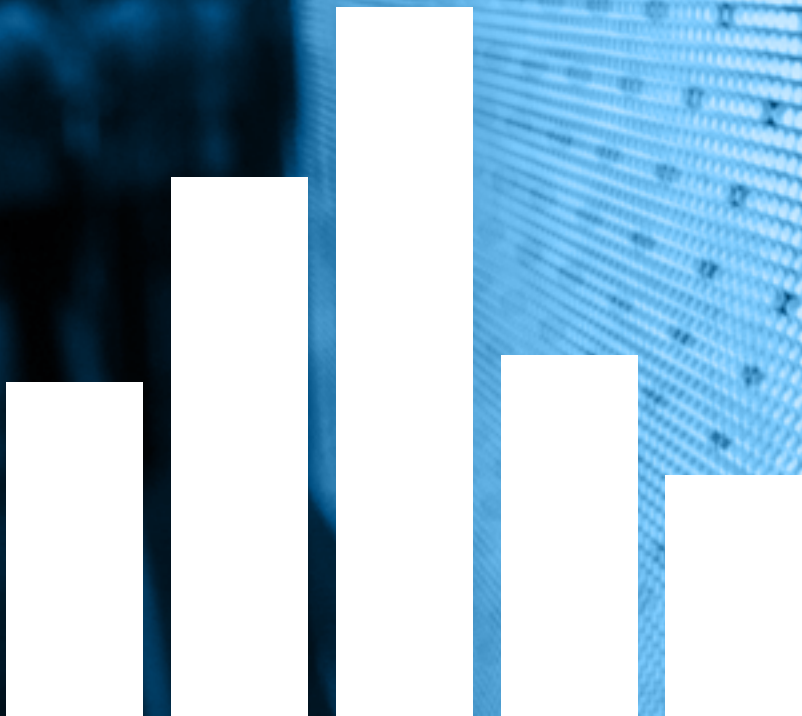


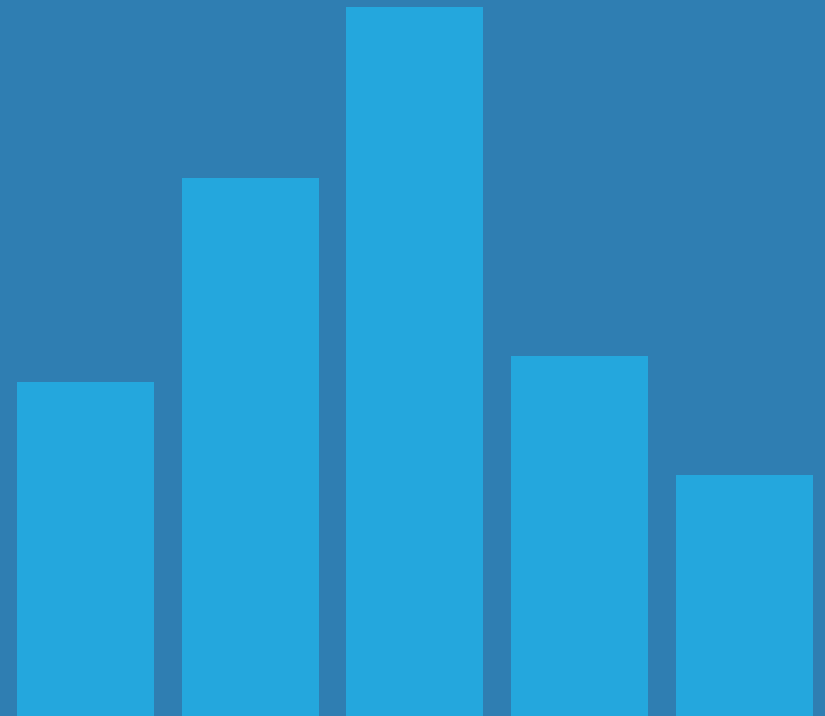


# A Practical Guide to Modeling Financial Risk with MATLAB



# A Practical Guide to Modeling Financial Risk with MATLAB

1. Introduction to Risk Management
2. Credit Risk Modeling
3. Market Risk Modeling
4. Operational Risk Modeling

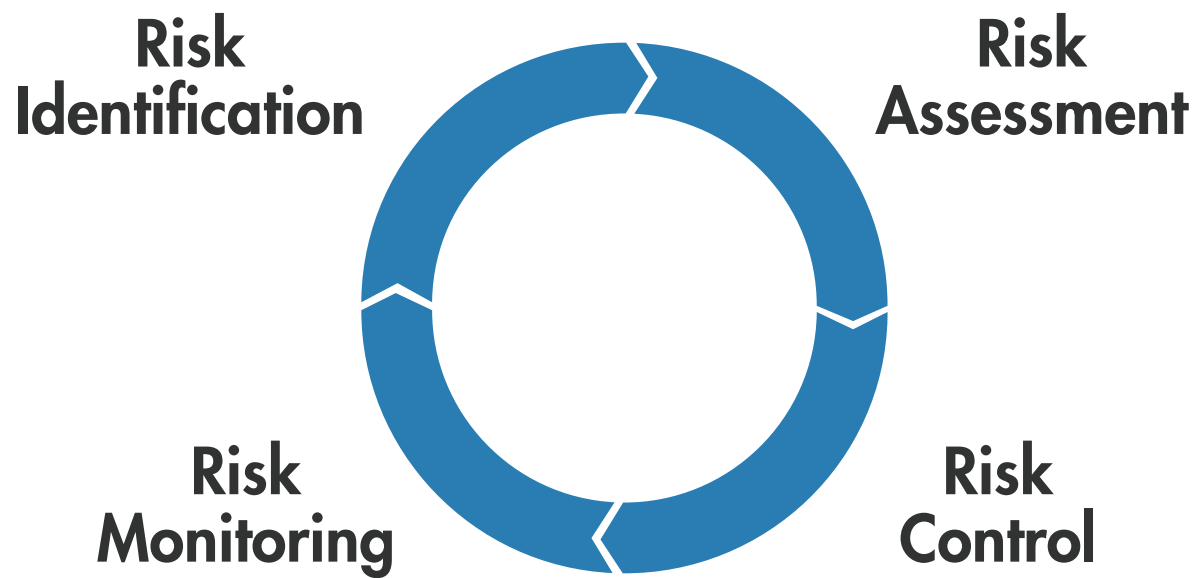


The background of the slide is a deep blue with a pattern of white dots that create a sense of depth and perspective, resembling a digital or architectural grid. In the bottom-left corner, there is a white bar chart with five vertical bars of varying heights. The first bar is medium, the second is taller, the third is the tallest, the fourth is medium, and the fifth is the shortest.

# Chapter 1: Introduction to Risk Management

# What is risk management?

Risk management is a process that aims to efficiently mitigate and control the risk in an organization. The life cycle of risk management consists of risk identification, risk assessment, risk control, and risk monitoring. In addition, risk professionals use various mathematical models and statistical methods (e.g., linear regression, Monte Carlo simulation, and copulas) to quantify the potential loss that could arise from each type of risk.



*The risk management cycle.*

# What is the origin of risk?

The major role of financial institutions in the economy is to be a middleman in credit card, mortgage, bond, stock, currency, mutual fund, and other financial transactions. By participating in these transactions, financial institutions expose themselves to a lot of uncertainty, such as price movements, the chance that a borrower may not repay a loan, or human error from the staff.

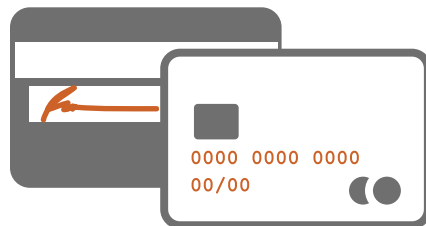
Risk regulation usually evolves rapidly in the aftermath of financial crisis. For instance, in 2007–2008, a subprime mortgage crisis not only led to a global banking crisis, but also played significant role in the development of the Dodd-Frank Act, Basel III, IFRS 9, and CECL.

“Risk comes from not knowing what you’re doing.”

— Warren Buffett

“The biggest risk is not taking any risk ... In a world that’s changing really quickly, the only strategy that is guaranteed to fail is not taking risks.”

— Mark Zuckerberg



*Products in intermediary services of financial institutions.*

# What types of risk do financial institutions face?

Large financial institutions have sophisticated holding structures with many financial subsidiaries. In addition, these financial institutions may operate under a universal banking model to provide a variety of services and products to clients. As a result, these financial institutions face many types of risks. The three most common risk types for an organization are:

- **Credit risk:** the potential for a loss when a borrower cannot make payments to a lender
- **Market risk:** the potential for a loss resulting from the movement of asset prices
- **Operational risk:** the potential for a loss arising from people, processes, systems, or external events that influence a business function

However, there are more specific types of risk that require the attention of risk professionals, such as liquidity risk, capital risk, business risk, reputational risk, systemic risk, model risk, concentration risk, legal risk, moral hazard, and financial crime.

Specialized financial institutions like central banks also face many of these risks. Even though the best-known role for central banks is a regulator, they also act as liquidity providers and lenders of last resort. These two roles alone require central banks to take huge risk exposure. The main differences are that risk mitigation tools for central banks include macroeconomic policy and regulatory interventions.



*Types of risk faced by financial institutions.*

# How do you quantify risk?

There are two major approaches for risk quantification: qualitative and quantitative approaches. Qualitative approaches, such as assessing a company's overall strategy, are subjective in nature and managed as part of the business decision-making process. Quantitative risk assessment involves defining the probability of occurrence and potential impact of each type of risk important to the organization's business. Quantitative assessment commonly uses statistical models, Monte Carlo simulations, time series models, optimization, machine learning, and other computational approaches.



*Techniques and issues concerning risk quantification (Word cloud generated using Text Analytics Toolbox™).*

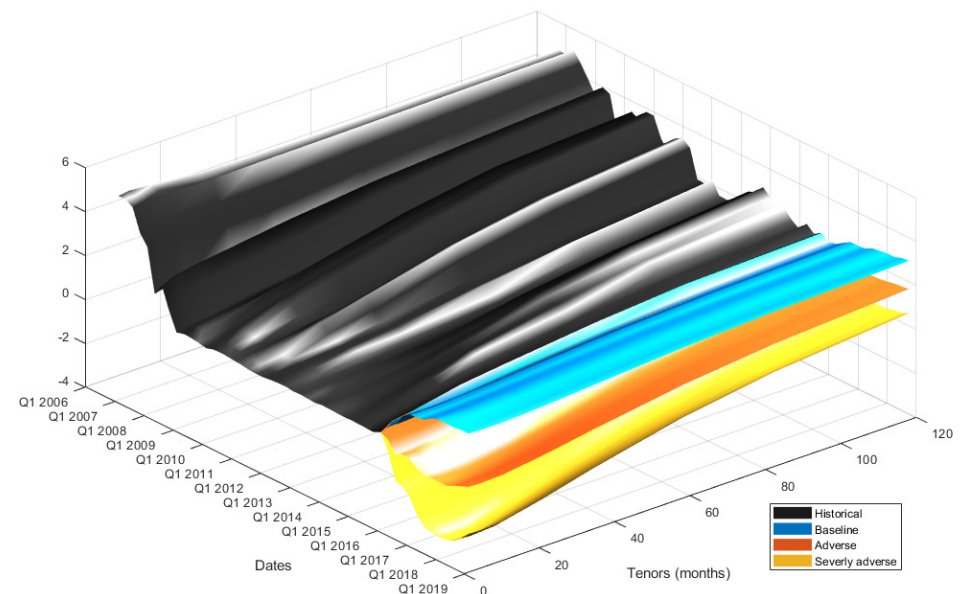
# Stress Testing

Stress testing is a form of scenario analysis used to gauge the impact of extreme scenarios (often called stress scenarios) on the financial institutions or investment portfolios. In the past decade, the importance of stress testing has escalated because regulators around the world adopted it as a tool to evaluate the strength of financial institutions under their supervision. For regulatory-based stress testing, regulators would predefine a set of stress scenarios, where one scenario consists of many variables. Variables for stress testing usually cover macroeconomic variables, equity prices, equity market volatility, real estate prices, and interest rates.

