Financial Risk Forecasting

Chapter 8

Backtesting and stress testing

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Introduction

• When making a risk forecast (or any type of forecast)
• It is important to validate the forecast

   **Ex post** ideally this is done after we make them — using *operational criteria*

   **Ex ante** but often we have to do it before

• VaRs are only observed infrequently, a long period of time would be required

• *Backtesting* evaluates VaR forecasts by checking how a VaR forecast model performs over a period in the past — *in-sample*
The focus of this chapter is on

- Backtesting
- Application of backtesting
- Significance of backtests
  - Bernoulli coverage test
  - Testing the independence of violations
  - Joint test
  - Loss-function-based backtests
- Expected shortfall backtesting
- Problems with backtesting
- Stress testing
Notation

\( W_T \)  Testing window size
\( W_E \)  Estimation window size
\( \eta \)  Indicates whether a violation occurs
\( \nu \)  Count of violations
Backtesting
What is backtesting?

- Procedure to compare various risk models, *ex-ante* (that is in-sample)
- Take ex-ante VaR forecasts from a particular model and compare them with *ex-post* realized return (i.e., historical observations)
- Whenever losses exceed VaR, a *VaR violation* is said to have occurred
- Can analyze violations in various ways
Forecasting VaR - Example

• Imagine you have 10 years of data, from 2007 to 2016
• And using the first 2 years of that
• Are trying to forecast risk for 1 January 2009
• You will be using the 500 days in 2008 and 2006 to make the forecast
• The 500 trading days in 2007 and 2008 constitute the first *estimation window*

• $W_E$ is then moved up by one day to obtain the risk forecast for the second day of 2009, etc.

<table>
<thead>
<tr>
<th>Start</th>
<th>End</th>
<th>VaR forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/1/2007</td>
<td>31/12/2008</td>
<td>VaR(1/1/2009)</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>31/12/2014</td>
<td>30/12/2016</td>
<td>VaR(31/12/2016)</td>
</tr>
</tbody>
</table>
Usefulness of backtesting

- Identifying the weaknesses of risk forecasting methods
- Hence providing avenues for improvement
  - Not very informative about the *causes* of weaknesses
- Models that perform poorly during backtesting should question
  1. model assumptions
  2. parameter estimates
- Backtesting can prevent underestimation and overestimation of risk
**Estimation window** ($W_E$): the number of observations used to forecast risk. If different procedures or assumptions are compared, the estimation window is set to whichever one needs the highest number of observations.

**Testing window** ($W_T$): the data sample over which risk is forecast (i.e., the days where we have made a VaR forecast).

$$T = W_E + W_T$$
$t = 1 \quad \text{Entire data sample} \quad t = T$
Backtesting

\[ t = 1 \quad \text{Entire data sample} \quad t = T \]

\[ t = 1 \quad \text{First estimation window} \quad t = W_E \quad \text{VaR}(W_E + 1) \]
Diagram showing backtesting violations application testing coverage independence SP-500 ES backtesting problems stress testing

$t = 1$ Entire data sample $t = T$

$t = 1$ First estimation window $t = W_E$ VaR($W_E + 1$)

$t = 2$ Second estimation window $t = W_E + 1$ VaR($W_E + 2$)
\[ t = 1 \quad \text{Entire data sample} \quad t = T \]

\[ t = 1 \quad \text{First estimation window} \quad t = W_E \quad \text{VaR}(W_E + 1) \]

\[ t = 2 \quad \text{Second estimation window} \quad t = W_E + 1 \quad \text{VaR}(W_E + 2) \]

\[ t = 3 \quad \text{Third estimation window} \quad t = W_E + 2 \quad \text{VaR}(W_E + 3) \]
\[ t = 1 \quad \text{Entire data sample} \quad t = T \]

\[ t = 1 \quad \text{First estimation window} \quad t = W_E \quad \text{VaR}(W_E + 1) \]

\[ t = 2 \quad \text{Second estimation window} \quad t = W_E + 1 \quad \text{VaR}(W_E + 2) \]

\[ t = 3 \quad \text{Third estimation window} \quad t = W_E + 2 \quad \text{VaR}(W_E + 3) \]

\[ \vdots \]
Backtesting

Violations

Application

Testing

Coverage

Independence

SP-500

ES backtesting

Problems

Stress testing

$t = 1$
Entire data sample
$t = T$

$t = 1$
First estimation window $t = W_E$
$VaR(W_E + 1)$

$t = 2$
Second estimation window $t = W_E + 1$
$VaR(W_E + 2)$

$t = 3$
Third estimation window $t = W_E + 2$
$VaR(W_E + 3)$

\vdots

$t = T - W_E$
Last estimation window $t = T - 1$
$VaR(T)$
• VaR forecasts can be compared with the actual outcome: the daily 2007 to 2016 returns are *already known*

