Practical Applications of

Market-Driven Scenarios: *An Approach for Plausible Scenario Construction*

Practical Applications
Institutional Portfolio Research

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Overview

In **Market-Driven Scenarios: *An Approach for Plausible Scenario Construction***, from the Spring 2018 issue of ***The Journal of Portfolio Management***, authors **Bennett Golub**, **David Greenberg**, and **Ronald Ratcliffe** (all of **BlackRock**) explain the need for scenario analysis as part of a firm's overall approach to risk management, and they describe a framework for conducting rigorous and systematic scenario analysis. A key challenge in applying scenario analysis is constructing "tail event" scenarios that are severe but plausible. The authors address that challenge by providing a quantitative framework for assessing a scenario's plausibility by reference to the behavior of observable variables used to define the scenario (e.g., asset prices, bond yields, credit spreads, etc.). Different quantitative implementations of the framework naturally produce somewhat different results, but those differences can themselves offer a vehicle for understanding the dimensions of sensitivity associated with a particular scenario definition. The authors conclude with an illustration of the framework's application using Brexit as an example.

Practical Applications

- **Statistical risk management approaches like Value at Risk (VaR) proved largely ineffective in addressing the kinds of market movements that occurred with the 2008–2009 financial crisis.** Scenario analysis offers a tool to address some of the shortcomings of the statistical approaches.
- **Scenario analysis is forward looking and is also able to draw on historical experience that might not be represented in the development samples for statistical approaches.** However, the method can also be imprecise or vague.
- **Analytic rigor can be applied to scenario analysis by mathematically comparing a proposed scenario with past episodes of stress.** The comparison can thus furnish a probability estimate.

Key Definitions

Covariance

Covariance is a statistical measure of the degree to which two random variables tend to move in the same or opposite directions. The formula for covariance of random variables X and Y is

$$\mathrm{cov}(\mathrm{X},\mathrm{Y}) = \sigma_{X,Y} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$$

where n is the number of observations, x_i is the i^{th} observation of X, y_i is the j^{th} observation of Y, $\bar{x}$ is the expected valued of X, and $\bar{y}$ is the expected value of Y. Covariance is closely related to the concept of correlation, which expresses the degree to which two variables tend to move in the same or opposite direction on a scale from –1 to 1. The correlation of two random variables X and Y can be calculated from their covariance as follows:

$$\mathrm{corr}(\mathrm{X},\mathrm{Y}) = \rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_x \sigma_y}$$

where σ_x is the sample standard deviation of X and σ_y is the standard deviation of Y.

Covariance matrix

A covariance matrix is a matrix that contains the covariances between pairs of random variables within a list of random variables. The element in the i^{th} row and j^{th} column of the matrix indicates the covariance between the i^{th} and j^{th} random variables in the list. The elements along the diagonal of the matrix are

Discussion

The 2008 financial crisis exposed the limitations of statistical risk management approaches such as Value at Risk (VaR). Overreliance on such approaches produced disappointing outcomes and highlighted the need to augment the statistical approaches. Scenario analysis has become the chosen method to fulfill that need because it allows (and requires) risk managers to consider what *might happen* in the future. However, scenario analysis also presents two key challenges: assessing the likelihood (or plausibility) of a given scenario and relating the scenario to specific consequences for financial markets. The authors describe a "market-driven scenario" (MDS) framework for meeting those challenges.

The first step in the framework is to collect market views from a diverse range of sources within an organization, including not only the firm's risk management group but also investor and economic research teams. Ideally, scenario input comes from investment professionals across "different asset classes, geographies, and functional units."

> "In contrast to purely statistical or risk models, scenario analysis has the singular virtue of being forward looking, even at the risk of being less scientific."
>
> ***—Market-Driven Scenarios: An Approach for Plausible Scenario Construction***