Given the importance of stress testing and the complexity of financial instruments held by financial institutions, risk managers need to have a platform they can use to easily develop and deploy their risk models.

Learn how to use MATLAB® for:

- *Macroeconomic stress testing*
- *Consumer credit stress testing*
- *Contagion risk analysis using graph theory and hidden Markov models*
- *Incorporating stress scenarios into a forecasting model of corporate default rates*



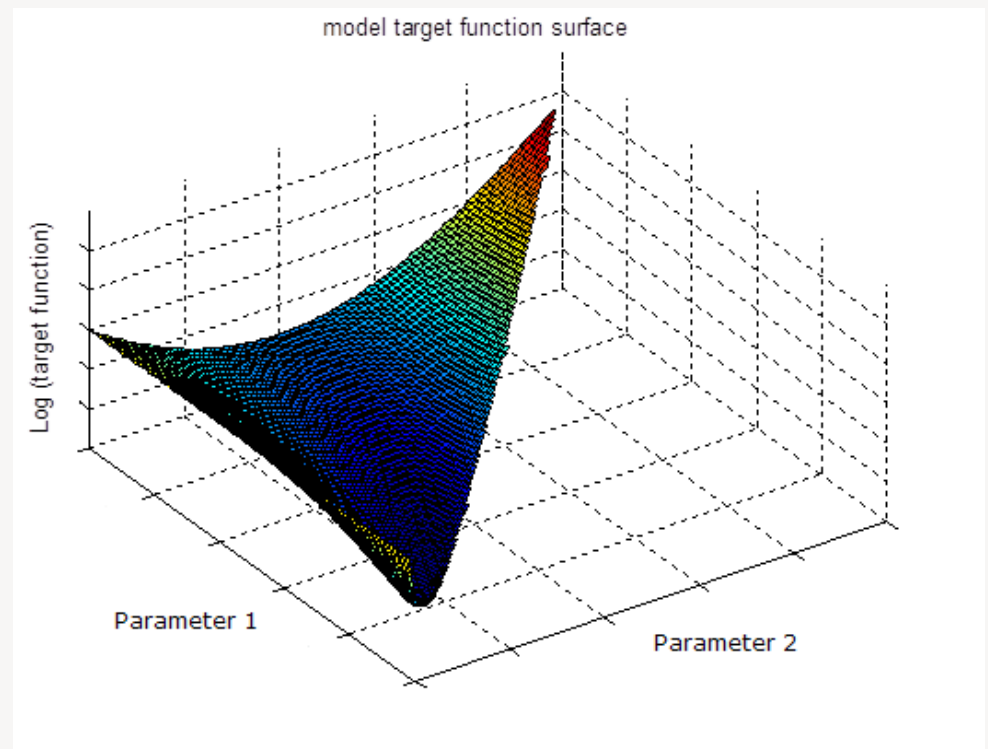
*Stress testing based on macroeconomic variables.*

# Real-World Examples

Practically speaking, risk management systems require modifications and customizations over time. Risk managers usually need to adjust their risk management models to conform to new regulations or to address new types of risk factors.

PZU Group developed a complete production-ready market risk solution to comply with the Solvency II Directive. Such solutions could highly accelerate development time and computational time.

Read the story: [\*PZU Group Develops Market Risk Model for Solvency II Compliance\*](#)



*Plot showing how minimizing the differences between real and expected probability densities helps PZU identify the risk-neutral density function.*

## Learn More

*Ready for a deeper dive? Explore these resources to learn more about risk management methods, examples, and tools.*

### Watch

[Munich Re Trading Creates a Risk Analytics Platform with MATLAB: Demonstration \(3:32\)](#)

[Use of MATLAB for Solvency II Capital Modelling: The Prudential Risk Scenario Generator \(22:44\)](#)

[MATLAB Production Server for Financial Applications \(38:28\)](#)

### Read

[7 Chief Risk Officer Priorities for 2017](#)

[Reforming Risk Management. Again?](#)

[Can we fix Risk Management? Yes, we can.](#)

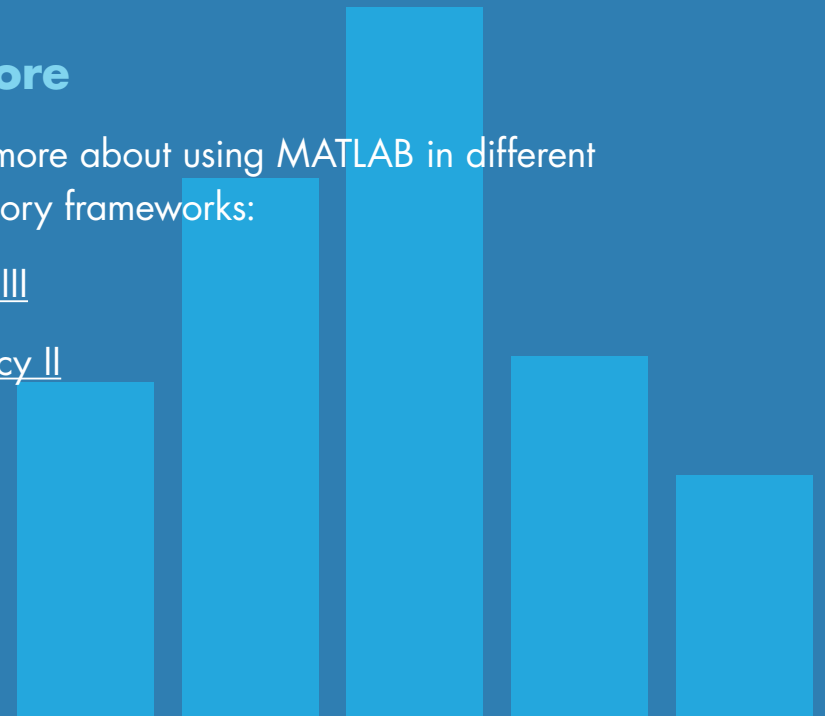
### Explore

Learn more about using MATLAB in different regulatory frameworks:

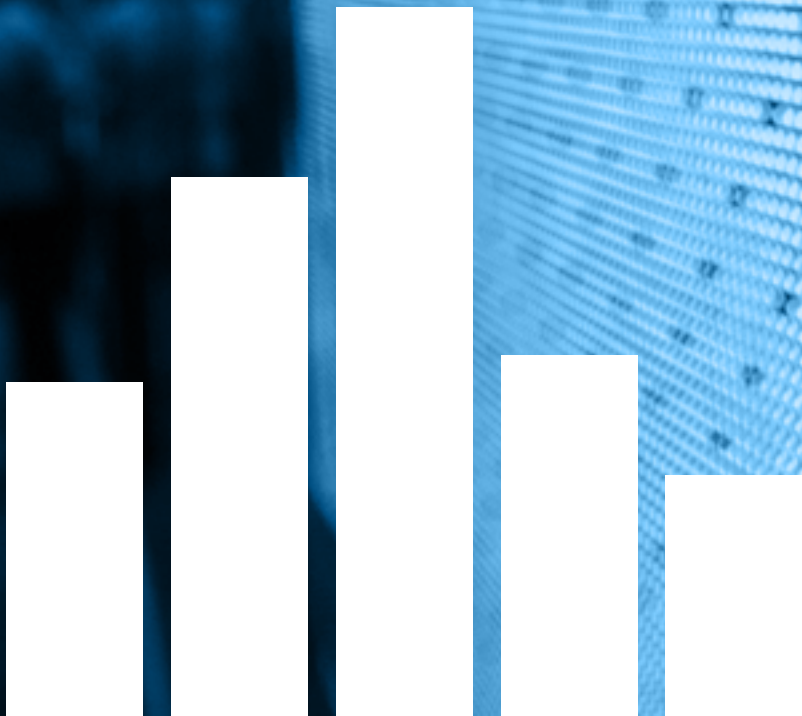
[BASEL III](#)

[Solvency II](#)

[IFRS 9](#)



# Chapter 2: Credit Risk Modeling



# What is the expected loss from credit risk?

The most common measure of credit risk is expected loss, which is the average loss in value of the credit portfolio over a given time period or the lifetime of the credit instrument. Depending on the nature of credit instruments, two alternative ways to estimate the expected loss are by looking at default events only and by looking at the loss in value due to the changes in credit quality or credit rating.



# Expected Loss Based on Default Risk

Typically, the expected loss (EL) of a loan portfolio (e.g., credit card, home and auto loans, personal lending) can be measured through three independent factors: probability of default (PD), loss given default (LGD), and exposure at default (EAD).

$$EL = PD \times LGD \times EAD$$

## Example:

If the amount of the loan is \$100 and the expected value of the collateral in the next year is \$75, then:

$$LGD = (100 - 75) / 100 = 25\%$$

Given there is a 5% chance that car owners will default on auto loan, then:

$$EL = 5\% \times 25\% \times 100 = \$1.25$$



# Expected Loss Based on Changes in Credit Rating

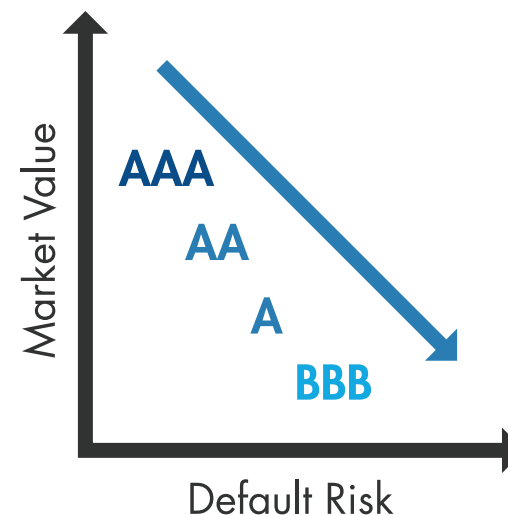
Even though the default event has not occurred yet, the value of a credit portfolio may change with credit rating. Such scenarios are readily apparent in the bond market. In this case, you can adjust the earlier formula of expected loss (EL) to make it more generic as follows:

$$EL = \text{Reference Value} - \sum_i P_i \times \text{Value}_i$$

$P_i$  is the transition probability that the instrument would migrate from its current rating to rating  $i$ .

$\text{Value}_i$  is the dollar value of the instrument after migrating from the current rating to rating  $i$ .

Reference value is the end-of-period value at the current rating in dollars.



