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

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Prior to the global financial crisis of 2008, stress testing was typically used as an adjunct to statistical approaches to risk measurement and management (e.g., Value at Risk [VaR] and ex ante tracking error) to quantify the profit and loss (P&L) associated with potential tail events. The perceived mathematical sophistication of these models lulled some risk managers into overlooking the limits of relying on models calibrated exclusively with historical data to forecast future market risk.

The extreme market moves during the financial crisis exposed the limitations of standard risk models and highlighted the need to augment their insights. Post-financial crisis, market risk has become increasingly difficult to forecast as prolonged monetary policy intervention by central banks and sudden political shocks have overtaken economic fundamentals or technical data in driving financial markets.[1] These policy shocks have triggered sudden regime shifts and breakdowns in historical relationships between market variables.

Given the unpredictability in the current market environment, scenario analysis provides a critical complement to VaR and other related statistical risk measures. Scenario analysis forces risk managers to think about what may happen in the future, create direct and explicit links between changes in the macroeconomic environment and financial markets, and then apply them to portfolio exposures to determine hypothetical investment outcomes. 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. This has led regulators to increasingly emphasize scenario analysis (i.e., stress tests) as an important element of the supervisory process.[2] However, this virtue proved to be a double-edged sword because, unlike more traditional historical approaches, there is no established standard or framework for constructing scenarios. In fact, the greatest challenge in stress testing is how to effectively define and generate hypothetical yet plausible stress scenarios. Furthermore, research on best practices in scenario generation has been limited.[3]

In this article, we describe a market-driven scenario (MDS) framework designed to mitigate the subjective and often ad hoc nature of hypothetical scenario generation. In the MDS framework, economic forecasts and market views are collected from a wide number of firm constituents, including risk management, investor, and economic research teams. These views are then distilled using a disciplined process that incorporates statistical best practices to form a final set of scenarios.

The MDS framework has some elements in common with the decision-making approach advocated in James Surowieki's [2004] best-selling book *The Wisdom of Crowds*. Surowieki argued that a decision reached by aggregating information across many individuals is often better than a decision made by any single individual. According to Surowieki, the aggregation of individual information is likely to be most efficient if three separate criteria are met:

1. Each individual has some private information and specialized knowledge not available to others.
2. Individuals' opinions are independent and not subject to groupthink.
3. There is some independent mechanism for turning the private views into a collective view.

The MDS framework satisfies these three criteria. Namely, scenarios are developed by drawing on input from a diverse set of investment professionals across different asset classes, geographies, and functional units. Each group has specialized knowledge not available to other groups. A firm's risk and quantitative analysis team is the central mechanism by which information is aggregated and used to inform the creation of an economic scenario. The entire MDS process is led by this team.

The MDS procedure starts by having risk managers, investors, and economists periodically identify current issues of focus or concern in the market, such as was the case with the 2016 U.K. referendum on European Union membership (Brexit). Once an important issue is identified, a set of idealized economic outcomes are envisioned that seek to span the space of likely outcomes for that event. Those outcomes are then translated into instantaneous shocks to a relatively small set of *policy variables*.

The process of translating alternative economic outcomes into sets of policy variable shocks (e.g., moves in major equity, bond, commodity market indexes; foreign exchange [FX] rates) is highly subjective, and the methodologies used by investors for identification and sizing of variable shocks are diverse. Approaches range from relying on the expert opinion of portfolio and risk managers to, at least theoretically, using highly granular structural macroeconomic models.[4] Because this demands a lot of a structural macroeconomic model, both in granularity and the ability to forecast out-of-sample, in this discussion and in our professional endeavors, we rely upon informed prognostication. Regardless of the chosen methodology, a set of statistical tools can be developed to help evaluate the plausibility of a specified set of policy shocks, and that sense of plausibility has the potential to shift our imaginations away from the implausible (accepting that this may accentuate Black Swan biases). Specifically, we compute a multivariate measure called the Mahalanobis distance (MD) to determine the plausibility and magnitude of a policy shock and then convert this distance into an objective probability or scenario likelihood using a nonparametric approach described later.

Once the policy variable shocks are specified, the shocks to all relevant market risk factors are imputed through a factor covariance matrix. This imputed set of shocks, the *perturbation vector*, is then vetted for plausibility, and the process is iterated several times before convergence upon a final scenario specification. The finalized shocks are then put into a valuation engine, which is run against the portfolios being analyzed, yielding hypothetical P&Ls that can be decomposed into their underlying drivers. From this point, risk managers can assess whether portfolio construction in the face of event risks is consistent with portfolio managers' intent and the asset owner's (client's) risk appetite. The risk manager then can ascertain whether the positioning is deliberate, diversified, and scaled.

A wary reader might point out now that the process we are describing is necessarily subjective and only as good as the forecast scenarios. We would agree. Although we will provide a quantitative framework to express those subjective views, they are, ultimately, nothing but prognostication. Although the quality of the forecast is certainly critical, the formal scenario construction process, in our experience, adds significant additional value by forcing the risk taker and associated risk managers to go through a structured process of quantifying their subjective beliefs, making them transparent to others and therefore subject to critique and challenge. In fact, our experience is that the process of creating transparency and the resulting challenge forces all participants in the process to think more clearly. Although this does not guarantee that the resulting scenarios are correct, it does guarantee that the involved parties are thinking explicitly and carefully. On average, that can only be a good thing.

This article highlights the use of specific econometric techniques and the application of a disciplined multistep organization process of checks and balances in the construction of an MDS. The following sections first describe the statistical techniques used to size and evaluate the internal consistency and plausibility of the scenario shocks. The final section walks through the example of constructing a specific Brexit scenario (Soft Brexit), which illustrates both the econometrics and subjective aspects of constructing a hypothetical scenario.

## IMPLIED STRESS TESTING FRAMEWORK

### Market-Driven Scenario Framework

MDS follows a conditional stress testing approach in which a set of policy risk factors are shocked and the remaining risk factors are regressed onto the policy risk factors. The academic literature refers to MDS as conditional stress testing (Kupiec [1999]), and the policy and perturbation vectors are referred to in the literature as core and peripheral factors, respectively.

Assume there are $M$ risk factors in the system. An implied scenario is conjectured by users, specifying their view on a small subset of $K$ policy risk drivers and then letting the shocks to the remaining $M - K$ factors be implied through a multivariate regression.

$$r_j = \sum_{k=1}^{K} \beta_{j,k} r_k + \varepsilon_j \quad \text{for} \quad j = K+1, K+2, \ldots, M \tag{1}$$

where $\beta_{j,k}$ is the $\beta$ of factor $j$ to policy factor $k$. Estimating $\beta$ coefficients is mathematically equivalent to estimating the covariance matrix of the $M$ risk factor returns. In the following sections, we will discuss the calibration of the factor covariance matrix at length because that matrix implicitly pins down all the $\beta_{j,k}$ terms in Equation (1). With a perturbation vector $r_j$ in hand, we may calculate P&L based on the factor exposures of the portfolio. Assuming for the moment the returns of the assets are linear in the risk factor returns, the return of any portfolio given shocks to the $k$ policy variables can be computed as

$$\begin{aligned} \tilde{R}_{portfolio} &= R_{policy} + \tilde{R}_{implied} = \sum_{k=1}^{K} L_k S_k + \sum_{j=K+1}^{M} L_j S_j \\ &= \sum_{k=1}^{K} L_k S_k + \sum_{j=K+1}^{M} L_j \sum_{k=1}^{K} \tilde{\beta}_{j,k} S_k \end{aligned} \tag{2}$$

where $L_k$ represents the portfolio loading on factor $k$, and $S_k$ represents the shock to factor $k$. Those positions with embedded optionality that exhibit nonlinear payoff functions are usually fully revalued given the entire perturbation vector of factor shocks.