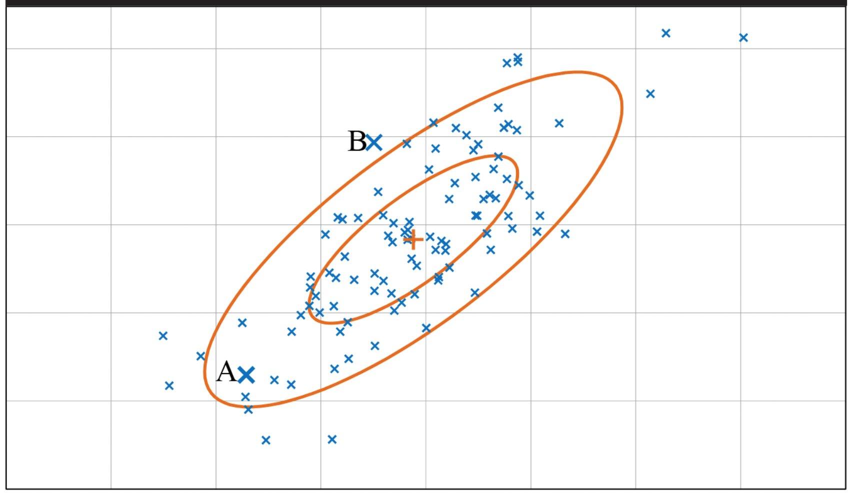
The next step is for the firm's risk management team to define a set of economic outcomes associated with a scenario and then translate those outcomes into a set of instantaneous shocks to key risk factors called *policy variables* (e.g., asset prices, yields, spreads, FX, etc.). This step is highly qualitative and relies on "informed prognostication." However, it includes the use of statistical tools to assess the plausibility of specified shocks to policy variables based on historical experience. Ideally, the selection of policy variables leans toward those with the lowest degree of correlation. The MDS approach uses a measure called the *Mahalanobis distance* to assess the plausibility of a given shock to policy variables, based on how similar or different the specified shocks are to shocks that have the variances of the random variables.

Mahalanobis distance

Mahalanobis distance is a statistical measure of the degree to which a given observation of a multidimensional phenomenon (e.g., observations of two variables such as height and weight) is an outlier relative to a prior sample of observations. It accounts for correlations among the variables. It indicates an observation's distance from the prior sample's center of mass in terms of standard deviations.

> “Once the policy variable shocks are specified, the shocks to all relevant market risk factors are imputed through a factor covariance matrix.”
>
> ***—Market-Driven Scenarios: An Approach for Plausible Scenario Construction***

Exhibit 1: Mahalanobis Distance



Note: The blue marks represent data observations of two correlated random variables. For example, each mark might represent measures of horsepower (on the x-axis) and acceleration (on the y-axis) for a car. The fact that the marks cluster around a diagonal line shows the correlation. The orange ellipses show two-dimensional confidence ranges for the data. The smaller ellipse indicates one standard deviation, and the larger ellipse indicates two standard deviations. Data point A lies between one and two standard deviations from the center of mass of the observations (marked with an orange cross). Data point B lies more than two standard deviations from the center of mass. Although B is geometrically closer to the center of mass than A, it has a greater Mahalanobis distance because it is farther in terms of standard deviations.

occurred before. The Mahalanobis distance attempts to account for the correlation among the selected policy variables (see Exhibit 1).

The effects on other risk factors are estimated from a statistical regression based on the selected policy variables. Solving the regression is the equivalent of estimating the covariance matrix among all the risk factors (including the policy variables and all others).

The authors note that their framework necessarily embodies subjectivity and is only as good as the forecast scenarios. Nevertheless, they argue that the formal process of scenario construction is beneficial because it disciplines risk managers to quantify their subjective beliefs.

The authors explain the mathematical steps in their process of quantifying a scenario's probability. A key point is that the policy variables define the scenario. Estimating the covariance matrix that describes the correlation among the risk factors is a critical element in the process. Once that matrix is determined, it figures into the calculation of a *scenario Z-score* (using the Mahalanobis distance), which indicates a scenario's likelihood in terms of standard deviations.

The method for estimating the covariance matrix matters a lot. Exhibit 2 shows how different methods of calculating the covariance matrix affect implied probability. The exhibit shows the implied probabilities of selected historical events using three different methods of calculating the covariance matrix. The first two methods use a covariance matrix based on data as of the time of the event, with different schemes for weighting recent observations more heavily than older ones. The one labeled "slow" gives more weight to older observations (older observations decay more slowly). The third method uses observations as of December 2017, using the slow decay rate for older observations.

The value of 1.8 in the third column for "U.S. Downgrade" indicates that the downgrade of the U.S. was a 1.8-standard-deviation event based on the historical covariance slow model. Likewise, the value 23.9 in the third column for "Global Financial Crisis" indicates that the global financial crisis was a 23.9-standard-deviation event based on the data as of December 2017 at the slow decay rate.