*Characteristics of default risk and market value of credit instruments by rating.*

Rating at the end of the period	AAA	AA*	A	BBB	BB	B	CCC	Default
P (%)	1.00	90.00	5.50	1.70	1.10	0.40	0.20	0.10
Value (\$)	102	101	99	95	90	85	80	30



$$\begin{aligned} \sum_i P_i \times \text{Value}_i \\ = \\ 100.50 \end{aligned}$$

\*Current rating

Given the reference value of \$101,  $EL = 101 - 100.50 = \$0.50$

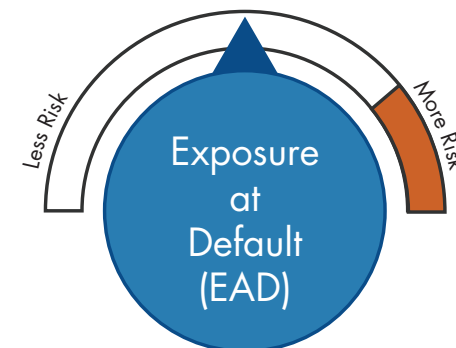
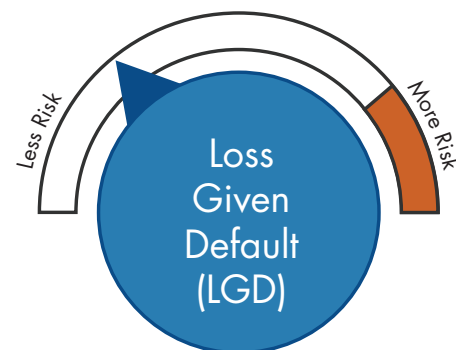
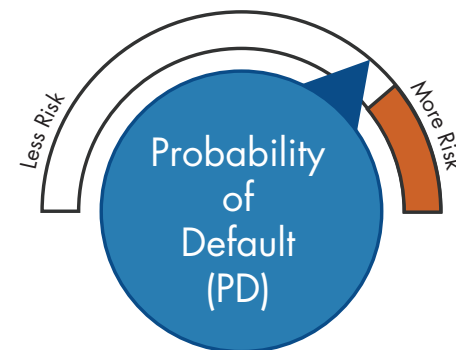
*Calculation example of expected loss from credit migration.*

# Estimating Risk Parameters

Each credit risk model has its own parameters and assumptions depending on the definition of expected loss. One of the most practical steps in building a successful risk model is to get accurate assessment of risk parameters. For credit risk, the common risk parameters you need to estimate are:

- Default-based model:
  - Probability of default (PD)
  - Loss given default (LGD)
  - Exposure at default (EAD)
- Credit migration-based model:
  - Credit migration matrix (also known as transition probability matrix)

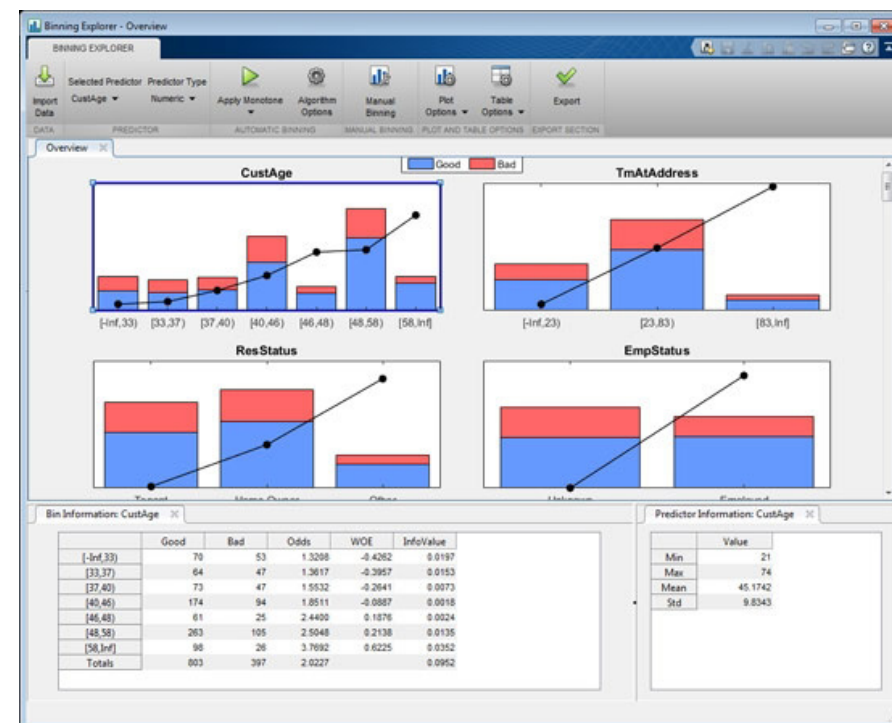
The very common statistical technique for estimating risk parameters is regression (see `fitglm` or `fitlm`).



# Probability of Default

There are many ways to estimate probability of default (PD); your choice will depend very much on assumptions and the availability of data. Commonly used models for estimating probability include:

- **Structural models:** The models use information from the company's capital structure (e.g., asset, liability, and equity) to estimate PD. One of the most popular structural models is the *Merton model*.
- **Reduced-form models:** The PD can be estimated by extracting the default risk implied by market prices of credit instruments such as *bond* or *credit default swap*.
- **Historical credit ratings migrations:** Instead of directly model PD, you can use credit history to estimate the *transition probabilities* that a credit instrument will migrate from one rating to another rating.
- **Statistical approaches:** A variety of statistical methods can be applied to estimate the PD based on the given characteristics of the credit instruments, for example:
  - *Regression models* (e.g., linear, logistic, probit, or *Cox-proportional hazards*)
  - *Machine Learning* (e.g., tree bagger, random forest, or discriminant analysis)
  - *Credit scoring models*



The Binning Explorer app.

# Credit Migration Matrix

A credit migration matrix (also known as transition probability matrix) is a matrix in which each element represents the probability of the credit instruments migrating from one rating to another rating over a period of time. The typical period for calculating credit migration matrix is one year. Two major ways to estimate the credit migration matrix from historical credit rating migration data are:

- **Cohort estimation:** The probabilities are estimated based on a sequence of snapshots of credit ratings at regularly spaced points in time. However, if there is more than one change in credit rating between two snapshot dates, only the final rating will influence the estimates.
- **Duration estimation (also known as hazard rate or intensity):** The transition probabilities are estimated based on continuous time assumption using the full credit rating history, looking at the exact dates on which the credit rating migrations occur.

**Learn more:** [Estimating a Credit Migration Matrix Using MATLAB](#)

## RATING HISTORY

ID	Date	Rating
1	10-Nov-84	CCC
1	12-May-86	B
1	29-Jun-88	CCC
1	12-Dec-91	D
2	9-Feb-85	A
2	24-Feb-94	AA
2	10-Nov-00	BBB
3	23-Dec-82	B
3	20-Apr-88	BB
3	16-Jan-98	B
3	25-Nov-99	BB



## CREDIT MIGRATION MATRIX

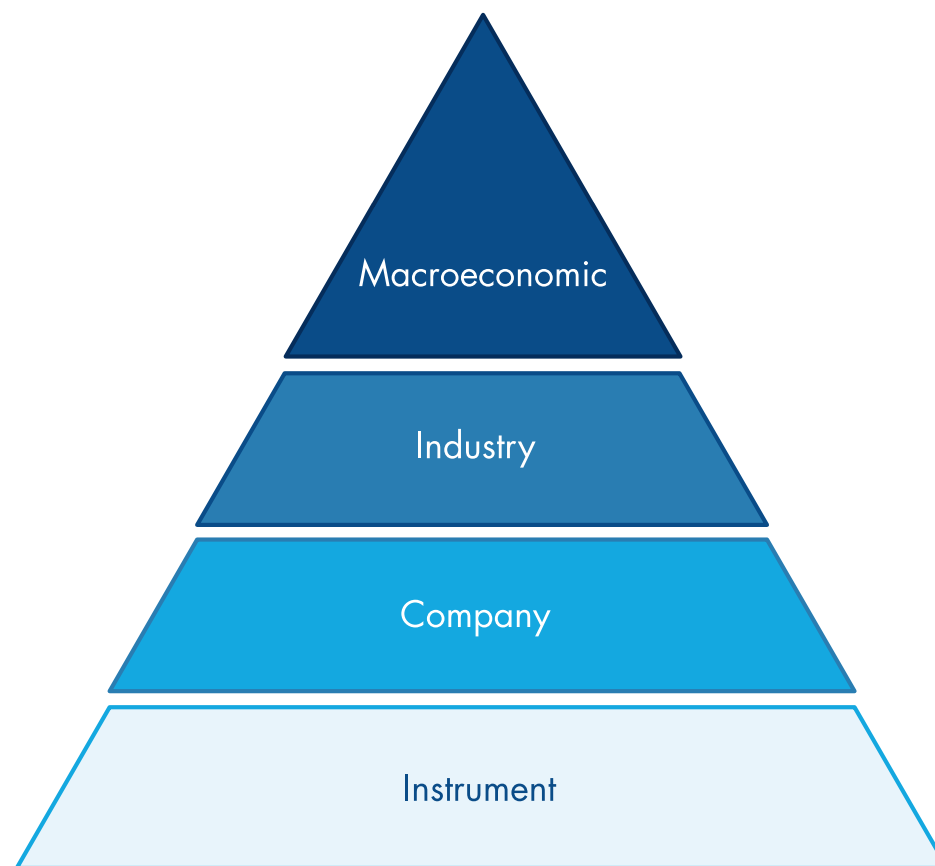
	AAA	AA	A	BBB	BB	B	C	D
AAA	93.1170	5.8428	0.8232	0.1763	0.0376	0.0012	0.0001	0.0017
AA	1.6166	93.1518	4.3632	0.6602	0.1626	0.0055	0.0004	0.0396
A	0.1237	2.9003	92.2197	4.0756	0.5365	0.0661	0.0028	0.0753
BBB	0.0236	0.2312	5.0059	90.1846	3.7979	0.4733	0.0642	0.2193
BB	0.0216	0.1134	0.6357	5.7960	88.9866	3.4497	0.2919	0.7050
B	0.0010	0.0062	0.1081	0.8697	7.3366	86.7215	2.5169	2.4399
C	0.0002	0.0011	0.0120	0.2582	1.4294	4.2898	81.2927	12.7167
D	-	-	-	-	-	-	-	100.0000

# Loss Given Default

Loss given default (LGD) is a loss from the event of default that is presented as a percentage of the exposure at default. Fundamentally, LGD is associated with many factors, including:

- Instrument-specific factors:
  - Loan collateral
  - Debt seniority
- Company-specific factors:
  - The company's financial ratio
- Industry-specific factors
- Macro-level factors

In fact, LGD can be defined as  $1 - \text{recovery rate}$ . Regression models, scorecard models, and statistical learning techniques, in general, can be used to predict recovery rates. These models can include some of the factors mentioned above (credit scores, financial ratios, macro variables) as predictors.



*Factors associated with loss given default (LGD).*

# Exposure at Default

Exposure at default (EAD) is the amount of exposure at the time of default. In fact, EAD is closely related to LGD because the multiplication of these two parameters will give us the amount of loss at the time of default. For this reason, EAD is also an instrument-specific parameter. The EAD's distribution for fixed-income instruments is different from that for credit card loans.

Mathematically, EAD can be modeled as a function of current exposure and future potential exposure. The latter is more complicated because it usually deals with undrawn credit lines. For example, credit card loans and home equity lines of credit (HELOCs) are basic credit instruments in which a borrower can borrow up to a credit limit given by the lender. In the event of default, borrowers are likely to utilize more or max out the undrawn credit line.

The table shows popular indicators for estimating EAD.

Indicator	Mathematical Definition in Relation to EAD
Loan Equivalent (LEQ)	$EAD = \text{Drawn Credit Line} + LEQ \times \text{Undrawn Credit Line}$
Credit Conversion Factor (CCF)	$EAD = CCF \times \text{Drawn Credit Line}$
EAD Factor (EADF)	$EAD = EADF \times \text{Total Credit Line}$

In addition to these indicators, the estimation of credit exposure for derivative contracts (e.g., swaps or options) can be more computationally intensive because the credit exposure depends on the market price of the underlying asset in the derivative contract too.

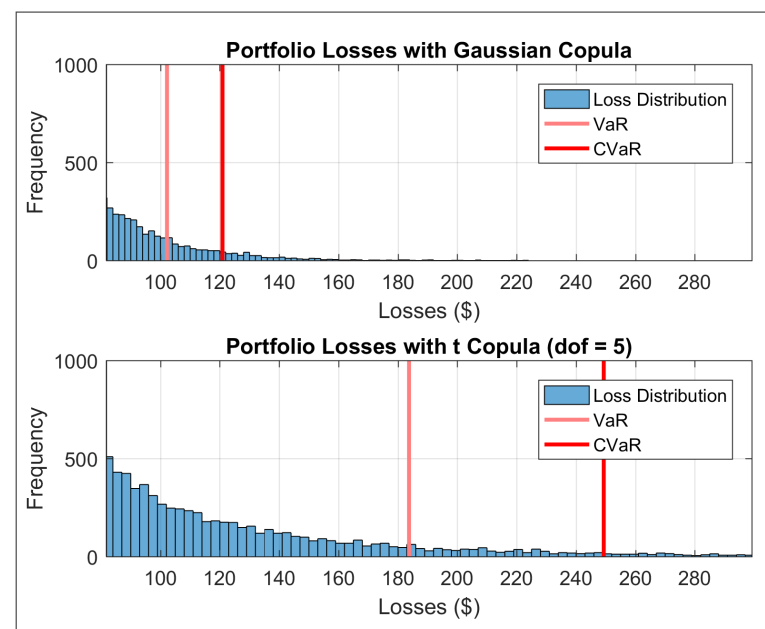
# Credit Portfolio Simulation

Unlike the analysis of credit risk on an individual basis you need to understand more about the aggregated credit risk, diversification, and concentration characteristics at the credit portfolio level. For this reason, default correlations between counterparties and issuers play an important role to help us understand the credit risk at a portfolio level.