• Instead of referring to calendar dates (e.g., 1/1/2007), refer to days by indexing the returns, assuming 250 *trading days* per year:
  - $y_1$ is the return on 1/1/2007
  - $y_{2,500}$ is the return on the last day, 31/12/2016
The estimation window $W_E$ is set at 500 days, and the testing window $W_T$ is therefore 2,000 days.

<table>
<thead>
<tr>
<th>$t$</th>
<th>$t + W_E - 1$</th>
<th>$\text{VaR}(t + W_E)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>500</td>
<td>$\text{VaR}(501)$</td>
</tr>
<tr>
<td>2</td>
<td>501</td>
<td>$\text{VaR}(502)$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>1,999</td>
<td>2,499</td>
<td>$\text{VaR}(2,500)$</td>
</tr>
</tbody>
</table>
Violation ratios
VaR violation

• If a financial loss on a particular day exceeds the VaR forecast, then the **VaR limit is said to have been violated**

**VaR violation**: an event such that:

\[
\eta_t = \begin{cases} 
1, & \text{if } y_t \leq -\text{VaR}_t \\
0, & \text{if } y_t > -\text{VaR}_t.
\end{cases}
\]
Counting violations

• Count the violations

\[ \nu_1 \]

and non-violations

\[ \nu_0 \]

\[ \nu_1 = \sum_{t=1}^{W_T} \eta_t \]

\[ \nu_0 = W_T - \nu_1 \]
Violation ratios

- The main tools used in backtesting are violation ratios
- The observed number of VaR violations are compared with the expected

Violation ratio:

\[ VR = \frac{\text{Observed number of violations}}{\text{Expected number of violations}} = \frac{\nu_1}{p \times W_T} \]

- If the violation ratio is greater than one the VaR model underforecasts risk
- If smaller than one the model overforecasts risk
Estimation window length

- $W_E$ determined by the choice of VaR model and probability level
- Different methods have different data requirements
  - **EWMA** c. 30 days
  - **HS** at least 300 days for VaR 1%
  - **GARCH** 500 or more days
Picking $W_E$

- The estimation window should be sufficiently large to accommodate the most stringent data criteria.
- So if comparing EWMA and HS, use at least 300 for both.
• Even within the same method, it may be helpful to compare different window lengths
• Maybe compare HS with 300, 500 and 1000 days
• Or GARCH with 500 and 5000 days
Testing window length

- VaR violations are infrequent events
- With a 1% VaR, a violation is expected once every 100 days, so that 2.5 violations are expected per year
- So the actual sample size of violations is quite small
- Causing difficulties for statistical inference
- At least 10 violations for reliable statistical analysis, or 4 years of data
- Preferably more
Violation ratios

- $VR=1$ is expected, but how can we ascertain whether any other value is statistically significant?

- A useful *rule of thumb*
  - If $VR \in [0.8, 1.2]$ the model is *good*
  - If $VR \in [0.5, 0.8]$ or $VR \in [1.2, 1.5]$ the model is *acceptable*
  - If $VR \in [0.3, 0.5]$ or $VR \in [1.5, 2]$ the model is *bad*
  - If $VR < 0.5$ or $VR > 2$ the model is *useless*

- Both bounds narrow with increasing testing window lengths

- As a first attempt

- Plot the actual returns and VaR together

- And then do a statistical test
Application of backtesting
Volatility and VaR: extreme example

Returns

-100% -60% -20% 20% 60% 100%

day

0 500 1000 1500 2000
Volatility and VaR: extreme example

![Graph showing volatility and VaR with EWMA]