The policy risk factors are typically market-traded instruments such as S&P 500 returns, bond yields, or factor-mimicking portfolios (e.g., momentum, growth). The goal is to use a small number of policy variables to capture the macro shock and minimize the degree of arbitrariness in the resulting perturbation vector.

### Scenario Likelihood

Assume a set of experts proposes a vector of policy shocks $r$ to represent a specific economic scenario. How can we objectively evaluate the plausibility of these shocks? An implausible shock is in some sense an outlier. Given current information, an implausible shock is extremely inconsistent with all the data we have (i.e., it is an outlier). The most popular and oldest method for identifying outliers in the statistics literature is the MD.[5]

$$\mathrm{MD}(\mathbf{r}, \boldsymbol{\Sigma}) = \sqrt{(\mathrm{r} - \overline{r})' \Sigma^{-1} (\mathrm{r} - \overline{r})} \tag{3}$$

where $\mathbf{r}$ and $\boldsymbol{\Sigma}$ are the shock vector and covariance matrix of policy variables, respectively.

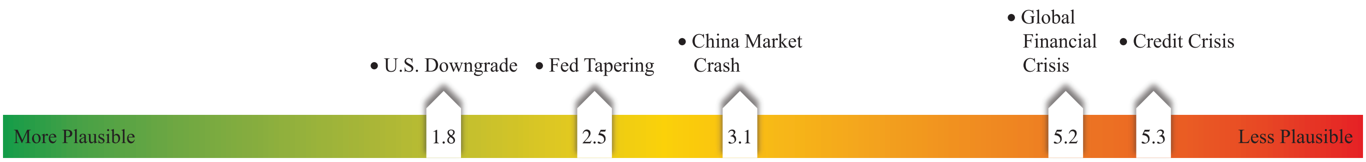
The MD is the multivariate generalization of a standardized return or $Z$-score. To prevent the MD from increasing at rate $\sqrt{n}$ in the number of policy variables, we define a new variable called the *scenario Z-score*:

$$Z(\mathbf{r}, \boldsymbol{\Sigma}) = \mathrm{MD}(\mathbf{r}, \boldsymbol{\Sigma}) / \sqrt{n} \tag{4}$$

Similar to an individual factor $Z$-score, a scenario $Z$-score represents the severity of a given scenario. Provided asset returns follow a certain class of probability distributions known as *elliptical distributions* (this class contains most distributions used to describe asset returns, including the normal and Student's $t$-distribution),[6] scenario $Z$-scores allow us to directly compare the relative likelihood of different scenarios. If Scenario A has a lower scenario $Z$-score than Scenario B, we can say that Scenario A is more probable than Scenario B.

The simplest way to calibrate a stress scenario is to compare the scenario $Z$-score with other realized risk events. We can first create a library of well-known historical scenarios and construct a risk ruler, as shown in Exhibit 1. Then we ask where we believe a new hypothetical scenario falls on the risk ruler. For example, if the analyst views the new scenario as less likely than

## Exhibit 1
### Risk Ruler of Scenario Z-Scores




| U.S. Downgrade | Fed Tapering | China Market Crash | Global Financial Crisis | Credit Crisis |
|---|---|---|---|---|
| ***Jul 21– Sept 20, 2011*** | ***May 21– June 24, 2013*** | ***Jun 12– Aug 26, 2015*** | ***Sep 12– Nov 3, 2008*** | ***Jul 01, 2007– Jun 01, 2008*** |
| The period starts with 50% chance U.S. downgrade indication from S&P Standards and ends with Operational Twist announcement by Fed. Stock market included losses while bonds markets saw gains due to flight to safety. | Tapering Talks stirred the market since Congress Testimony by Bernanke with both equity and bond markets sold off. Emerging Market suffered badly due to hot money flight back to U.S. | Chinese stock market crash beginning with the popping of the stock market bubble on 12 June 2015. | Credit & liquidity crisis and equity market crash set off by Lehman Brothers bankruptcy. Significant credit spreads widening caused by massive deleveraging. | Credit & liquidity crisis stemming from a severe slowdown in the housing market causing significant widening of credit spreads and increased implied volatility. |

*Notes: Covariance matrices are computed using five years of weekly, equally-weighted data prior to the scenario dates shown. Specifically, data as of July 20, 2011 for US Downgrade, May 20, 2013 for Fed Tapering, June 11, 2015 for China Market Crash, September 11, 2008 for Global Financial Crisis, and June 29, 2007 for Credit Crisis.*

*Source: BlackRock Aladdin, authors' calculations.*

the credit crisis, which is estimated as a 5.3 standard deviation scenario using the selected covariance matrix, the analyst may scale down all policy shocks such that the scenario $Z$-score is less than 5.3. The risk ruler can be thought of as a way to compare a given scenario to other multisigma events that ex ante were extremely implausible but nonetheless happened. Thus, when we prognosticate, we make a subjective choice about how extreme we want to define the event based on other prior historical outliers. This is purely a judgment call; the risk ruler allows us to gain context in making that call.

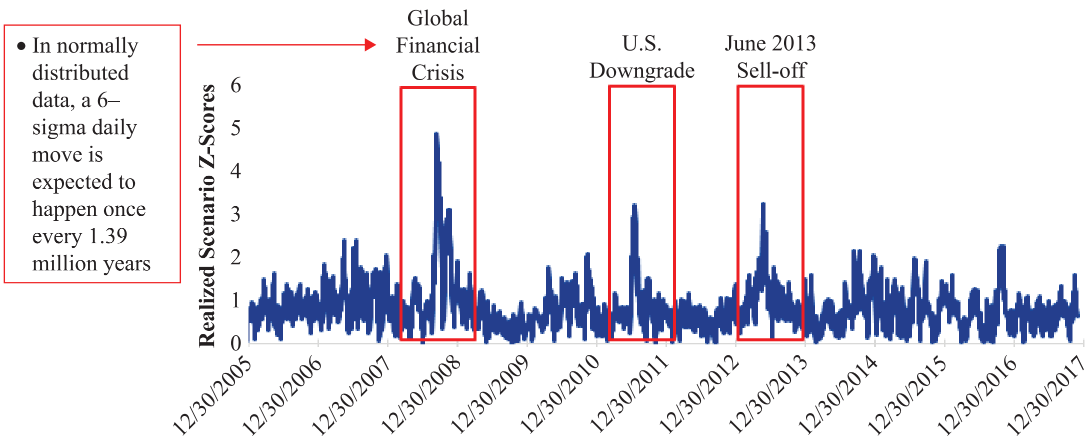
**From likelihood to probability.** Scenario $Z$-scores allow us to measure the *relative* probability of different events provided asset returns follow an elliptical distribution, but we need to make further assumptions if we want to convert a scenario $Z$-score to an *absolute* probability. Two approaches are available: (1) a parametric approach, in which we assume a probability distribution for the $Z$-scores, and (2) a nonparametric approach, in which we estimate the empirical distribution of $Z$-scores over a historical observation window. We choose the nonparametric approach because estimating the parameters of a multivariate probability distribution can be extremely challenging, especially in the tails of the distribution. Also, we know that market risk is highly susceptible to fat tails (unlikely events).