Two alternative frameworks for performing credit portfolio simulation are:

- Under the assumption that the credit instruments have only two stages (default and non-default), you can simulate correlated variables and use the copula method to map these variables to default and non-default states to preserve the individual default probabilities.
- Given that the value of credit instruments may change with credit ratings, you can simulate correlated variables, map these variables to a credit rating based on a credit migration matrix, and use the simulated credit rating scenarios to compute credit risk at a portfolio level.

Both the default and credit migration simulations have an underlying one-factor or multifactor model. The parameters of the factor model can be estimated from market data, and these parameters imply a default or credit migration correlation between counterparties that influences the credit portfolio risk measures.



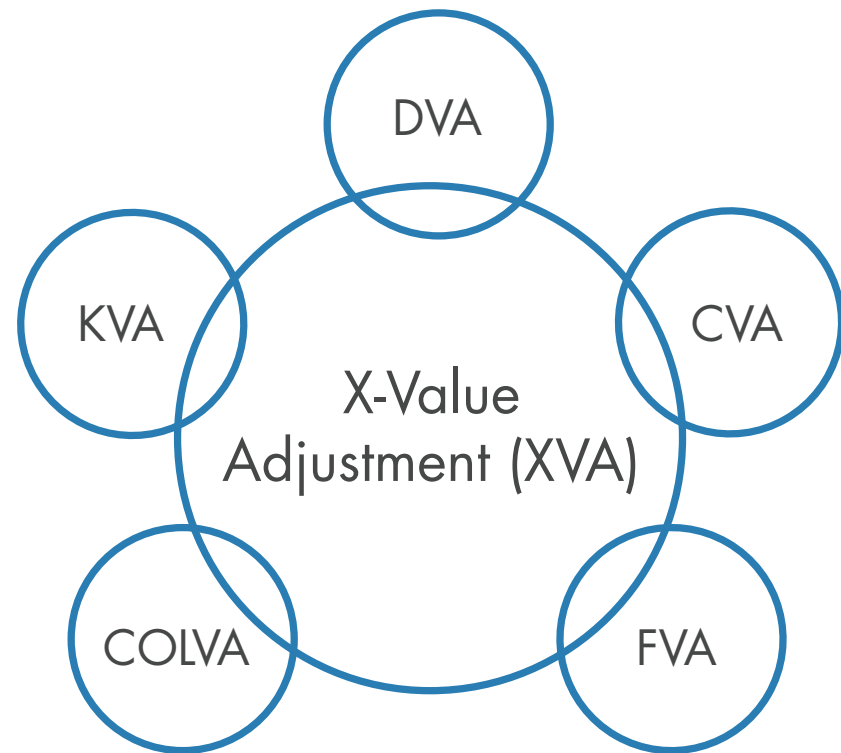
*Losses from credit portfolio simulation.*

## Learn more:

- [Credit Portfolio Simulation with MATLAB](#)
- [Credit Portfolio Simulation Based on Correlated Defaults](#)
- [Credit Portfolio Simulation Based on a Credit Migration Matrix](#)

# Counterparty Credit Risk of Derivative Contracts

Counterparty credit risk is the potential for a loss if the counterparty to a derivative contract is unable to fulfill the contractual obligations. Such counterparty risk can be measured in terms of valuation adjustments. The most popular valuation adjustment is credit valuation adjustment (CVA), which is designed to capture the market value of counterparty risk to a derivative contract. Other valuation adjustments include funding valuation adjustment (FVA), debt valuation adjustment (DVA), collateral valuation adjustment (COLVA), and capital valuation adjustment (KVA). Unlike OTC derivatives, the counterparty risk of listed derivatives is assumed to be zero because of the existence of a central counterparty. However, the market participants may be required to place initial margin and variation margin. For this reason, only margin valuation adjustment is used to address these costs for listed derivatives. These valuation adjustments are collectively known as X-value adjustment (XVA).



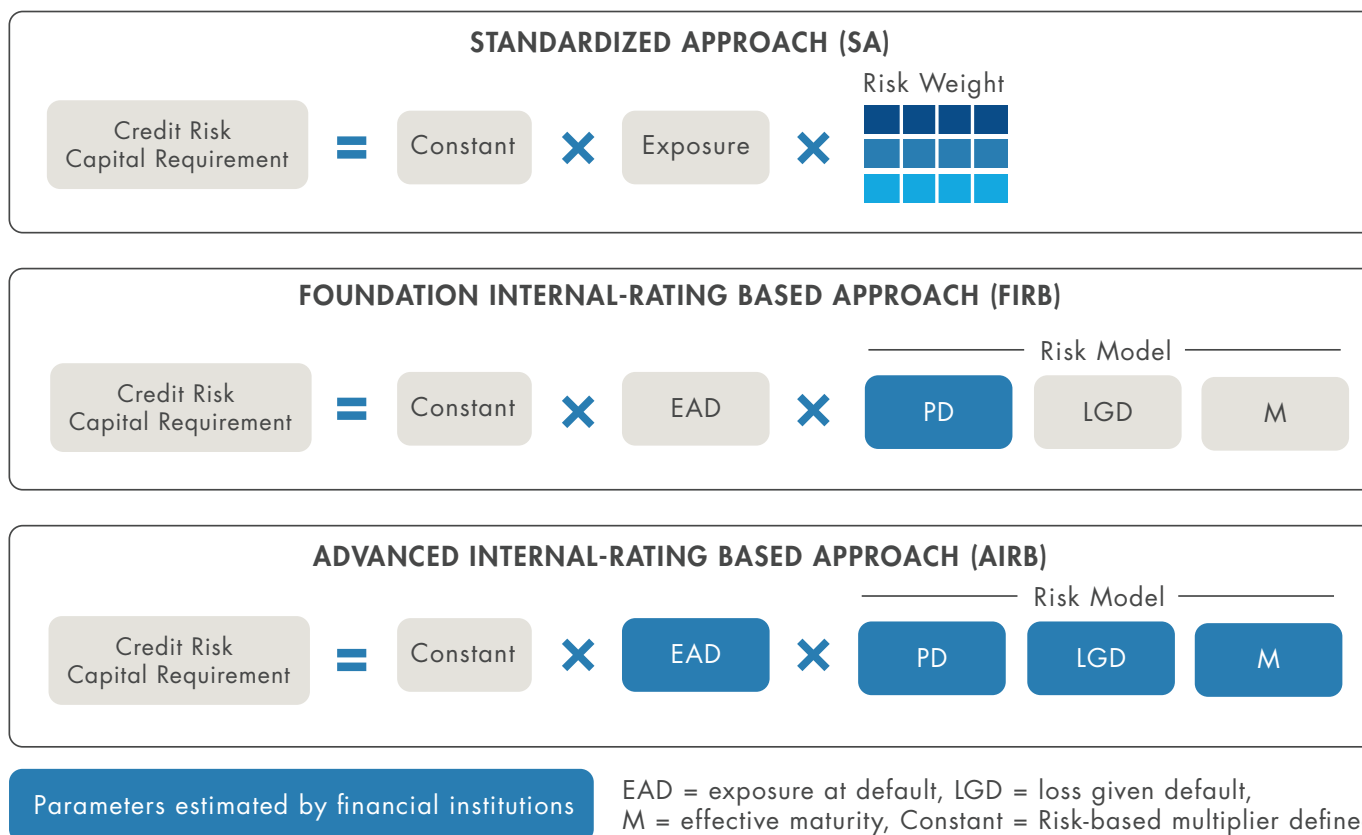
*X-value adjustment.*

## Explore MATLAB examples on:

- [Calculating counterparty risk and CVA](#)
- [Calculating wrong-way risk](#)

# Calculating Regulatory Capital for Credit Risk

Financial institutions are obligated to maintain their capital level above a minimum requirement, which is calculated based on their risk exposure. Since credit risk was responsible for many of the greatest losses in the financial history, calculating of regulatory capital for credit risk is an essential task for financial institutions to help them perform efficient capital management, risk budgeting, and financial modeling.



SA and IRBs for calculating credit risk capital.

# Calculating Regulatory Capital for Credit Risk

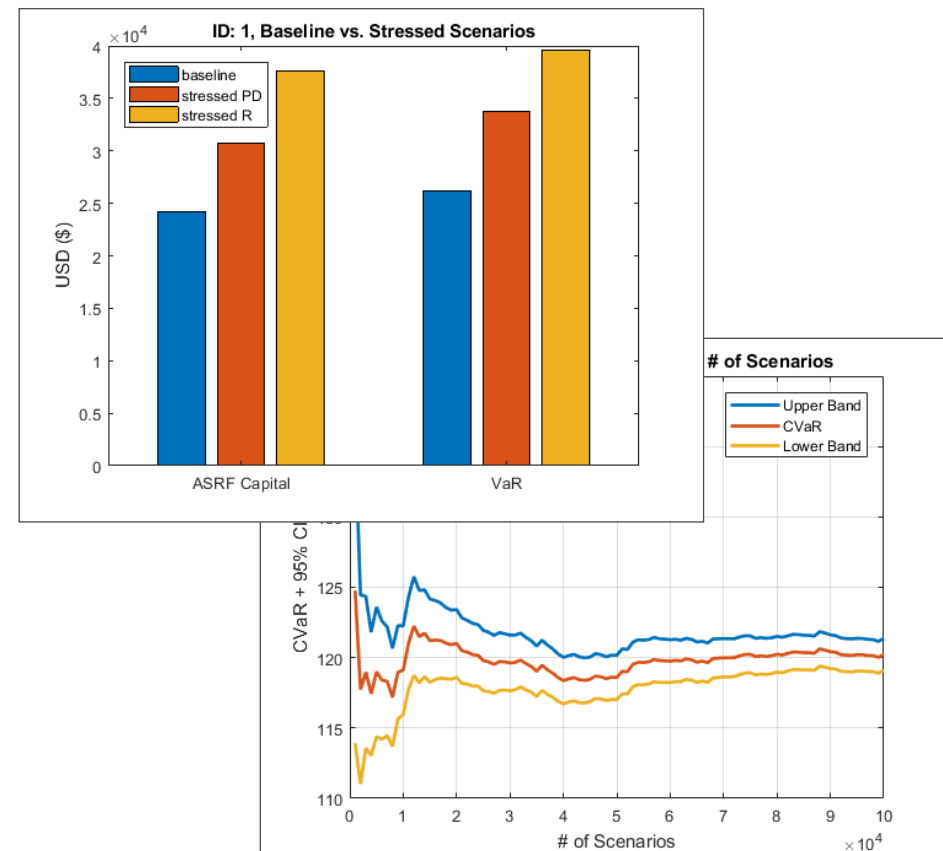
## *continued*

Per the Basel Accords, two major approaches for calculating credit risk capital are:

- **Standardized approach (SA).** Financial institutions can easily calculate capital requirements using a simplified framework provided by the regulator. However, it usually produces higher capital requirements than the IRB approach.
- **Internal-rating based approach (IRB).** The IRB can be categorized based on the complexity level into foundation IRB (FIRB) and advanced IRB (AIRB). Financial institutions need to estimate only probability of default (PD) by themselves in FIRB, while they need to estimate more parameters in AIRB. To simplify the IRB framework and make it scalable, the asymptotic single risk factor (ASRF) model was introduced as a tool for calculating regulatory capital for credit risk. Because it is more complex than SA, IRB is more expensive in terms of administration and supervision, but it is likely to achieve lower regulatory capital requirements.

