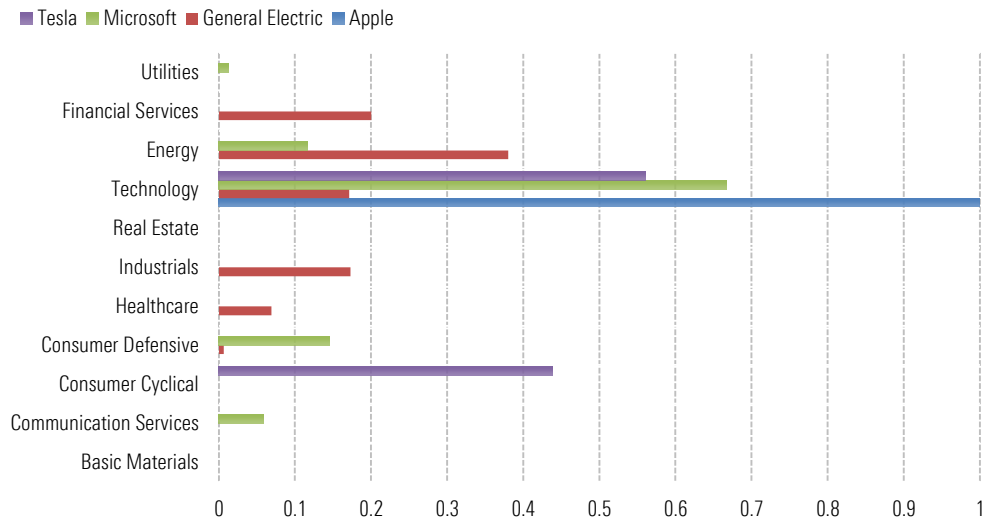
A major part of the Risk Model are sector factors that measure the partial economic exposure of a company or portfolio to the 11 Morningstar sectors. Relying on sector classification to assess sector risk can be quite limiting as sector classification is a binary yes or no. As a consequence, sector risk may be under- or overstated for many large conglomerates that operate multiple business lines across traditional sector lines.

Sectors

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

To better capture company-specific risk associated with multiple sectors, we estimate partial economic exposure of each company to all 11 Morningstar sectors. Below, we show several examples of the partial economic exposures. Apple is the only one of the four examples shown where the entirety of its economic exposure is captured by its classification as a Technology company. Tesla, on the other hand, has more than half of its exposure in the Technology sector despite being classified as a Consumer Cyclical company. Microsoft and GE are even more extreme examples that show the breadth of their sensitivity to performance in various sectors. Using Morningstar's sector exposures will more accurately represent the concentration and sensitivity of your investments and portfolios to sector risk.

Exhibit 23 Sector Exposures



Source: Morningstar.

To capture these partial exposures, we perform a Bayesian time-series regression over the past 5 years 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 be individually lie between 0 and 1. Higher scores indicate higher levels of sensitivity to individual sectors.

$$r_t^i - r_t^f = \alpha^i + \beta_1^i(r_t^1 - r_t^f) + \dots + \beta_k^i(r_t^k - r_t^f) + \varepsilon_t^i$$

r_t^i = weekly return on the *i*th stock

r_t^f = weekly return on 3 – mo US TBill

r_t^k = weekly return on the *k*th sector benchmark (e.g. Basic Materials)

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

Region Exposures

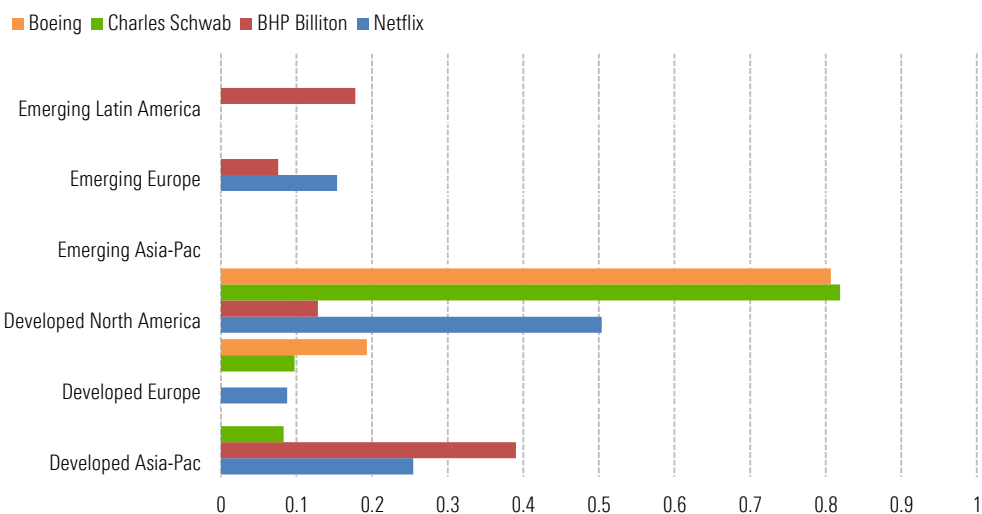
Contained within the Risk Model is the inclusion of region factors that measure the partial economic exposure of a company or portfolio to seven geographic regions. This method of risk measurement is superior to standard methods that rely on measuring geographic risk according to where the stock is listed, incorporated, or headquartered. With the increasingly globalized marketplace, firms are frequently operating across multiple countries and regions. Using Morningstar's region exposures will more accurately represent the sensitivity of your investments to geographic risks and allow you to better target developed or emerging market exposure.