In the nonparametric approach, we first compute $T$ distinct $Z$-scores corresponding to each $h$-period risk factor return vector (and associated ex ante risk factor covariance matrix) within a historical window of length $T$. There are $T$ rather than $T/h$ total $Z$-scores because we compute $Z$-scores from overlapping $h$-period returns. We then compute the fraction of these $T$ historical $Z$-scores that are less than the $Z$-score of the proposed policy risk factor shocks. More formally, we define a cumulative empirical distribution function $\hat{F}$:

$$\hat{F}(Z(r^*,\Sigma_\tau)\,|\,\mathcal{F}_T) := \frac{1}{T}\sum_{t=1}^{T} 1\{Z(r_{t,t+h},\Sigma_t) \le Z(r^*,\Sigma_\tau)\} \quad (5)$$

where $r^*$ represents the scenario shocks to the policy risk factors; $1\{\ \}$ represents the indicator function; $\mathcal{F}_T$ represents the information set as of time $T$; and $Z\,(r_{t,t+h},\Sigma_t)$ represents the scenario $Z$-score of the policy variables over a given historical date range and horizon (i.e., the policy variables' historical realizations from time $t$ to $t+h$ scaled by the ex ante covariance matrix $\Sigma_t$). Note that the covariance matrix used to compute the $Z$-score for the policy shocks can be estimated using the most recent date or any historical date (for this reason we label this date $\tau$). Because the policy shocks are hypothetical, it is not immediately obvious that

## EXHIBIT 2
### From Scenario Z-Scores to a Likelihood Measure




*Notes: Data as of December 29, 2017. Scenario Z-scores calculated using a 252-day covariance matrix with a 40-day half-life. The empirical time-series of Z-scores is generated by computing rolling Z-scores across daily return observations.*

*Source: BlackRock Aladdin, authors' calculations.*

the most appropriate date used is the most recent date. Later in this article, we discuss in more detail how to select an appropriate covariance matrix.

Having estimated Equation (5), one can state that for a scenario with policy factor shocks $r*$, only $X$% of historical periods had joint returns to policy variables as unlikely as $r*$, where $X = 100 * [1 - \hat{F}_{z(r)}[z(r*)]]$. In other words, we can define an exceedance probability for any scenario that is the historical probability of observing a $Z$-score greater than that of the scenario.

To illustrate these ideas more clearly, we choose the S&P 500 and the 10-year U.S. Treasury spot rate as the two policy variables in a hypothetical scenario. Exhibit 2 shows the rolling scenario $Z$-scores from the realized monthly changes in the S&P 500 and 10-year Treasury rate. The ex ante covariance matrix at each point in time is computed using exponential decay-weighted returns with a half-life of 40 days. The data in Exhibit 2 illustrate that there have been three $3\sigma$ and higher co-movements in the U.S. equity and bond markets over the last 10 years.

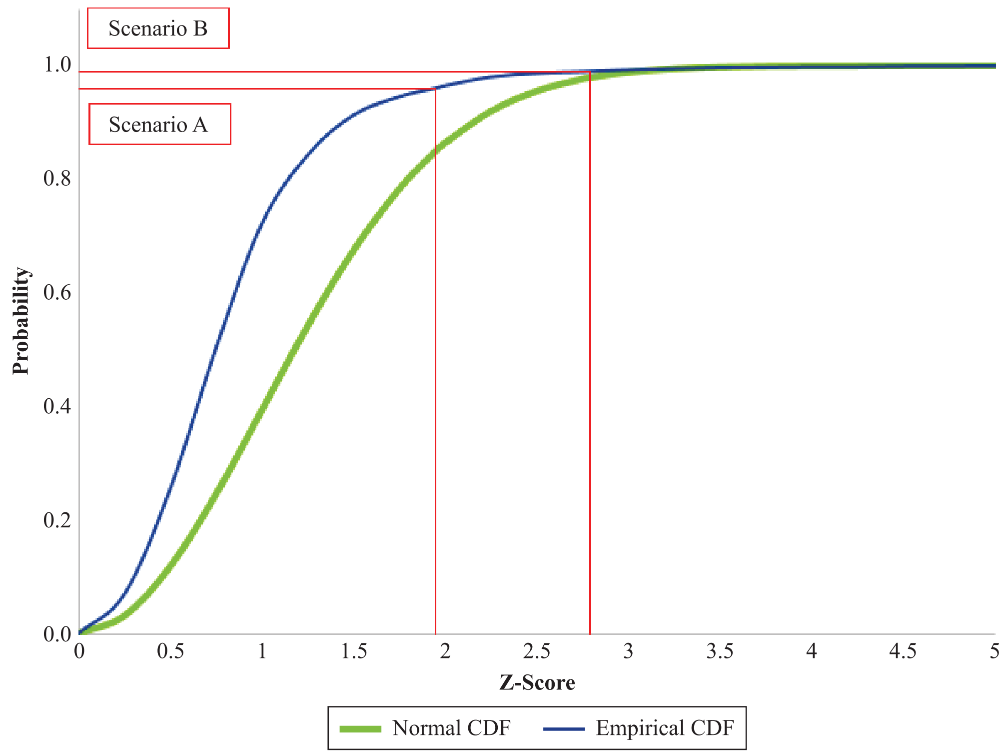
**Decomposing the scenario *Z*-score.** Using the nonparametric approach, we can now map $Z$-scores into a probability measure. Exhibit 3 shows the empirical (blue) versus the normal (green) cumulative probability density of empirical $Z$-scores. The empirical probability lies below the normal probability for extremely high $Z$-scores, indicating that high $Z$-scores are more likely under the empirical distribution.

Continuing with our example, we now construct two hypothetical scenarios using the S&P 500 and the Treasury rate as our policy variables. In these scenarios, the magnitude of the conjectured factor shocks is the same, but the signs differ. These two scenarios are defined in Exhibit 4. Scenario A corresponds to a standard *risk-off* scenario, in which risky assets sell off and there is a flight to quality. Scenario B represents an event like the 2013 taper tantrum, in which both stocks and Treasuries sell off. *Exceedance probability* refers to the likelihood of observing a scenario more extreme than the proposed scenario, as measured by the historical distribution of scenario $Z$-scores. The risk-off Scenario A is more than three times as likely as a scenario in which both stocks and bonds sell off. Scenarios A and B are labeled in Exhibit 3, where the exceedance probability equals 1 minus the cumulative probability on the $y$-axis. Note that the scenario $Z$-score and exceedance probability change through time as the covariance matrix changes. The probability of risk-off Scenario A increases, as shown in Exhibit 5, in periods of high market volatility.

Even though the magnitude of the shocks in Scenarios A and B are identical, Scenario B has a larger scenario $Z$-score because a sell-off in both equity and bond markets is not consistent with the December 30, 2017, covariance matrix used to compute the $Z$-score in Exhibit 3. Stock and bond returns generally have been negatively correlated during the long secular decline in bond yields since

## EXHIBIT 3

**Empirical Distribution of *Z*-scores**




*Notes: Data as of December 29, 2017. CDF is the cumulative distribution function. Scenario Z-scores calculated using a 252-day covariance matrix with a 40-day half-life. The empirical distribution of Z-scores is generated by computing rolling Z-scores across 15 years of daily return observations.*

*Source: BlackRock Aladdin, authors' calculations.*

the early 1980s, so Scenario B will usually have a higher $Z$-score than Scenario A (unless the covariance matrix used to measure the two $Z$-scores is estimated under an unusual regime, such as the taper tantrum in 2013).