Explore MATLAB examples on:

- *Calculating regulatory capital with the ASRF model*
- *Modeling correlated defaults with copulas*

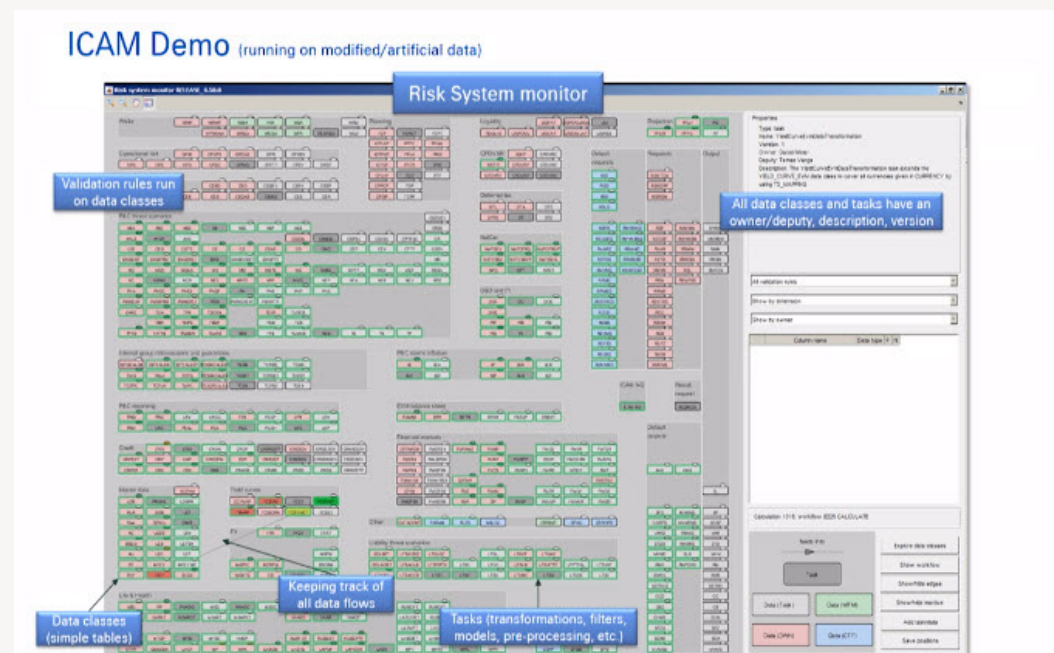


# Real-World Examples

Swiss Re, founded in 1863, based in Zurich, is the world's second largest reinsurer and has a long history of using an internal risk model to steer the company. The model defines its target capital, sets risk-based business volume limits, allocates capital costs across various lines of business, determines the company's solvency ratio for regulatory purposes (Swiss Solvency Test, Solvency II), and more.

For a decade, Swiss Re has used MATLAB to implement the Internal Capital Adequacy Model (ICAM), its internal risk model. Dynamic and increasingly complex internal and regulatory requirements create a challenging development environment, in which MATLAB proved to be the perfect development platform to quickly react to changing requirements. In 2017, Swiss Re concluded a major project to overhaul its internal risk model, the key goals being transparency, flexibility for future developments, speed, and precision of risk measures.

*Learn how Swiss Re develops and maintains its internal risk model in MATLAB.*



## Learn More

*Ready for a deeper dive? Explore these resources to learn more about credit risk modeling, examples, and tools.*

### Watch

[Credit Risk Modeling with MATLAB \(53:10\)](#)

[Financial Model Validation Using MATLAB \(33:01\)](#)

[Credit Scorecard Modeling Using the Binning Explorer App \(6:17\)](#)

### Read

[Basel II Compliance and Risk Management Analysis: Calculating Economic Capital](#)

[Modeling Corporate Credit Risk](#)

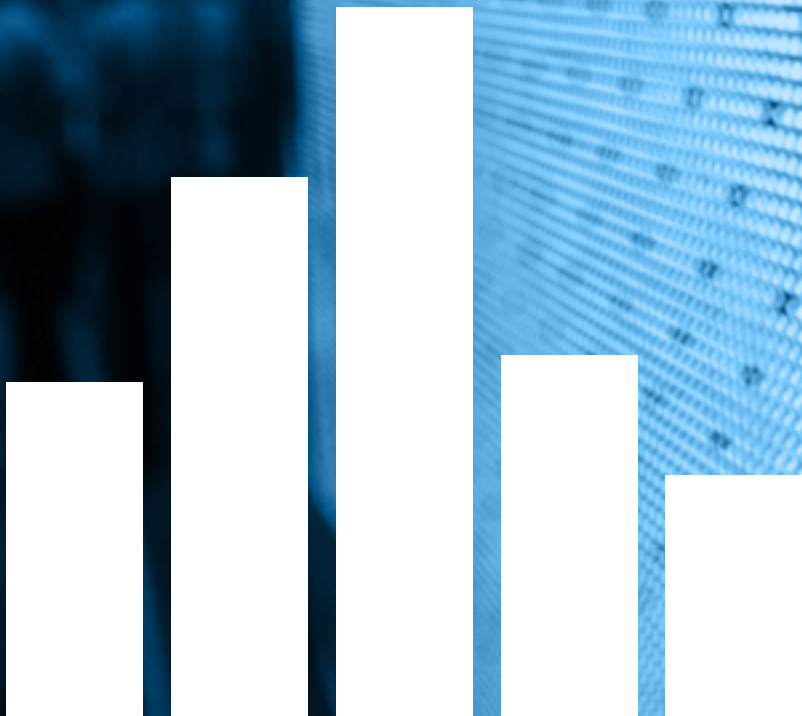
### Explore

[Risk Management Toolbox™](#)

[Risk Management with MATLAB](#)

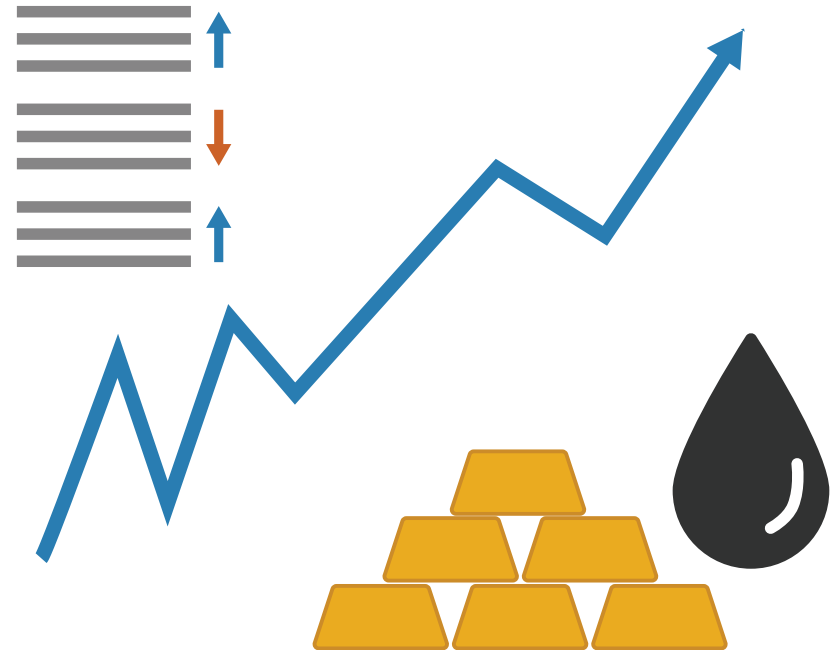


# Chapter 3: Market Risk Modeling



# What is market risk?

Market risk is the potential for a loss in the value of a portfolio due to the change in market prices. Commonly, market risk can be grouped by underlying assets or major factors that affect the pricing of financial instruments, for example, equity risk, commodity risk, foreign exchange risk, interest rate risk, and volatility risk. In addition, market risk is typically the largest exposure for buy-side financial institutions, such as asset management companies, hedge funds, and proprietary trading houses.



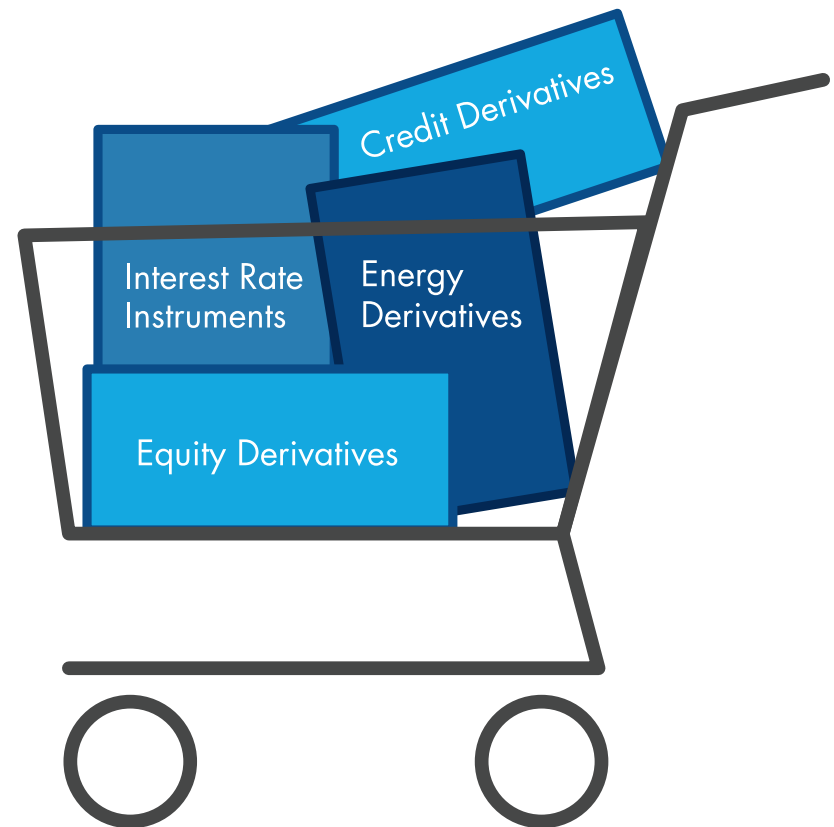
# Pricing of Financial Instruments

To measure market risk, it is essential to estimate the current value of the portfolio as well as the potential changes in value of all financial instruments within it. In some cases, a market risk analyst may need to calculate the theoretical prices of financial instruments when market prices do not exist. For this reason, a lot of work in market risk analysis involves pricing and modeling financial instruments.

In fact, the complexity of financial models varies greatly from one financial instrument to another. For example, European options can be simply priced by using a closed-form formula, whereas you may need to perform more complicated computation for exotic options. In addition, the model that works well in one market may not be able to produce the same result in another market. That is why market risk analysts often need to customize the pricing models in many circumstances, for instance, new products, changes in underlying assumptions, specific market practices, or constraints.

**Read more about pricing of these financial instruments:**

- *Equity derivatives*
- *Energy derivatives*
- *Credit derivatives*
- *Interest rate instruments*



# Estimating Market Risk Parameters

Several risk parameters are commonly used to estimate risk measures or price financial instruments like interest rates, volatilities, and correlations. Depending on your objectives and the importance of each variable, you might use a parameter estimate based on historical values, current value, implied value, or forecasted value as input in your financial models.