- Returns range from -100% to 100%.
- VaR values range from $10 to $130.
- The graph illustrates the movements of returns and VaR over time, with an emphasis on extreme events.
Volatility and VaR: extreme example

![Graph showing returns and VaR over time]

- EWMA
- MA 500

Returns:
- -100%
- -60%
- -20%
- 20%
- 60%
- 100%

VaR:
- $10
- $30
- $50
- $70
- $90
- $110
- $130

Days:
- 0
- 500
- 1000
- 1500
- 2000
Volatility and VaR: extreme example

Returns vs. day

-100%  -60%  -20%  20%  60%  100%

$10 $30 $50 $70 $90 $110 $130

-100% -60% -20% 20% 60% 100%

0 500 1000 1500 2000
day

EWMA
MA 500
GARCH

Volatility and VaR: extreme example

Volatility and Value at Risk (VaR) are important concepts in financial risk management. This graph illustrates the behavior of returns and VaR over time for different models: EWMA (Exponentially Weighted Moving Average), MA 500 (Moving Average over 500 days), GARCH (Generalized Autoregressive Conditional Heteroskedasticity), and HS 300 (Shanghai Stock Exchange 300 Index).

The graph shows the returns and VaR for each model. The x-axis represents days, and the y-axis represents returns and VaR values. The patterns and spikes in the graph highlight the volatility and risk associated with each model. The EWMA model, for instance, shows a smoother trend compared to the GARCH model, which exhibits more pronounced volatility spikes. This visual representation is crucial for backtesting and stress testing scenarios in financial risk forecasting.
Volatility and VaR: extreme example

![Graph showing returns and VaR over time for HS 300 and HS 500.]
Backtesting
Violations
Application
Testing
Coverage
Independence
SP-500
ES backtesting
Problems
Stresstesting

SP-500

Returns

EWMA


−5%
0%
5%
10%

$20
$40
$60
$80
$100
$120

$20
$40
$60
$80
$100
$120

VaR
Backtesting  Violations  Application  Testing  Coverage  Independence  SP-500  ES backtesting  Problems  Stresstesting

SP-500

- EWMA
- MA 1000
- GARCH

Returns


$20 $40 $60 $80 $100 $120 $140

VaR
Zoom into 2003-2006

Returns

-2% 0% 2%

2003 2004 2005 2006 2007
Zoom into 2003-2006

EWMA
Zoom into 2003-2006

Returns

EWMA

MA 1000

$10

$15

$20

$25

$30

$35

$40

$10

$15

$20

$25

$30

$35

$40

VaR

2003

2004

2005

2006

2007
Zoom into 2003-2006

Returns

2003 2004 2005 2006 2007

-2% 0% 2%

$10 $20 $30 $40

VaR

EWMA MA 1000 GARCH
Zoom into 2003-2006

Returns

2003 2004 2005 2006 2007

HS 1000 HS 300

VaR

$10 $15 $20 $25 $30 $35
Zoom into crisis

Returns

2007 2008 2009 2010

-5% 0% 5% 10%
Zoom into crisis

Returns

EWMA

VaR

2007 2008 2009 2010

$20 $40 $60 $80 $100 $120

−5% 0% 5% 10%
Zoom into crisis

EWMA  MA 1000

Returns

VaR

$20

$40

$60

$80

$100

$120

2007  2008  2009  2010
Zoom into crisis

Returns

VaR

$140

$120

$100

$80

$60

$40

$20

2007 2008 2009 2010

EWMA

MA 1000

GARCH

-5%

0%

5%

10%
Zoom into crisis

Returns

2007 2008 2009 2010

EWMA MA 1000 GARCH HS 1000

VaR

$20 $40 $60 $80 $100 $120 $140

$20 $40 $60 $80 $100 $120 $140
Zoom into crisis

Returns

VaR

-5%

0%

5%

10%

2007 2008 2009 2010

$20 $40 $60 $80

HS 1000 HS 300

-5%

Significance of Backtests
Testing violations

- We can test whether we get the expected number of violations and if there are patterns in the violations enumerate
  1. The number of violations (tested by the unconditional coverage)
  2. Clustering (tested by independence tests)
Distribution of violations