Kinlaw and Turkington [2014] suggested a method for decomposing the $Z$-score into the contribution from the magnitude of the individual shocks and the contribution from the degree of the shocks' consistency with the ex ante covariance matrix. We can isolate the magnitude effect by computing the scenario $Z$-score assuming all correlations between policy variables are zero. We call this quantity the *volatility $Z$-score* $\mathbf{V}(\mathbf{z})$:

$$\mathbf{V}(\mathbf{z}) = \sqrt{\frac{\mathbf{z}^{T}\mathbf{z}}{\mathbf{n}}} \tag{6}$$

The correlation $Z$-score can then be defined as the scenario $Z$-score $\mathbf{Z}(\mathbf{r},\Sigma)$ normalized by the volatility $Z$-score $\mathbf{V}(\mathbf{z})$.

## EXHIBIT 4

**Empirical Exceedance Probability—Two-Factor Example**

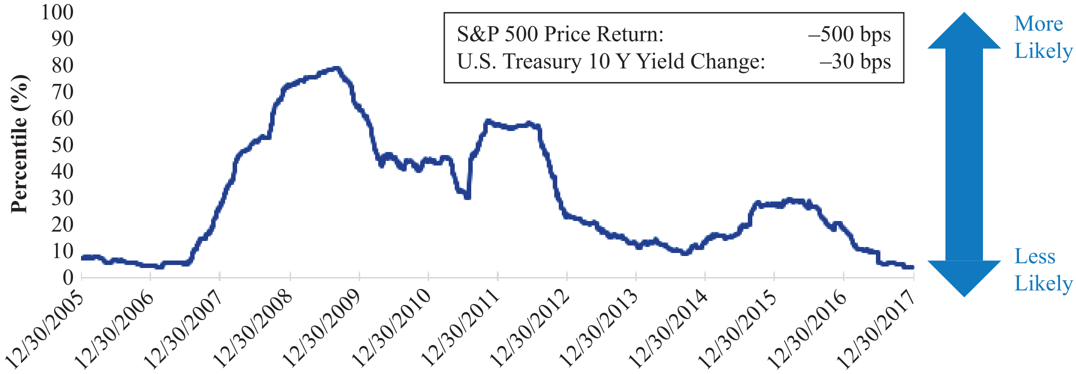
| A Two-Factor Example Continued: S&P 500 and 10-Year Treasury Yield | | | | |
|---|---|---|---|---|
| **Scenarios** | **S&P Price Return Shock (1-month)** | **Tsy Yield Change Shock (1-month)** | **Scenario Z-Score** | **Exceedance Probability** |
| A | –500 bps | –30 bps | 1.94 | 4.02% |
| B | –500 bps | +30 bps | 2.79 | 0.96% |

*Notes: Data as of December 29, 2017. Scenario Z-scores are calculated using a 252-day covariance matrix with a 40-day half-life. The exceedance probability of observing an event with Z-score higher than the scenario Z-score is generated by computing rolling Z-scores across 15 years of daily return observations.*

*Source: BlackRock Aladdin, authors' calculations.*

## EXHIBIT 5

**Changes in the Probability of Risk-Off Scenario A through Time**




*Notes: Data as of December 29, 2017. Scenario Z-scores are calculated using a 252-day covariance matrix with a 40-day half-life. The probability of a scenario is calculated as 1 minus the scenario's exceedance probability.*

*Source: BlackRock Aladdin, authors' calculations.*

$$\mathbf{C}(\mathbf{r},\Sigma) = \frac{\mathbf{Z}(\mathbf{r},\Sigma)}{\mathbf{V}(\mathbf{z})} \tag{7}$$

As shown in the Appendix, the correlation $Z$-score can also be represented explicitly in terms of the correlation matrix and individual factor $Z$-scores

$$\mathbf{C}(\mathbf{z},\Lambda) = \sqrt{\frac{\mathbf{z}^{\mathbf{T}}}{\sqrt{\mathbf{z}^{\mathbf{T}}\mathbf{z}}}\Lambda^{-1}\frac{\mathbf{z}^{\mathbf{T}}}{\sqrt{\mathbf{z}^{\mathbf{T}}\mathbf{z}}}} \tag{8}$$

where $\boldsymbol{\Lambda}$ represents the correlation matrix of the policy variables. Note that the factor $Z$-score vector has been normalized to have unit length. The correlation $Z$-score depends on the relative magnitudes (and signs) of the individual factor z-scores, not on their absolute magnitudes. In other words, the correlation $Z$-score is invariant to the scale of the shocks (i.e., a doubling of shock size will have no impact).

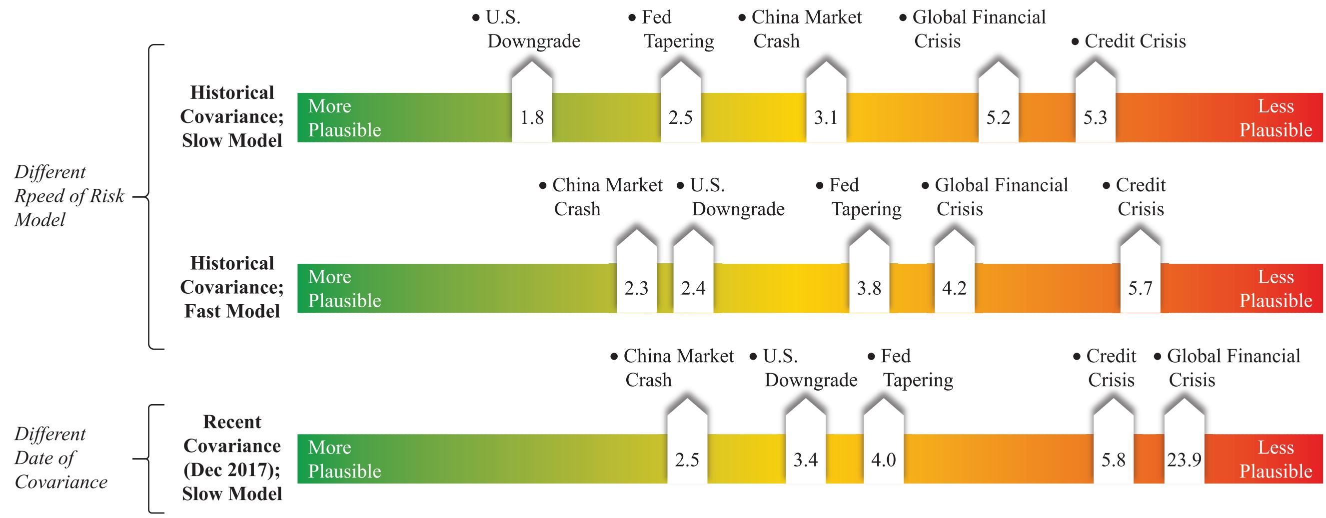
The correlation $Z$-score can be used as a very useful diagnostic to determine whether the sign and relative magnitude of the policy variable shocks are plausible, conditional on a certain covariance matrix. A correlation $Z$-score above one indicates that the policy variable shocks are more inconsistent with the chosen covariance matrix than they are with the same covariance matrix with zero correlations. If the sign of a policy variable shock is accidentally flipped, for example, the correlation $Z$-score will usually be above one, whereas the volatility $Z$-score will be unchanged.