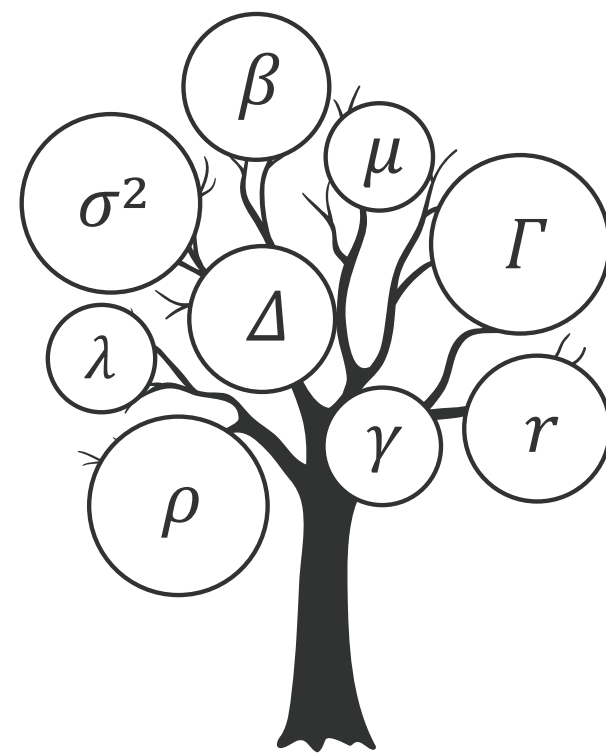
Volatilities are among the most important risk parameters. For pricing purposes, implied volatility values are important to determine prices that are consistent with the current market conditions. For risk analysis, you may prefer to forecast the volatility during the lifetime of the option contract using econometrics models (e.g., [GARCH](#), [EGARCH](#), or [GJR](#)).

On the other hand, if you are dealing with interest rate derivatives, there are multiple interest rate models to choose from, and these models may have different parameters. So, it is very important to determine the interest rate model before estimating its model parameters (e.g., drift term and volatility). Then you can perform simulation or forecast the interest rates based on the estimated model parameters to price interest rate derivatives or to calculate risk measures. Popular interest models include:

- [Heath-Jarrow-Morton Model](#)
- [Black-Derman-Toy \(BDT\) Model](#)
- [Black-Karasinski \(BK\) Model](#)
- [Hull-White \(HW\) Model](#)
- [Libor Market Model](#)
- [Diebold Li Model](#)
- [Nelson-Siegel Model](#)
- [Negative-rate models](#) (e.g., Shifted SABR Model and Shifted Black Model)

## Learn more:

- [Calibration and Simulation of Interest Rate Models](#)



*The growing set of risk parameters.*

# Monte Carlo Simulation

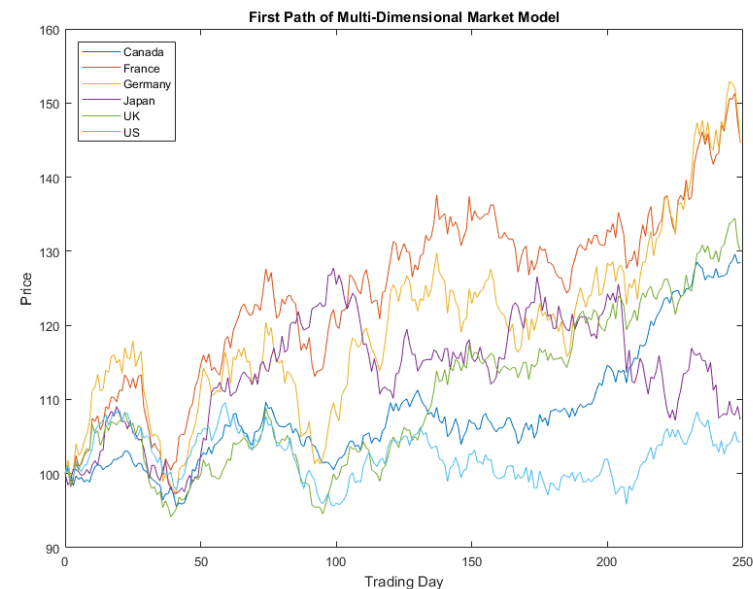
Among the mathematical techniques used in market risk modeling, Monte Carlo simulation is one of the most basic and most important frameworks that are widely used behind the scene. You can use Monte Carlo simulation in a variety of risk applications, such as:

- Analyzing worst-case scenarios and potential profit/loss
- Pricing and valuation of financial instruments
- Incorporating uncertainty factors into existing risk models
- Building the stochastic models for underlying variables (e.g., stock, interest rate, volatility)

The major drawback of Monte Carlo simulation is the computational time. The more parameters that you simulate, the longer it takes to complete the simulation. Computational speed can be improved by reducing the number of simulation points or paths required to estimate statistical measures and by applying parallel computing for simultaneous simulations. Example techniques for simulation reduction include antithetic variables, quasi-random numbers, and pseudorandom numbers. Hardware acceleration approaches include running different simulation paths on multiple CPUs and GPUs simultaneously instead of sequentially.

## Explore how to simulate:

- *Random numbers from the numerous distributions*
- *Term structure of interest rates for a LIBOR market model*
- *Conditional mean and variance models*
- *Equity markets using geometric Brownian motion (GBM)*
- *Multidimensional stochastic differential equations (SDEs)*



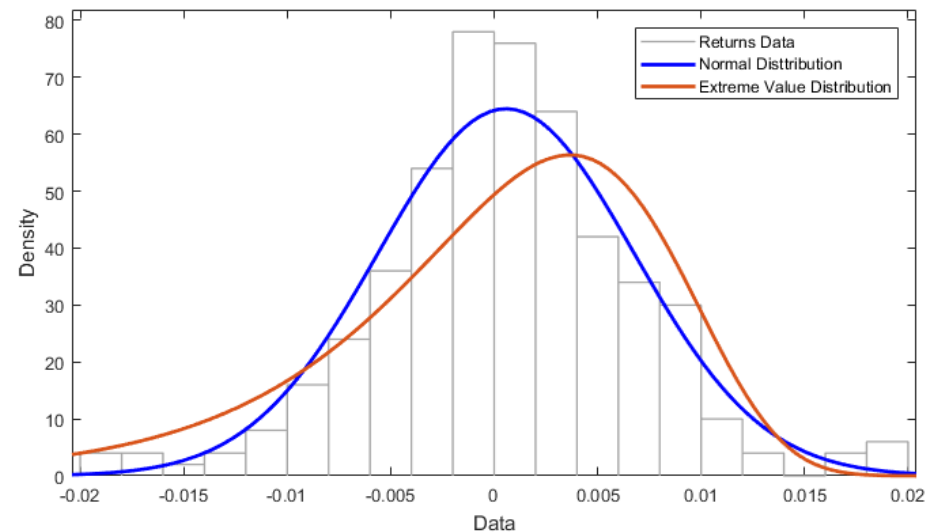
*Simulated price paths.*

# Probability Distribution Analysis

Commonly used probability distributions in finance include normal, lognormal, binomial, and uniform distributions. A better understanding of probability distributions is useful for many applications in finance, such as time series analysis, option pricing, calculation of risk measures, and other financial modeling. For example, different option pricing models assume different probability distribution on underlying asset.

There are many approaches for analyzing probability distribution. Basic approaches include:

- *Descriptive statistics.* From sample data, you can compute various statistical measures, for instance, mean, median, standard deviation, kurtosis, skewness, range, interquartile range, correlation, and covariance.
- *Statistical visualization.* A picture is worth a thousand words. For single-variable distributions, you can use histograms or box plots to visualize the data. Similarly, you can use bivariate histograms or scatter plots to show the relationship between variables.
- *Distribution fitting.* Fitting probability distributions to data is a very powerful technique that combines both statistical visualization and parameter estimation.



*Fitting probability distribution to data.*

# Market Risk Measures

There are many risk measures that can quantify the risk specifics to some type of financial instruments. For example, duration and convexity are used to measure interest rate risk of fixed-income instruments. Beta and standard deviation are used to measure equity risk. Greek variables (e.g., delta, gamma, vega) are used to capture the risk of derivative instruments. However, the portfolio of financial institutions typically holds more than one type of instruments.

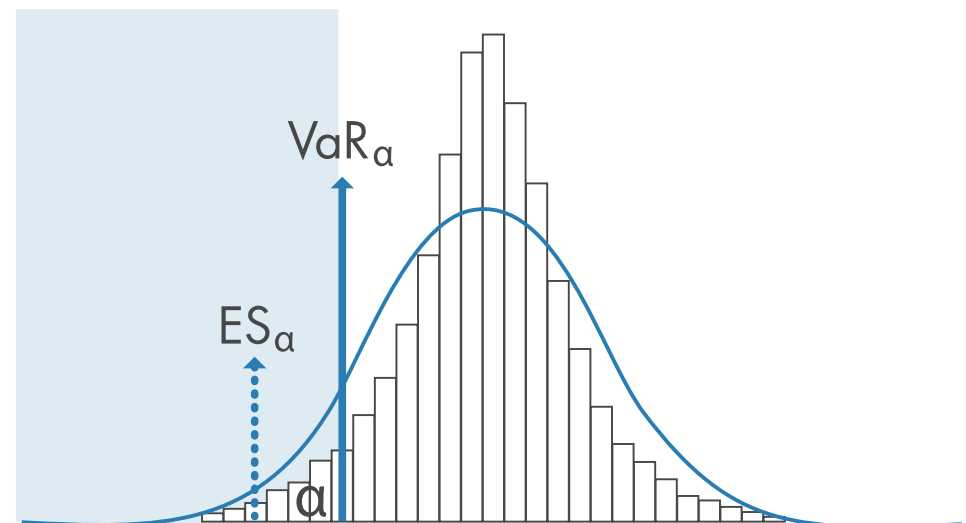
Value-at-risk (VaR) was introduced as an aggregate-measure market risk for all types of financial instruments. VaR was adopted by the Basel II Accord in 1999, and has since become the preferred risk measure for market risk.

VaR cannot capture the risk beyond the confidence level. Due to this limitation, another risk measure called expected shortfall (ES), also known as conditional VaR (CVaR), is used in practice to complement VaR. ES has become increasingly visible because of its adoption, instead of VaR, for calculating market risk capital in the fundamental review of the trading book (FRTB) by the Basel Committee on Banking Supervision (BCBS).

**Explore how to use MATLAB to evaluate market risk:**

- *Using Extreme Value Theory and Copulas to Evaluate Market Risk*

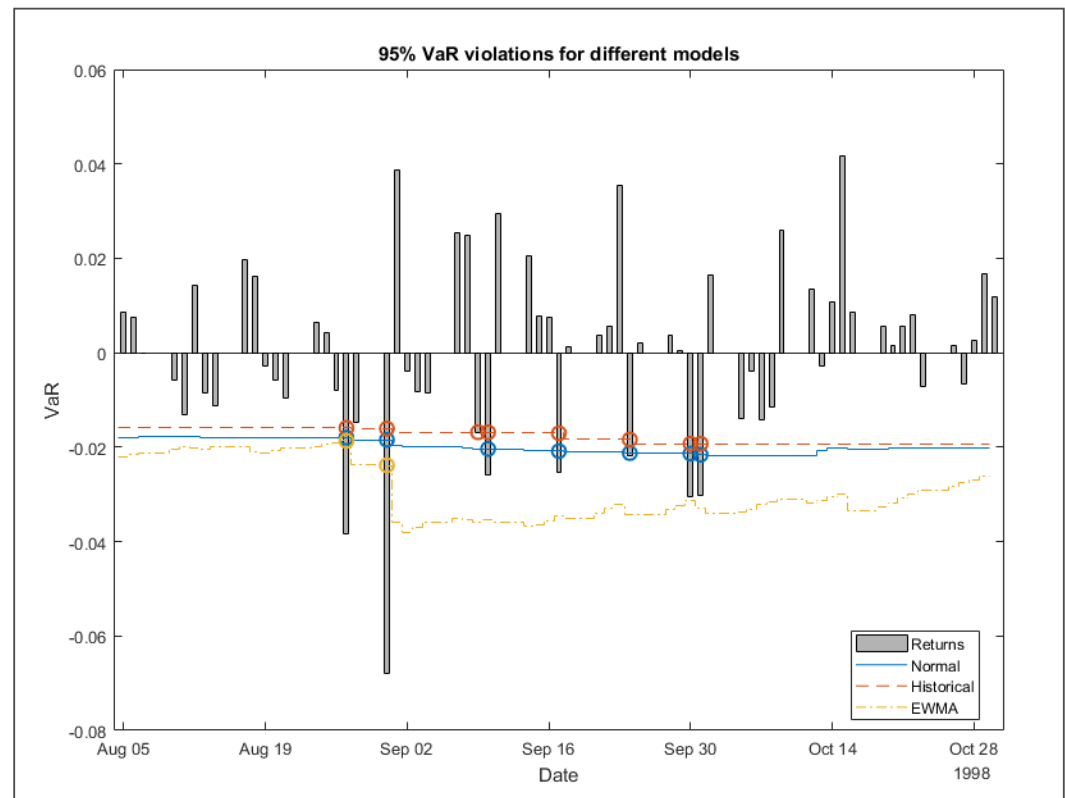
	Value-at-Risk (VaR)	Expected Shortfall (ES)
Definition	VaR is the risk measure that estimates the maximum potential loss given confidence level and time period.	ES is the extended VaR and quantifies the average loss over the unlikely scenarios beyond the confidence level and a time period.
Example	A one-day 99% value-at-risk of \$10 million means there is 1% chance that the potential loss over a one-day period will be greater than \$10 million.	A one-day 99% ES of \$12 million means that the expected loss of the worst 1% scenarios over a one-day period is \$12 million.