The authors suggest that the choice of a suitable covariance matrix for assessing a scenario's plausibility should be guided by giving

Exhibit 2: Sensitivity of Implied Scenario Probability to Methods of Calculating Covariance Matrix among Policy Variables
(probability in standard deviations)

Historical Event (sample scenario)	Dates	Method of Calculating Covariance Matrix among Policy Variables		
		Historical Covariance Slow Model	Historical Covariance Fast Model	Recent Covariance (Dec. 2017) Slow Model
U.S. Downgrade*	July 21–Sept. 20, 2011	1.8	2.4	3.4
Fed Tapering**	May 21–June 24, 2013	2.5	3.8	4.0
China Market Crash***	June 12–Aug. 26, 2015	3.1	2.3	2.5
Global Financial Crisis†	Sept. 12–Nov. 3, 2008	5.2	4.2	23.9
Credit Crisis‡	July 1, 2007–June 1, 2008	5.3	5.7	5.8

* Starts with S&P placing U.S. on CreditWatch and ends with Fed announcement of Operation Twist.
** Equity and bond market retreat following Bernanke Congressional testimony.
*** Starts with the popping of market bubble.
† Starts with Lehman Brothers bankruptcy.
‡ Triggered by housing market slowdown.

the most weight to data from historical environments that are most similar to the proposed scenarios

The bottom line is a five-step framework for developing useful scenarios. The first step is defining a scenario in terms of how it will be affected by financial markets. A scenario should satisfy four criteria:

- The scenario probability is small (but not impossible).
- The scenario's impact on markets is well defined (not subject to interpretation).
- The scenario will affect all relevant markets in a predictable way.
- The scenario has a well-defined trigger event.

The second step is the selection of policy variables, which also entails translating the scenario into specific shocks on the chosen variables. As noted earlier, selecting the policy variables and shocks leads to estimating the shocks on other risk factors through a statistical regression. The authors caution scenario designers to be parsimonious in selecting the policy variables.

The third step is to calibrate the magnitude of the shocks to the selected policy variables. This can be done by comparison with similar historical episodes or by using the scenario Z-score to tune the scenario to a desired level of likelihood.

The fourth step is to generate nonpolicy factor shocks from the policy factor shocks using the covariance matrix. Examining the implied shocks for all risk factors offers an opportunity to refine the scenario based on qualitative or ex ante views about the relationships among risk factors.

The fifth and final step is to translate the scenario into a stress test of portfolio profit and loss based on the chosen risk factor shocks and the portfolio's exposure to the various risk factors. The authors point out that in the absence of embedded optionality in a portfolio, the profit and loss is the product of the factor shocks times the portfolio exposures.

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He is a board member of the Global Association of Risk Professionals, a member of the MIT Sloan School of Management's North American Executive Board, and a member of the MIT Sloan Finance Group Advisory Board. He is also chairman of the Advisory Board of the MIT Golub Center for Finance and Policy and chairman of the International Partners Committee of the Asset Management Association of China.

Dr. Golub earned an SB in management in 1978, an SM in management in 1982, and a PhD in applied economics and finance in 1984, all from the MIT Sloan School of Management.

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David Greenberg is a managing director at BlackRock and is the head of the portfolio risk modeling group. He is responsible for the development, implementation, and maintenance of volatility, tail risk, optimization, and stress testing analytics applied to all portfolios managed by BlackRock and distributed to clients through BlackRock Solutions.

Dr. Greenberg received a BA degree in chemistry from Harvard and a PhD in finance from the Chicago Graduate School of Business.

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Ronald Ratcliffe, PhD, is a managing director at BlackRock, where he is head of multi-asset investment risk for Americas-West and a member of BlackRock's risk and quantitative analysis group. He is responsible for the risk management of multi-asset portfolios, including factor-based strategies.

Dr. Ratcliffe's service with BlackRock dates back to 2004, including his years with Barclays Global Investors (BGI), which merged with BlackRock in 2009. His prior roles at the firm included leading emerging-markets research for a fixed-income hedge fund and portfolio management/research for a global macro hedge fund. Prior to joining BGI, Dr. Ratcliffe was the chief economist for Latin America at SG Cowen Securities. Previously he was with Bankers Trust Company, where he was responsible for analyzing country risk for the credit and proprietary trading groups.

Dr. Ratcliffe earned a BA in economics from Stanford University, with departmental honors and university distinction. He received a PhD in economics from the University of Pennsylvania. He lives in the San Francisco Bay Area, where he participates actively in Stanford Masters Swimming.