**Specifying a covariance matrix.** The choice of matrix date and parameters in calibrating the risk factor covariance matrix can have a large impact on the relative ordering of the $Z$-scores of different scenarios. Exhibit 6 shows the risk ruler calibrated in three different ways. The first two risk rulers are based on the risk matrix immediately preceding the corresponding risk event, one being a slow (i.e., having a longer half-life) decay and the other being fast. The third risk ruler interprets the plausibility of shocks using the most recent covariance matrix. Depending on the view of the risk analyst, any of these three risk rulers could become the scale for the new hypothetical scenario being created.

The choice of covariance matrix to use in computing the perturbation vector and scenario $Z$-score should vary based on the scenario under consideration. If a scenario expresses a stressed market with a sharp sell-off in equities, the covariance matrix should be calibrated with historical data consistent with this kind of market event. Kim and Finger [2000] developed a *broken arrow* stress test, in which risk factor returns are modeled using a mixture of two normal distributions representing stressed and normal market conditions. The correlation matrix is estimated by measuring the ex post probability that the policy factor shocks come from the stressed regime. We use a method described by Silva and Ural [2011], in which the covariance matrix is constructed by weighting observations that are most similar to the proposed scenario. They showed that weighting observations based on their similarity to the proposed

## EXHIBIT 6

**Robustness of Scenario Plausibility**




| U.S. Downgrade | Fed Tapering | China Market Crash | Global Financial Crisis | Credit Crisis |
|---|---|---|---|---|
| ***Jul 21– Sep 20, 2011*** | ***May 21– June 24, 2013*** | ***Jun 12– Aug 26, 2015*** | ***Sep 12– Nov 03, 2008*** | ***Jul 01, 2007– Jun 01, 2008*** |
| The period starts with 50% chance U.S. downgrade indication from S&P Standards and ends with Operational Twist announcement by Fed. Stock market incurred losses while bonds markets saw gains due to flight to safety. | Tapering Talks stirred the market since Congress Testimony by Bernanke with both equity and bond markets sold off. Emerging Market suffered badly due to hot money flight back to U.S. | Chinese stock market crash beginning with the popping of the stock market bubble on 12 June 2015. | Credit & liquidity crisis and equity market crash set off by Lehman Brothers bankruptcy. Significant credit spreads widening caused by massive deleveraging. | Credit & liquidity crisis stemming from a severe slowdown in the housing market causing significant widening of credit spreads and increased implied volatility. |

*Notes: Data for recent covariance as of December 29, 2017 and otherwise using the covariance matrix prior to the scenario dates shown. For the slow model, covariance matrices are computed using five years of weekly, equally-weighted data. For the fast model, one year of weekly, equally-weighted data was used.*

*Source: BlackRock Aladdin, authors' calculations.*

scenario yields more predictive stress tests. Intuitively this makes sense because in a major risk-off scenario we expect risky assets to be more highly correlated than suggested by a covariance matrix calibrated over normal periods.[7] Stress scenario losses calibrated using data from other risk-off scenarios will both be more severe and more accurate than scenarios calibrated using normal periods.

## DEVELOPING USEFUL SCENARIOS

### Scenario Definition

Although constructing an MDS requires the application of subjective judgment, there are guidelines and diagnostic tools that can remove some of the subjectivity and rule out unintentionally highly implausible scenarios (some of these guidelines have been described in Cheng, Fagan, and Greenberg [2014]). Hypothetical scenarios should be defined with sufficient precision and specificity to allow them to be clearly translated into a set of quantitative shocks to market factors. Key risk factors used to define the scenario should not be highly correlated and should be as parsimonious as possible. Scenario $Z$-score metrics can be used to assess scenario plausibility and provide guidance on the magnitudes, signs, and relative sizing of specified shocks. A covariance matrix chosen to generate implied shocks should be consistent with the scenario's specified shocks. Scenario $Z$-score metrics can also be used to identify the historical covariance matrix most consistent with the stress scenario. After the portfolio stress test P&L is computed, statistical criteria can be used to determine whether the scenario needs to be refined by adding or removing risk factors or by restricting the impact of factors to a subset of the portfolio's factors.

**Step 1: Define a market event or macro regime.** Defining scenarios for potential market events is subject to two levels of uncertainty: uncertainty about whether the scenario will occur and uncertainty around the impact on asset returns if the scenario does occur. Scenarios should be defined so as to remove as much of the second source of uncertainty as possible. The first step requires defining a hypothetical scenario that will be affected by financial markets in a reasonably predictable manner. Any scenario related to a market event should satisfy certain basic criteria.

*Criterion 1: Scenario probability is small (but not impossible).* A scenario that is viewed as nearly certain will already be fully priced into the markets by investors. Scenarios chosen should be severe but well within the realm of the possible, as well as having the potential to have a significant impact on markets. Within the MDS process, we often attempt to summarize the probability space with three scenarios from the perspective of the scenario authors: an upside event, a downside event, and a tail event, with each defined relative to market consensus.

*Criterion 2: Scenario definition is precise.* The scenario should be defined with sufficient precision such that the scenario's impact on markets (both in terms of magnitude and direction) is not subject to interpretation of the scenario definition itself.

*Criterion 3: Scenario will affect markets that are relevant to the portfolio in a reasonably predictable manner.* This point is related to the previous one. The scenario definition may need to be refined depending on the types of portfolios that are being stressed. For instance, a scenario that involves large exchange shocks may not have any material impact on a single-currency portfolio. The impact of a value versus growth shock may not be particularly interesting when applied to a U.S. Treasury portfolio.

*Criterion 4: Scenario has a well-defined catalyst.* Because the scenario is unlikely, it is helpful to define a catalyst that will likely trigger the scenario.

**Step 2: Selecting policy variables.** Now that the scenario has been defined conceptually, we need to translate that definition into specified shocks to a set of policy factors. These key risk factors will anchor the scenario and allow shocks to be implied for all other risk factors through the factor covariance matrix.

The most important maxim in choosing policy variables is to be as parsimonious as possible. The larger the number the variables, the greater the likelihood of unintentionally introducing multicollinearity. Even if all factors are not collinear given today's matrix, having too many factors increases the likelihood of collinear factors in the future with a different covariance matrix. As a general rule, adding any candidate policy variable with an adjusted $R^2$ greater than 90% to the already selected policy variables should be avoided.

In cases in which parsimony is impossible and the scenario definition requires using a large number of policy variables, users can restrict by asset block to minimize multicollinearity. Restriction by block means that different groupings of implied risk factors are regressed on a different subset of policy variables.

**Step 3: Calibrating shock sizes to the policy variables.** One approach to setting initial shock sizes is to look for historical periods that resemble the desired hypothetical scenario. A second way to calibrate initial shock sizes to policy variables is to set a target frequency based on some subjective view of the likelihood of the scenario. Note that the target likelihood does not represent the likelihood of the scenario actually occurring, but rather the likelihood of observing a scenario at least as extreme as the target scenario as measured by the scenario *Z*-score. The Brexit scenario calibration described later goes into more detail on how to calibrate the shocks to the policy variables.

**Step 4: Generate nonpolicy factor shocks from the policy factor shocks.** Shocks to all nonpolicy factors are mainly implied through the risk model covariance matrix. The choice of covariance matrix is crucial in determining the implied shocks. When generating implied shocks, we want to choose a matrix date at which the covariance matrix is consistent with the relationships between the scenario's policy variable shocks. For example, if we want to simulate the end of quantitative easing in the United States through a backup at the short-end of the curve, we would like to select a covariance matrix in which the key rates at the short end of the curve are more volatile. It is important to note that we do not always imply nonpolicy variable shocks based on the prescribed variance/covariance matrix. In some instances, risk managers or investors may have a specific view of the correlation across blocks of risk factors, such as equities and credit spreads. After the financial crisis, the traditional negative correlation between equities and credit spreads has diverged in a number of market environments. Depending on the MDS, risk managers may decide to specify correlations across major market equity factors and credit spreads rather than rely on correlations implied by the covariance matrix. This ability to override correlations at the factor block level provides an important nuance when defining MDS.