# Value-at-Risk and Expected Shortfall Backtesting

Once a risk model is in production, its performance must be assessed. The performance of a risk model depends on how accurately it measures the risk it is supposed to estimate. Value-at-risk (VaR) and Expected shortfall (ES) models are among the main risk measures that are widely used by regulators, top management, and business units. To ensure the safety of financial system, a regulator is very interested to know that VaR and ES models do not underestimate the risk. On the other hand, business units would prefer not to have an overestimated VaR and ES because it means higher costs of doing business. Therefore, risk management teams should develop VaR and ES models that balance the needs of all stakeholders.

By comparing the potential loss calculated from VaR or ES models with actual profit/loss, you can assess the performance of VaR and ES models. In fact, many different statistical tests can be used for backtesting, each with its own strengths and weaknesses. In practice, more than one backtest should be used to evaluate the performance of VaR and ES models.



*Market risk backtesting.*

# Value-at-Risk and Expected Shortfall Backtesting *continued*

Read more about *VaR backtesting* tools, including:

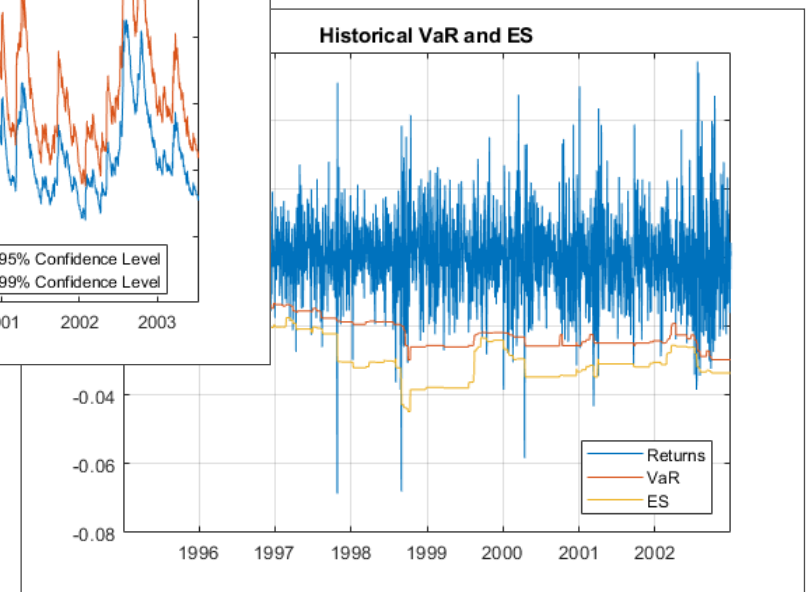
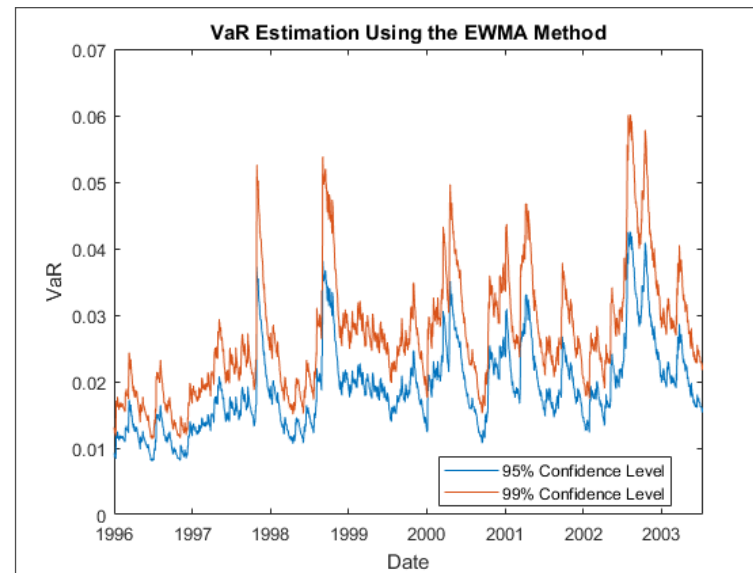
- Traffic light test
- Binomial test
- Kupiec's tests
- Christoffersen's tests
- Haas's tests

Read more about *ES backtesting* tools, including:

- Table-based (simulation-free) tests
  - Unconditional normal
  - Unconditional T
- Simulation-based test
  - Conditional
  - Unconditional
  - Quantile

Explore how to use MATLAB to perform VaR and ES backtesting:

- *Value-at-Risk Estimation and Backtesting*
- *Expected Shortfall Estimation and Backtesting*



# Real-World Examples

The challenges of market risk modeling are much greater when you want to *scale the models into production*. Typically, you would use complicated pricing and risk models for a large amount of data either on a real-time basis or at the end-of-day calculation. It clearly is a time-critical job. The risk system needs to be fast, accurate, scalable, and easy to connect with other systems.

## Example 1: Quantitative Risk Management

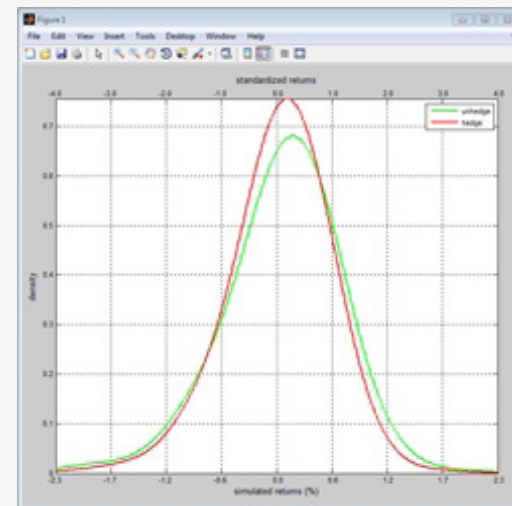
Learn how Fulcrum Asset Management developed a custom quantitative risk management engine and scaled up their infrastructure to real-time production environment by integrating with various databases and datafeeds.

» [Read the story](#)

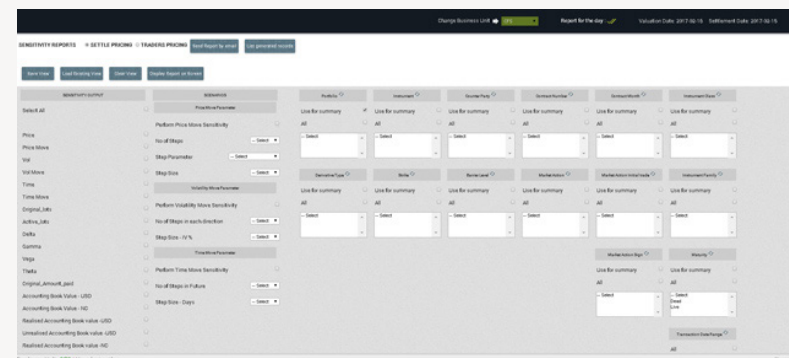
## Example 2: Trade Management for Commodity and Derivative Markets

Processing large amounts of market data on daily basis has already become a requirement for market risk systems. See how Olam International, a leading agribusiness based in Singapore, efficiently developed and deployed a risk management system that can process a large amount of data for derivatives analytics.

» [Read the story](#)



Distribution of standardized and unstandardized simulated portfolio returns before and after hedging.



Olam's trade analytics and risk management system.

## Learn More

*Ready for a deeper dive? Explore these resources to learn more about market risk modeling, examples, and tools.*

### Watch

[Building an Internal Risk System with MATLAB \(24:55\)](#)

[ARPM and KKR Find Practical Quantitative Solutions to Problems in Risk and Portfolio Management \(2:24\)](#)

### Read

[Estimating Option-Implied Probability Distributions for Asset Pricing](#)

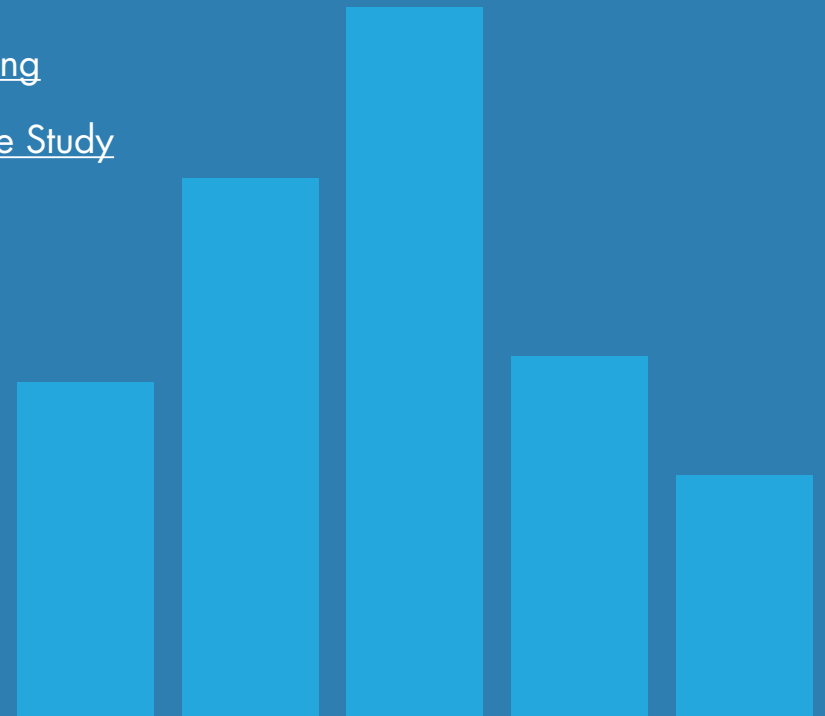
[Real Options Valuation with MATLAB: A Mining Economics Case Study](#)

### Explore

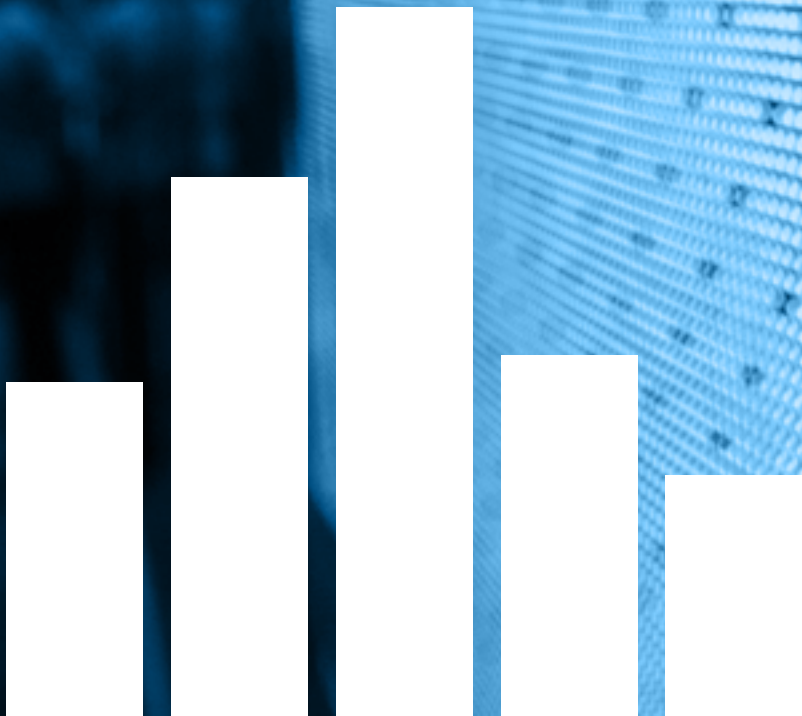
[Monte Carlo Simulation in Finance](#)

[Pricing and Valuation of Financial Instruments](#)

[GARCH Models](#)



# Chapter 4: Operational Risk Modeling



# What is operational risk?

Operational risk is the potential for a loss arising from people, processes, systems, or external events that influence a business function. To financial institutions, operational risk is simply the risk to operate the financial business. Given the large number of events that can trigger an operational loss, operational risk cannot be completely mitigated, but it can be managed.