- We have a sequence of returns, VaR and violations $\eta_t$

<table>
<thead>
<tr>
<th>$\eta$</th>
<th>1</th>
<th>0</th>
<th>1</th>
<th>0</th>
<th>0</th>
<th>1</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>VaR</td>
<td>1.9</td>
<td>2.0</td>
<td>2.1</td>
<td>2.0</td>
<td>2.1</td>
<td>2.2</td>
<td>2.3</td>
<td>2.2</td>
<td>2.3</td>
<td>2.4</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-2.1</td>
<td>1.4</td>
<td>-5.2</td>
<td>2.3</td>
<td>0.4</td>
<td>-3.7</td>
<td>4.1</td>
<td>0.1</td>
<td>3.2</td>
<td>-0.2</td>
</tr>
</tbody>
</table>

- The $\{\eta_t\}_{t=W_E+1}^T$ is a sequence of 1 or 0
- And hence follows the Bernoulli distribution
- Note that the sequence starts at $W_E + 1$ and ends at $T$
  and is hence $W_T$ long
Estimation

- The sample probability $\hat{p}$ can be estimated by the average number of violations
  \[ \hat{p} = \frac{\nu}{W_t} \]

- The Bernoulli density (on day $t$) is given by:
  \[ (1 - p)^{1-\eta_t} p^{\eta_t}, \quad \eta_t = 0, 1. \]
Bernoulli coverage test
**Unconditional coverage**

- Does the expected number of violations, as given by $p$ match the observed number of violations
  - For a VaR(1%) backtest, we would expect to observe a violation 1% of the time
  - If violations are observed more often the VaR model is *underestimating risk*
  - And similarly if we observe too few violations
Bernoulli coverage test

• We can therefore test if the sequence \( \{ \eta_t \}_{t=W_E+1}^T \) has the expected number of 1 and 0

• Use the Bernoulli coverage test

• The null hypothesis for VaR violations is:

\[
H_0 : \eta \sim B(p),
\]

where \( B \) stands for the Bernoulli distribution
• Recall from chapter 2 that the likelihood function is the product of the densities, and therefore

• The likelihood function is given by:

\[
L_U(\hat{p}) = \prod_{t=W_E+1}^{T} (1 - \hat{p})^{1-\eta_t}(\hat{p})^{\eta_t} = (1 - \hat{p})^{\nu_0}(\hat{p})^{\nu_1}
\]

• Denote this as the unrestricted likelihood function

• Because it uses estimated probability \( \hat{p} \)

• Under \( H_0 \), \( p = \hat{p} \), so the restricted likelihood function is:

\[
\mathcal{L}_R(p) = \prod_{t=W_E+1}^{T} (1 - p)^{1-\eta_t}(p)^{\eta_t} = (1 - p)^{\nu_0}(p)^{\nu_1}
\]
• We can use a likelihood ratio (LR) test to see whether $\mathcal{L}_R = \mathcal{L}_U$ or, equivalently, whether $p = \hat{p}$:

$$LR = 2(\log \mathcal{L}_U(p) - \log \mathcal{L}_R(\hat{p}))$$

$$= 2 \log \left( \frac{(1 - \hat{p})^{\nu_0}(\hat{p})^{\nu_1}}{(1 - p)^{\nu_0}(p)^{\nu_1}} \right)$$

asymptotic $\sim \chi^2(1)$

• Choosing a 5% significance level for the test, the null hypothesis is rejected if $LR > 3.84$

Matlab

\texttt{chi2inv} (1 - 0.05, 1)

3.8415

R

\texttt{qchisq} (p=1 - 0.05, df=1)

3.841459
Bernoulli coverage test

Matlab

```matlab
function res=bern_test(p,v)
    a=p^(sum(v))*(1-p)^(length(v)-sum(v));
    b=(sum(v)/length(v))^(sum(v))*(1-(sum(v)/length(v)))^(length(v)-sum(v));
    res=-2*log(a/b);
end
```

R

```r
bern_test=function(p,v){
    lv=length(v)
    sv=sum(v)
    al=log(p)*sv+log(1-p)*(lv-sv)
    bl=log(sv/lv)*sv + log(1-sv/lv)*(lv-sv)
    return(-2*(al-bl))
}
```
Independence property
Distribution of violations