**Step 5: Generate portfolio stress test P&L.** Portfolio stress test P&L over a given time horizon is calculated using the policy and nonpolicy variable factor shocks and the portfolio factor exposures. If there is no embedded optionality in the portfolio, portfolio P&L is simply the product of factor shocks and exposures. (Those positions with embedded optionality are often fully revalued given the factor shocks.)

## A MARKET-DRIVEN SCENARIO EXAMPLE: BREXIT

### Describing Different Brexit Scenario Outcomes

Although Brexit was viewed as a low-probability event, the referendum on continuing EU membership was one of the key event risks facing the United Kingdom in 2016. This risk was identified early in the year, and we created MDS scenarios in February around a vote to remain or to leave (i.e., Brexit), well ahead of the vote in June. The leave outcome was evaluated through two separate scenarios: (1) *Soft Brexit*, in which trade relationships with the EU were negotiated and intact; and (2) *Adverse Brexit*, in which there was a negative outcome for the United Kingdom with regard to trade when negotiating to leave the EU.

All three of these Brexit-related MDS scenarios were relevant to any portfolio with exposure to the British real economy and security markets and to the broader European markets. Specifically, a view for each scenario needed to be articulated regarding the impact on the British pound, gilts, and equity and credit markets, as well as the broader impact on European equity and fixed-income markets. In an extreme scenario, spill-overs to global markets on panic selling would be expected. Prime Minister David Cameron, having completed his negotiations for Britain's EU membership, announced in February that the referendum would take place on June 23, 2016. The key negotiation points included sovereignty, migrants, welfare benefits, economic governance, and excessive regulation. Although the reaction to the deal was mixed, the stay camp boasted a 10% lead in the polls in early June 2016, although polls tightened leading up to the referendum. The vote to leave ultimately surprised markets, despite the narrowing of the polls in the final days before the vote.

The goal of MDS is to identify a range of potential outcomes on all sides of the event risk spectrum. This means defining scenarios that reflect reasonable outcomes of how an event may unfold and affect markets. As noted earlier, in this case, the MDS captured three possibilities: (1) United Kingdom remains in EU, (2) Soft Brexit, and (3) Adverse Brexit. For purposes of exposition, in what follows, we will focus on the Soft Brexit scenario, which reflects a decision by the United Kingdom to leave the EU while retaining favorable trade and labor agreements. Examples of potential post-exit relationships between the United Kingdom and EU that informed the Soft Brexit scenario construction included the following: (1) the United Kingdom leaving the EU but remaining in the single market (e.g., Norway); (2) implementation of a customs union membership (e.g., Turkey); and (3) negotiation of an "EU Single Market-lite" agreement (e.g., Switzerland). Consensus among the investment teams and risk professionals was that a Soft Brexit scenario would be followed by risk-off sentiment in local markets and a dovish tone from the Bank of England.

### Identifying Key Policy Shocks in Soft Brexit Scenario

We start by identifying policy variables spanning U.K. markets across asset classes such as the FTSE All Share, 10-year gilt yields, and sterling FX rate. Differentiating this scenario from a generic U.K. negative economic shock requires including additional sector granularity in the policy variables. In the case of Brexit, financial services could be forced to shift to the European continent, and property demand would likely slump after an exodus of workers. The added policy variables therefore include shocks to U.K. banking equity and spreads factors and to real estate stocks.

The full set of policy variables is listed in Exhibit 7. Note the absence of policy variables specific to Europe. The transmission to European markets was assumed to be captured adequately using implied shocks.

Several shocks were chosen to dampen contagion outside the United Kingdom, namely on Italian rates and the Mexican peso. That is, unless we forced these shocks to be relatively small, the covariance matrix

## EXHIBIT 7
**Soft Brexit Scenario Policy Variable Selection**

| Factor Block | Factor | Shock | Shock (monthly σ) | Applied To | Calibration Comments |
|---|---|---|---|---|---|
| **Equities** | FTSE All Share | –5% | –0.8 | All-below | U.K. equity markets fall with financials and real estate sectors hit hardest. |
| | U.K. Banks | –2.50% | –0.6 | | |
| | U.K. Real Estate | –2.50% | –1 | | |
| **Rates** | GBP 10 yr | –10 bps | –0.5 | Rates & Inflation Ex Euro Spreads | GBP curve steepens with expectation of dovishness from BoE |
| | GBP 2 yr | –25 bps | –2.1 | | |
| | ITL 10 yr | +10 bps | 0.4 | Euro Spreads | Limited contagion to peripheral rates. |
| **Spreads** | U.K. Credit | +20 bps | 1 | Spreads | U.K. credit spreads widen with financials underperforming non-cyclicals. |
| | U.K. Banking | +35 bps | 1.1 | | |
| | U.K. Noncyclical | +10 bps | 0.7 | | |
| **FX** | GBP/USD | –5% | –2 | GBP/USD, EUR/USD & EMEA FX | GBP weakens suddenly against USD and depreciates across the board. |
| | MXN/USD | –1% | –0.2 | FX ex-GBP/USD, EUR/USD, EMEA FX | Limited contagion to Non-Euro FX. |

*Note: Data as of February 23, 2016.*
*Source: BlackRock Aladdin, authors' calculations.*

would amplify the shocks from the policy variables. Furthermore, we restricted the policy variable shocks to the same asset class (or subset thereof) in most cases to avoid the effects of spurious correlations.

A Soft Brexit scenario was designed to be more plausible than many of the past stress events shown on the plausibility ruler. Plausibility is evaluated using the MD and related multivariate scenario $Z$-scores. The impact of this particular scenario is more local in nature than the U.S. credit downgrade, for example (see Exhibit 8).

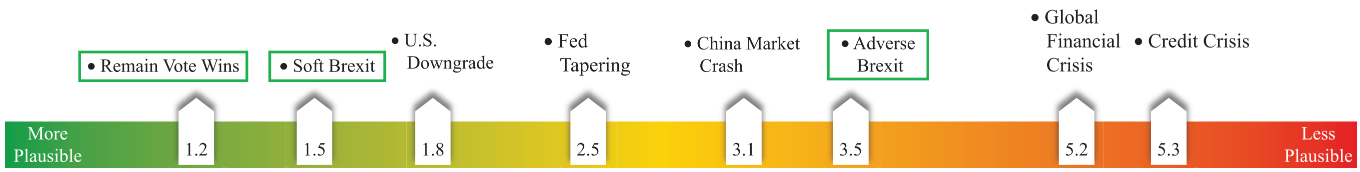
For sizing the shocks, direct historical comparisons, which are frequently part of the MDS definition process, provide limited guidance. For instance, the British pound's departure from the exchange rate mechanism in 1992 is somewhat related to the 2016 vote but is more focused on currency policy alone. The EU referendum is more wide reaching. Scotland's referendum is closer in substance but only provides a look at one outcome, the remain outcome. Rather, we need to consider the relative plausibility of the EU referendum scenarios relative to the scenario $Z$-score of some major economic/financial events, although their relative impact can be reasonably assumed. Our expectation was that the Soft Brexit scenario would have more of an impact than what was expected to be the remain vote and less than an Adverse Brexit scenario in which trade and financial relations are damaged. Furthermore, we expect that a Soft Brexit outcome is more plausible than the U.S. credit downgrade, for example.