Regions

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

To better capture company-specific risk associated with multiple geographies, we estimate partial economic exposure of each company to all 7 regional benchmarks. Below, we show several examples of the partial economic exposures.

Exhibit 24 Region Exposures



Source: Morningstar.

To capture these partial exposures, we perform a Bayesian time-series regression over the past 5 years with a prior based on the discrete country classification of Morningstar's data analysts. We enforce constraints that our region exposures, including the intercept term, must sum to 1 and must be individually lie between 0 and 1. Higher scores indicate higher levels of sensitivity to individual regions.

$$r_t^i - r_t^f = \alpha^i + \beta_1^i(r_t^1 - r_t^f) + \dots + \beta_k^i(r_t^{11} - r_t^f) + \varepsilon_t^i$$

r_t^i = weekly return on the i th stock

r_t^f = weekly return on 3 – mo US TBill

r_t^k = weekly return on the k th region benchmark (e.g. Developed North America)

$$\text{constraints: } 0 < \beta_k^i < 1; \sum_k \beta_k^i = 1$$

Currency Exposures

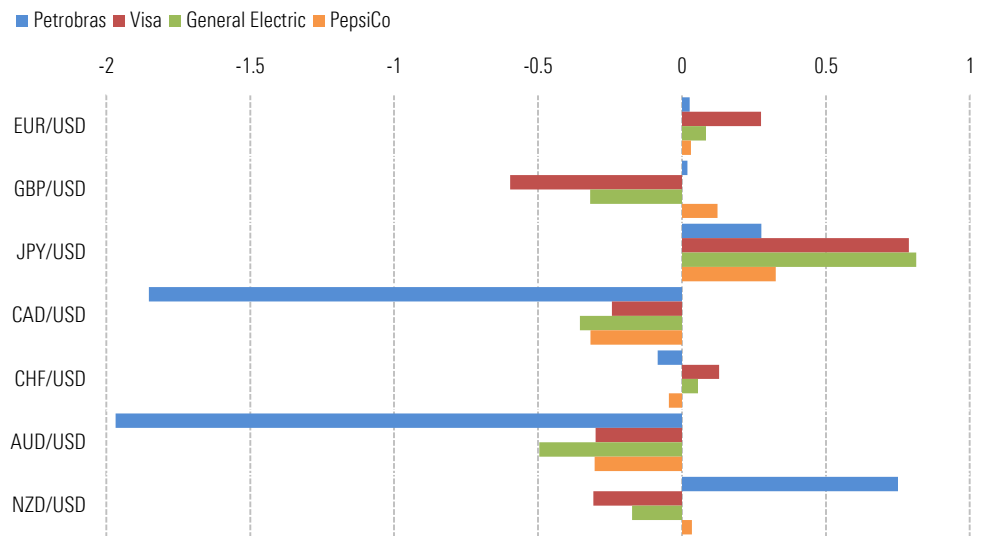
Part of the Risk Model is the inclusion of currency factors that measure the partial economic exposure of a company or portfolio to seven exchange rates. With the increasingly globalized marketplace, firms are frequently operating across multiple countries and regions. Certain types of businesses, furthermore, may be more sensitive than others to certain exchange-rate fluctuations. Using Morningstar’s currency exposures will more accurately represent the sensitivity of your investments to currency risks and allow you to better target specific types of exchange-rate exposure.

Currencies

- ▶ Euro
- ▶ Japanese Yen
- ▶ British Pound
- ▶ Swiss Franc
- ▶ Canadian Dollar
- ▶ Australian Dollar
- ▶ New Zealand Dollar

To better capture company-specific risk associated with multiple exchange rates, we estimate partial economic exposure of each company to all 7 exchange rates. Below, we show several examples of the partial economic exposures.

Exhibit 25 Currency Exposures



Source: Morningstar.

To capture these partial exposures, we perform a time-series quantile regression over the past 5 years on a rolling, weekly frequency. Higher scores indicate higher, positive correlation to individual exchange rates. These exposures generally fall between -1 and 1. ■■■

$$r_t^i - r_t^f = \alpha^i + \beta_1^i(r_t^1) + \dots + \beta_k^i(r_t^k) + \varepsilon_t^i$$

r_t^i = weekly return on the i th stock

r_t^f = weekly return on 3 – mo US TBill

r_t^k = weekly return on the k th exchange rate return (e.g. % change in $\frac{EUR}{USD}$)

About Morningstar® Quantitative Research™

Morningstar Quantitative Research is dedicated to developing innovative statistical models and data points, including the Quantitative Equity Ratings and the Global Risk Model.

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