- Suppose the violations cluster

<table>
<thead>
<tr>
<th>η</th>
<th>0</th>
<th>1</th>
<th>1</th>
<th>1</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>VaR</td>
<td>2.0</td>
<td>1.9</td>
<td>2.1</td>
<td>2.2</td>
<td>2.1</td>
<td>2.0</td>
<td>2.3</td>
<td>2.2</td>
<td>2.3</td>
<td>2.4</td>
</tr>
<tr>
<td>y</td>
<td>1.4</td>
<td>-2.1</td>
<td>-5.2</td>
<td>-3.7</td>
<td>0.4</td>
<td>2.3</td>
<td>4.1</td>
<td>0.1</td>
<td>3.2</td>
<td>-0.2</td>
</tr>
<tr>
<td>days</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
</tr>
</tbody>
</table>

- Then we are violating the independence property
Independence test

- Do two violations follow each other?
- They should not because
- If they do, we can predict a violation today if there was one yesterday
- And a good VaR model would have increased the VaR forecast following a violation
• The probabilities of two consecutive violations is

\[ p_{11} \]

• The probability of a violation if there was no violation on the previous day

\[ p_{01} \]

• and

\[ p_{10} \]

• and

\[ p_{00} \]

• More generally, the probability that:

\[ p_{ij} = \Pr(\eta_t = j|\eta_{t-1} = i) \]

• where \( i \) and \( j \) are either 0 or 1
• The violation process can be represented as a Markov chain with two states

• So the first order transition probability matrix is defined as:

\[ \Pi_1 = \begin{pmatrix} 1 - p_{01} & p_{01} \\ 1 - p_{11} & p_{11} \end{pmatrix} \]

• The likelihood function is:

\[ L_1(\Pi_1) = (1 - p_{01})^{v_{00}} \cdot p_{01}^{v_{01}} \cdot (1 - p_{11})^{v_{10}} \cdot p_{11}^{v_{11}} \] (8.5)

• Where \( v_{ij} \) is the number of observations where \( j \) follows \( i \)
• Likelihood function

\[
\hat{\Pi}_1 = \begin{pmatrix}
\frac{v_{00}}{v_{00} + v_{01}} & \frac{v_{01}}{v_{00} + v_{01}} \\
\frac{v_{10}}{v_{10} + v_{11}} & \frac{v_{11}}{v_{10} + v_{11}}
\end{pmatrix}.
\]

• Under the null hypothesis of no clustering, the probability of a violation tomorrow does not depend on today being a violation.

• Then \( p_{01} = p_{11} = p \) and the transition matrix is simply:

\[
\Pi_2 = \begin{pmatrix} 1 - p & p \\ 1 - p & p \end{pmatrix}
\]

• and the ML estimate is:

\[
\hat{p} = \frac{v_{01} + v_{11}}{v_{00} + v_{10} + v_{01} + v_{11}}.
\]
• so

\[ \hat{\Pi}_2 = \begin{pmatrix} 1 - \hat{p} & \hat{p} \\ 1 - \hat{p} & \hat{p} \end{pmatrix} \]

• The likelihood function then is

\[ L_2(\Pi_2) = (1 - p)^{v_{00} + v_{10}} p^{v_{01} + v_{11}} \]  \hspace{1cm} (8.6)
Likelihood ratio test

• In (8.6) we impose independence but do not in (8.5). Replace the $\Pi$ by the estimated numbers, $\hat{\Pi}$
• The LR test is then:

$$LR = 2 \left( \log L_1 \left( \hat{\Pi}_1 \right) - \log L_2 \left( \hat{\Pi}_2 \right) \right) \overset{\text{asymptotic}}{\sim} \chi^2(1).$$
• The main problem with tests of this sort is that they must specify the particular way in which independence is breached.