The initial shocks chosen for policy variables led to a scenario $Z$-score in line with expectations and on the more plausible end of the ruler. Subsequent fine-tuning of the shocks by speaking with asset class experts did not lead to significant changes in this case. By far the most contentious issue was rates. Would gilts act as a safe haven asset and rally, or would investors flee the U.K. fixed market altogether? In the Soft Brexit scenario, we went with the safe haven interpretation. However, in the Adverse Brexit case, we assumed that U.K. yields rise.

The assumption on the shocks to U.K. yields has the largest impact on the plausibility of both the Adverse Brexit and Soft Brexit scenarios. Exhibit 9 includes a column labelled "Scenario $Z$-score delta" which is defined as how much the scenario $Z$-score would decrease if the policy variable shock for that row changed from its value as defined in the scenario to its expected value conditional on the value of the shocks to all other policy variables in the scenario. Note that the scenario $Z$-score delta for all factors except U.K. rates is near zero in Exhibit 9, indicating that all other factor shocks are consistent with one another; that is, we cannot lower the scenario $Z$-score by individually changing any other policy factor. The U.K. policy factor shocks, however, do express a strong view that is inconsistent with the remaining policy variables, as illustrated by the large value of the scenario $Z$-score delta for those factors.

## Exhibit 8

### Plausibility Ruler with Brexit Scenarios




| Remain Vote Wins | Soft Brexit | U.S. Downgrade | Fed Tapering | China Market Crash | Adverse Brexit | Global Financial Crisis | Credit Crisis |
|---|---|---|---|---|---|---|---|
| *June 2016* | *June 2016* | *Jul 21–Sep 20, 2011* | *May 21–Jun 24, 2013* | *Jun12–Aug 26, 2015* | *June 2016* | *Sep 12–Nov 03, 2008* | *Jul 01, 2007–Jul 01, 2008* |
| Vote to "remain" wins, improving political stability and strengthening the position of the current U.K. government. | Vote for the U.K. exiting the EU wins the Referendum, but governments still manage to negotiate and agreement. | The period starts with 50% chance U.S. downgrade indication from S&P Standards and ends with Operational Twist announcement by Fed. Stock market incurred losses while bonds markets & saw gains due to flight to safety. | Tapering Talks stirred the market since Congress Testimony by Bemanke with both equity and bond markets sold off. Emerging Market suffered badly due to hot money flight back to U.S. | Chinese stock market crash beginning with the popping of the stock market bubble on 12 June 2015. | The British public votes to leave the EU, and political and economic uncertainity follows. Having backed the vote to staty, the pressure mounts for Prime Minister David Cameron to resign. | Credit & liquidity crisis and equity market crash set off by Lehman Brothers bankruptcy. Significant credit spreads widening caused by massive deleveraging. | Credit & liquidity crisis stemming from a severe slowdown in the housing market causing significant widening of credit spreads and increased implied volatility. |

*Notes: Data as of February 23, 2016 for the Brexit scenarios and otherwise using the covariance matrix prior to the scenario dates shown. Covariance matrices are computed using five years of weekly, equally-weighted data.*

*Source: BlackRock Aladdin, authors' calculations.*

In generating nonpolicy factor shocks, the risk analyst should select a covariance matrix that best models the cross-asset linkages that are expected to occur in the particular scenario. For instance, an analyst who constructs a risk-off scenario may select a regime-weighted covariance matrix estimated using returns that occurred during turbulent economic environments, whereas a geopolitical risk scenario may call for a covariance matrix estimated using returns from a time that includes dynamic political change. In the Brexit example, given that we lack reasonably comparable historical events, we mainly rely on the current covariance matrix that reflects a period of rising populist sentiment. Even if we had chosen the exit from the European exchange rate mechanism event, the changes over ensuing decades would likely have rendered a matrix from that period unusable. The perturbation vector reflects the implied factor moves from the shocks to the policy variables, as seen in Exhibit 10. The negative shock to the U.K. equity market is transmitted to other global equity markets, and rates rally broadly. However, we do not rely entirely on the naïve covariance matrix

## Exhibit 9

### Soft Brexit Scenario Z-score

| Factor Block | Factor | Shock | Factor Z-Score | Scenario Z-Score Delta |
|---|---|---|---|---|
| Equities | FTSE All Share | –5% | –0.8 | 0.04 |
| | U.K. Banks | –2.50% | –0.6 | 0.08 |
| | U.K. Real Estate | –2.50% | –1 | –0.05 |
| Rates | GBP 10 yr | –10 bps | –0.5 | 0.49 |
| | GBP 2 yr | –25 bps | –2.1 | 0.56 |
| | U.K. Credit | +20 bps | 1 | –0.07 |
| Spreads | U.K. Banking | +35 bps | 1.1 | 0.08 |
| | U.K. Noncyclical | +10 bps | 0.7 | –0.04 |
| FX | GBP/USD | –5% | –2 | 0.09 |
| | | | Scenario Z-Score | 1.5 |
| | | | Scenario M-distance | 4.5 |

*Notes: Data as of February 23, 2016.*

*Source: BlackRock Aladdin, authors' calculations.*

## Exhibit 10
**Soft Brexit Perturbation Vector**

| | | "Soft Brexit" | |
|---|---|---|---|
| **Asset Class** | **Risk Factor** | **Implied Shock (bps)** | **Implied Shock in σ** |
| Equity Styles | Value | –19 | –0.47 |
| | Dividend Yield | 4 | 0.08 |
| | Growth | –36 | –0.69 |
| | Momentum | –7 | –0.05 |
| Equity Sector | MSCI World Financials | –611 | –0.90 |
| | MSCI World Materials | –407 | –0.57 |
| | MSCI World Technology | –494 | –0.71 |
| | MSCI World Utilities | –231 | –0.53 |
| Equity Markets | MSCI EM—MSCI DM | 40 | 0.11 |
| | MSCI Europe (EUR) | –671 | –0.86 |
| | FTSE100 | –523 | –0.76 |
| | S&P 500 | –383 | –0.70 |
| | MSCI World | –422 | –0.75 |
| | MSCI Japan | –640 | –0.68 |
| | VIX Implied Vol | 589 | 0.69 |
| Rates | Tsy 10Y | –9 | –0.46 |
| | GBP 10Y | –10 | –0.46 |
| | DEM 30Y | –19 | –0.82 |
| | JPY 30Y | –13 | –1.27 |
| Muni Spreads | Muni Spread 7Y | 6 | 0.42 |
| | State GO | 2 | 0.60 |
| Spreads | U.S. Cash Bonds IG | 12 | 0.77 |
| | U.S. Cash Bonds HY | 26 | 0.34 |
| | CMBS | 3 | 0.30 |
| | EUR Cash Bonds IG | 8 | 0.49 |
| Sov Spread | EMBI Global (EM) | 0 | –0.01 |
| | Spain 5y | 7 | 0.32 |
| | Italy 5y | 7 | 0.35 |
| Mortgages | 15Y Mtg Basis | 0 | –0.08 |
| | 30Y Mtg Basis | –3 | –0.60 |
| Inflation | CPI 10yr | 2 | 0.14 |
| | EUR INF 10yr | 7 | 0.53 |
| | JPY INF 10yr | –10 | –0.59 |
| FX | DXY U.S. Dollar Index | –16 | –0.07 |
| | AUD/USD | –39 | –0.12 |
| | EUR/USD | –292 | –0.96 |
| | GBP/USD | –500 | –1.99 |
| | JPY/USD | 37 | 0.11 |
| | MXN/USD | –100 | –0.23 |
| Commodity | Gold COMEX 1 | 301 | 0.56 |
| | Brent Crude Oil | –791 | –0.50 |
| | Copper | –179 | –0.30 |

*Note: Data as of February 23, 2016.*
*Source: BlackRock Aladdin, authors' calculations.*

## Exhibit 11
**Soft Brexit P&L**

| Potential Outcome | Hypothetical Portfolio Impact (PnL in bps) Index Portfolio Equity | Index Portfolio Bonds | Index Portfolios Multi-Asset |
|---|---|---|---|
| | FTSE 100 | iBoxx GBP | 60% FTSE 100, 40% iBoxx GBP |
| **Soft Brexit** The U.K. also votes to leave, but favorable trade and labor agreements are retailed, leading to some local risk-off sentiment and a more dovish tone from the BoE | –506 | +64 | –180 |

*Note: Data as of February 23, 2016.*
*Source: BlackRock Aladdin, authors' calculations.*

to imply shocks across the perturbation vector, which are predicated on the specific regime against which it was estimated. In this case, it is important to note that, while broadly relying on the covariance matrix, we had a specific view about the correlation between equity prices and credit spreads in the Soft Brexit scenario. Thus, in addition to applying policy variable shocks to U.K. and European equity indexes, we also implicitly specified a negative correlation between equities and credit spreads in major markets.

Once the full set of shocks is specified, the P&L impact on portfolios can be calculated. Exhibit 11 shows the impact of the Soft Brexit scenario on a hypothetical 60/40 portfolio invested in the FTSE 100 equity index and the Markit iBoxx GBP index as well as allocation to each index separately. The portfolio losses are driven by the sell-off in equities, whereas the bond exposure acts as a partial hedge. Notably, the goal of the MDS exercise is not to quantify tail loss and require portfolio managers to reduce risk to any specific MDS and related outcome. The goal is to define MDS in an optimal fashion, leveraging investor, risk manager, and economist insights; to apply the MDS process to portfolios; and to quantify the potential set of return outcomes from each scenario. When the portfolio scenario returns are generated, portfolio managers are asked to review the hypothetical returns and confirm that the implied risk positioning is deliberate, diversified, and scaled based on a portfolio manager's conviction level. Portfolios will invariably have varying exposure to any given scenario depending on the respective investment theses of the corresponding portfolio managers. The risk management goal is to ensure that portfolio managers are aware of the risk and potential return of different outcomes associated with a Brexit event and confirm that risk is consistent with expectations. Specific funds in which portfolio managers had a high level of conviction that Soft Brexit would not occur scaled their positions accordingly.

## CONCLUSION

Never wasting a good crisis, risk management has evolved in the last decade with a more flexible approach to identifying and protecting portfolios against extreme event risk. Historical analysis continues to play a role, but it is possible to entertain a wider range of dangers beyond what has happened in recent years while providing some boundaries on pure speculation about the future. Furthermore, technology developments have made possible faster on-the-fly evaluation of portfolio outcomes, especially where options are involved. Another wave of change may entail wider use of forecasting models, perhaps based on machine learning, for scenario inputs.

We have illustrated the market-driven scenarios approach for the U.K. Brexit referendum, spelling out alternate hypothetical outcomes and providing portfolio managers with a guidepost on risk management and hedging decisions. Looming geopolitical risks linked to international trade, for example, provide opportunities for risk managers to hone these techniques. In addition, the proposed approach should be extended to take into account the passage of time. Although in many cases, the gain or loss related to carry will be de minimus, for other scenarios that are less extreme, the carry impact might be relevant.

# APPENDIX

## DECOMPOSITION OF SCENARIO *Z*-SCORE

Kinlaw and Turkington [2014] suggested a method for decomposing MD into contributions from the magnitude of the individual shocks and contributions from the correlation between shocks.

As a first step, we can re-express the MD in terms of the correlation matrix and factor *Z*-scores:

$$\mathbf{MD}(\boldsymbol{r},\Sigma) := \sqrt{\boldsymbol{r}^T\,\Sigma^{-1}\,\boldsymbol{r}} = \sqrt{\boldsymbol{r}^T(\Sigma_{\sigma,\mathbf{diag}}\,\Lambda\,\Sigma_{\sigma,\mathbf{diag}})^{-1}\boldsymbol{r}}$$
$$= \sqrt{(\boldsymbol{r}^T\,\Sigma^{-1}_{\sigma,\mathbf{diag}})\Lambda^{-1}(\Sigma^{-1}_{\sigma,\mathbf{diag}}\,\boldsymbol{r})/\boldsymbol{n}} = \sqrt{\mathbf{z}^T\Lambda^{-1}\mathbf{z}} \quad \text{(A-1)}$$

where $\mathbf{\Lambda}$ is the correlation matrix and $\Sigma_{\sigma,\mathbf{diag}}$ is a diagonal matrix with factor volatilities along the diagonal. The diagonal matrixes are then pulled outside the inverse and combined with the shock vector $\boldsymbol{r}$ to construct a vector of *Z*-scores.

Having re-expressed the MD in terms of the correlation matrix $\mathbf{\Lambda}$ and *Z*-scores, we can now decompose the scenario *Z*-score in terms of correlation and volatility components.

$$\mathbf{Z}(\mathbf{z},\Lambda) = \sqrt{\mathbf{z}^T\Lambda^{-1}\mathbf{z}/\boldsymbol{n}}$$
$$= \sqrt{\frac{\mathbf{z}^T}{\sqrt{\mathbf{z}^T\mathbf{z}}}\Lambda^{-1}\frac{\mathbf{z}^T}{\sqrt{\mathbf{z}^T\mathbf{z}}}}\sqrt{\mathbf{z}^T\mathbf{z}/\boldsymbol{n}} = \boldsymbol{C}(\mathbf{z},\Lambda)\boldsymbol{V}(\mathbf{z}) \quad \text{(A-2)}$$

where $\mathbf{C}(\mathbf{z},\mathbf{\Lambda})$ and $\mathbf{V}(\mathbf{z})$ are the correlation and volatility components, respectively.

## ENDNOTES

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[1]It is also possible to treat monetary policy as part of the economic fundamentals in recognition of the endogeneity. We thank Jean Boivin for providing this insight.

[2]Although we use the words *scenarios* and *stress tests* interchangeably in this article, there is, strictly speaking, a distinction. Whereas scenarios in some cases are designed to represent tail events (the definition of a stress test), they may also encompass more likely events. Quantifying the latter makes application to portfolios of assets and evaluation of exposures in stable times possible.

[3]One notable exception is an article by Clemens and Winkler [1999] that studied the optimal composition of the team that designs the scenario.

[4]The Lucas critique would apply to most approaches, with the exception of a model based on microfoundations. However, most investors would not have available a micro model based on deep foundations in which preferences would be invariant to changes in government policy variables.

[5]The MD used in a financial context can be found in the work of Kritzman and Yuanzhen [2010].

[6]This follows from the fact that the probability density function of elliptical distributions takes the form of the MD, that is, $f(x) = k \cdot g(x^T\,\Sigma^{-1}\,x)$.

[7]Consistent with the well-worn trope among risk managers that correlations go to one in times of market stress.

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