• However, there are many possible ways in which the independence property is not fulfilled:
  • Is the violation on day 1, 3, 5, 5?
  • Test can’t detect
Testing the SP-500
# Testing S&P 500 1998 to 2009

<table>
<thead>
<tr>
<th>Model</th>
<th>Coverage test</th>
<th>Independence test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Test statistic</td>
<td>p-value</td>
</tr>
<tr>
<td>EWMA</td>
<td>18.1</td>
<td>0.00</td>
</tr>
<tr>
<td>MA</td>
<td>81.2</td>
<td>0.00</td>
</tr>
<tr>
<td>HS</td>
<td>24.9</td>
<td>0.00</td>
</tr>
<tr>
<td>GARCH</td>
<td>16.9</td>
<td>0.00</td>
</tr>
</tbody>
</table>

1998 to 2006

<table>
<thead>
<tr>
<th>Model</th>
<th>Coverage test</th>
<th>Independence test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Test statistic</td>
<td>p-value</td>
</tr>
<tr>
<td>EWMA</td>
<td>2.88</td>
<td>0.09</td>
</tr>
<tr>
<td>MA</td>
<td>6.15</td>
<td>0.01</td>
</tr>
<tr>
<td>HS</td>
<td>0.05</td>
<td>0.82</td>
</tr>
<tr>
<td>GARCH</td>
<td>1.17</td>
<td>0.28</td>
</tr>
</tbody>
</table>
Joint test

- We can jointly test

\[ LR(\text{joint}) = LR(\text{coverage}) + LR(\text{independence}) \sim \chi^2_2 \]

- The joint test has less power to reject a VaR model which only satisfies one of the two properties
Expected Shortfall Backtesting
• It is harder to backtest expected shortfall ES than VaR because we are testing an *expectation* rather than a single *quantile*
• We know if VaR is violated, but cannot know that for ES
• There exists a simple methodology for backtesting ES that is analogous to the use of violation ratios for VaR
• For days when VaR is violated, normalized shortfall NS is calculated as:

\[ NS_t = \frac{y_t}{ES_t} \]

where \( ES_t \) is the observed ES on day \( t \)
• From the definition of ES, the expected $Y_t$ given VaR is violated, is:

$$\frac{E[Y_t | Y_t < -VaR_t]}{ES_t} = 1$$

• Therefore, average $\bar{NS}$, $\overline{\bar{NS}}$, should be one

$$H_0 : \overline{\bar{NS}} = 1$$
• The reliability of any ES backtest procedure is much lower than that of VaR
  • With ES, we are testing whether the mean of returns on days when VaR is violated is the same as average ES on these days.
  • Much harder to create formal tests to ascertain whether normalized ES equals one or not than the coverage tests developed above for VaR violations
• Hence, backtesting ES requires many more observations than backtesting VaR
• In instances where ES is obtained directly from VaR, and gives the same signal as VaR (i.e., when VaR is subadditive), it is better to simply use VaR
Problems with Backtesting
• Backtesting assumes that there have been no structural breaks in the data throughout the sample period:

• But financial markets are continually evolving, and new technologies, assets, markets and institutions affect the statistical properties of market prices

• Unlikely that the statistical properties of market data in the 1990s are the same as today, implying that a risk model that worked well then might not work well today
• **Data mining and intellectual integrity:**
  
  • Backtesting is only statistically valid if we have no ex ante knowledge of the data in the testing window.
  
  • If we iterate the process, continually refining the risk model with the same test data and thus learning about the events in the testing window, the model will be fitted to those particular outcomes, violating underlying statistical assumptions.
Stresstesting
Stresstesting

- Create artificial market outcomes
- To see how risk management systems and risk models cope with the artificial event
- Assess the ability of a bank to survive a large shock
- The main aim is to come up with scenarios that are not well represented in recent historical data but are nonetheless possible and detrimental to portfolio performance
# Examples of historical scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Period</th>
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</thead>
<tbody>
<tr>
<td>Stock market crash</td>
<td>October 1987</td>
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<tr>
<td>ERM crisis</td>
<td>September 1992</td>
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<tr>
<td>Bond market crash</td>
<td>April 1994</td>
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<tr>
<td>Asian currency crisis</td>
<td>Summer 1997</td>
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<tr>
<td>LTCM and Russia crisis</td>
<td>August 1998</td>
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<tr>
<td>Global crisis</td>
<td>2007 - 2009</td>
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<tr>
<td>Eurozone crisis</td>
<td>Since 2010</td>
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<tr>
<td>Brexit</td>
<td>2017</td>
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</tbody>
</table>

- Two types:
  - Shocks that have never occurred or are more likely to occur than historical data suggest
  - Shocks that reflect permanent or temporary structural breaks—where historical relationships do not hold