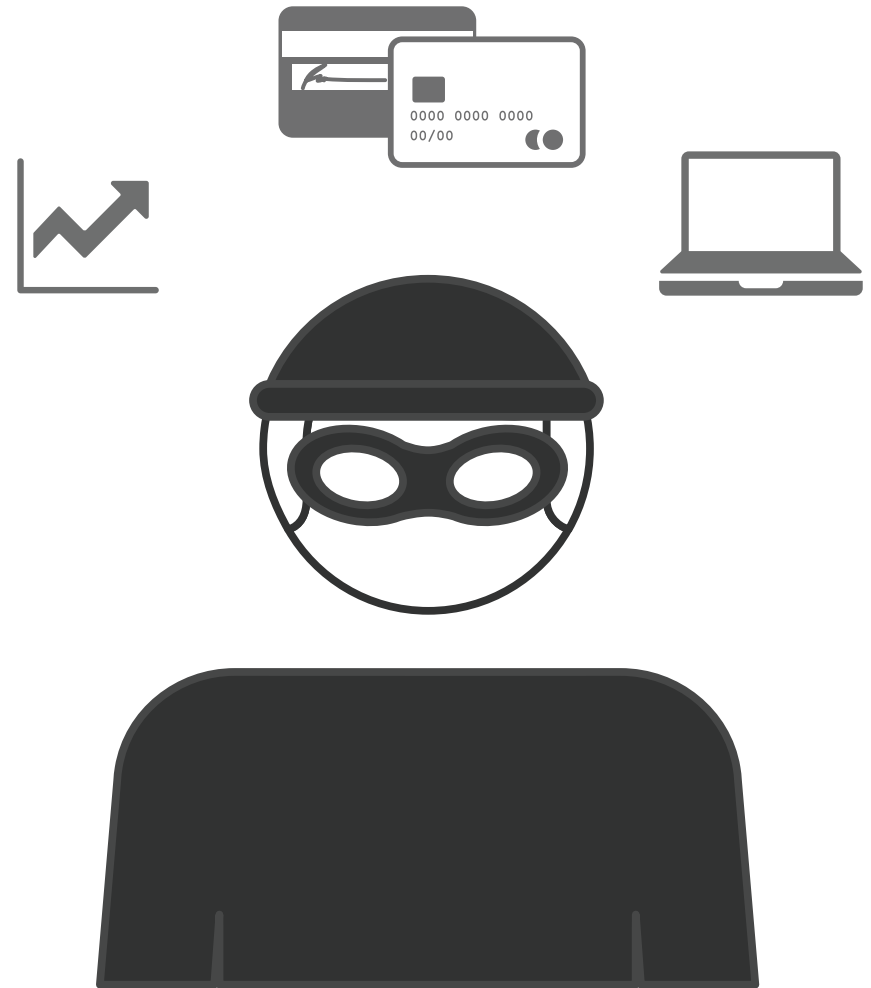


*Sources of operational risk.*

# Top Activities of Operational Risk

Operational loss may happen very frequently, but its individual amounts might be minimal. However, some types of operational loss could have significant impacts to financial institutions. According to the Basel Accords, examples of such activities include:

- Fraudulent activities:
  - Internal fraud: intentional misreporting, employee theft, and insider trading
  - External fraud: cybercrime, theft, robbery, forgery, and theft of information
- Employment practices and workplace safety: neglect or violation of employment practices and safety rules
- Clients, products, and business practices: Failure to perform Know Your Client (KYC) procedure, improper trading activities on company's account, participating in market abuse, and sale of unauthorized products
- Damage to physical assets: terrorism, vandalism, and natural disasters
- Business disruption and system failures: hardware failures, software failures, and utility outages
- Failures to deliver or execute business transactions



# The Nature of Operational Risk

Generally, the loss from operational risk can be incurred because of both internal and external factors, many of which are related to human activities. Additionally, the loss from operational risk for operating the same type of business (e.g., consumer credit business, commodity trading, or asset management) can vary because of business process, risk culture, and management oversight. In other words, there is no one-size-fits-all approach to operational risk modeling.

For financial institutions, two typical objectives for calculating operational risks are to obtain regulatory capital requirements and to provide a business insight. The former is mandatory function to fulfill regulatory requirements; the latter objective is critical for making business or risk management decisions.



# How to Measure Operational Risk

Given its uniqueness, operational risk is not simple to model. Per the Basel Accords, financial institutions could use the basic indicator approach (BIA), the standardized approach (TSA), or the advanced measurement approach (AMA) as a framework to quantify capital requirement for operational risk. To reduce complexity and improve comparability, the guidance has recently been updated to propose a [standard measurement approach \(SMA\)](#), which is extended from TSA.

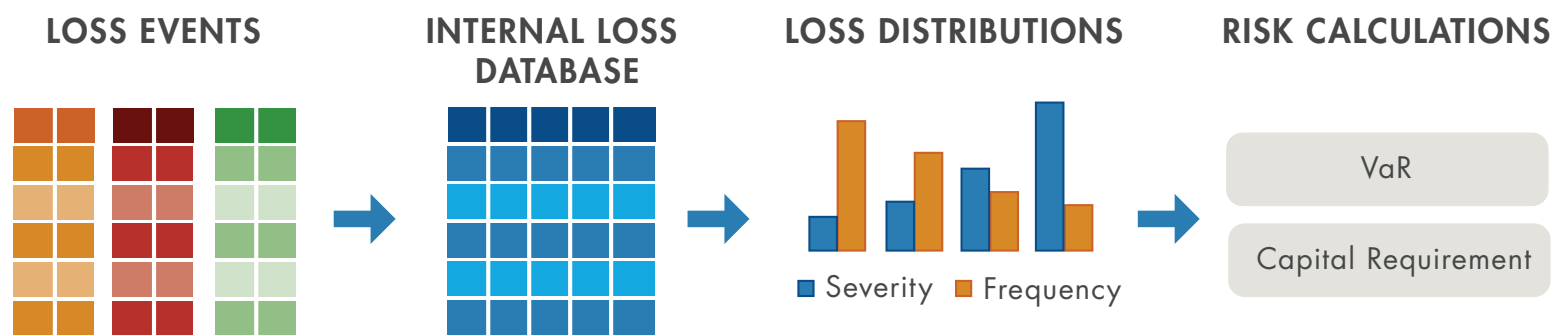
By its design, SMA is likely to become the most adopted approach for calculating operational risk. Regardless of the modeling approaches, internal loss data is still an essential input that will be used throughout the calculation. In SMA, the internal loss multiplier was introduced to reflect the historical loss resulting from operational risk of an organization to the regulatory capital requirements. Therefore, operational risk managers need to focus on building an internal loss

database to produce high-quality data essential for operational risk calculations.

It is worth noting that in the cases where internal data is limited or insufficient, the use of external loss data can provide valuable information for accessing operational risk based on the experiences of other financial institutions.

## Read how to:

- [Use the Distribution Fitter App to fit the data](#)
- [Model data with the generalized extreme value distribution](#)
- [Generate correlated samples using copulas](#)



Converting loss events into risk measures.

# Scenario Analysis of Operational Risk

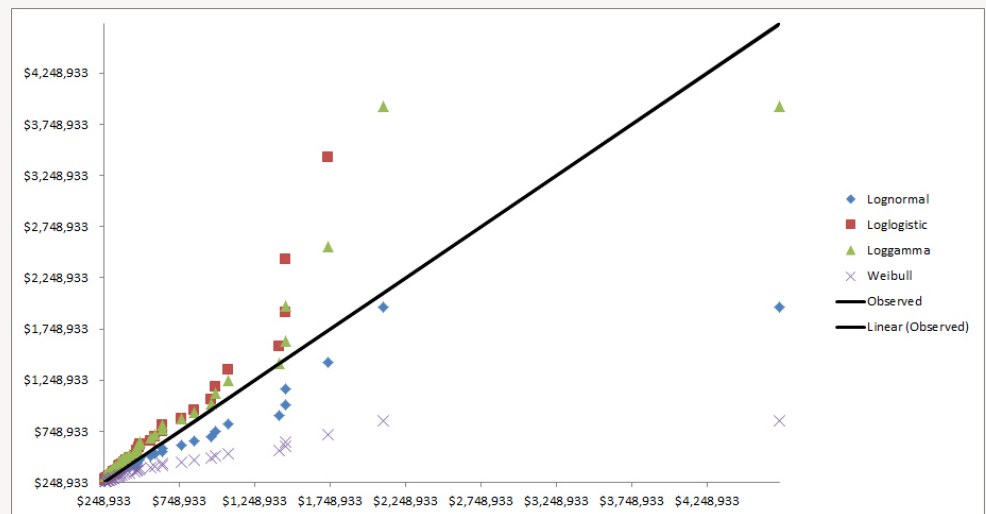
One of most common tasks in risk management is scenario analysis or what-if analysis. For market risk, the scenarios are usually related to the changes in market prices or model variables. Similarly, credit scenarios are commonly related to variables used in expected loss calculation. However, it might not be so straightforward in the case of operational risk. One popular method for performing scenario analysis of operational risk is the Change of Measure (COM), proposed by Kabir Dutta and David Babbel<sup>1</sup>.

<sup>1</sup> Dutta, K., and Babbel, David F. "Scenario Analysis in the Measurement of Operational Risk Capital: A Change of Measure Approach." *Journal of Risk and Insurance*, 2013 (<http://onlinelibrary.wiley.com/doi/10.1111/j.1539-6975.2012.01506.x/abstract>)

## Real-World Example

Learn how Wolters Kluwer helped many financial institutions rapidly implement the COM methodology to perform the scenario analysis of operational risk.

» [Read the story](#)



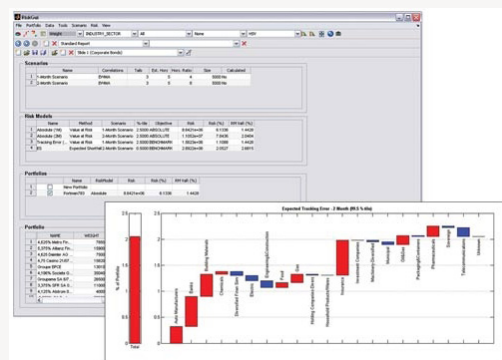
QQ plots for scenario-augmented data.

# Mitigating Operational Risk

Strategies for mitigating operational risk commonly involve reduction of manual process, removing redundant systems or processes, and improving data quality and traceability. In many cases, businesses can lower operational risk and reduce costs by implementing operational risk mitigation strategies. Although it is almost impossible to completely eliminate operational risk, you can definitely enjoy the benefit of mitigating and managing operational risk.

## Real-World Examples: How to Use Technology to Mitigate Operational Risk

Usually, the operational risk of using spreadsheet calculations is underestimated because of its flexibility. A minor change in spreadsheet could easily produce an error, which results in a huge loss. Nykredit developed risk management and portfolio analysis applications to minimize such operational loss. In addition, Nykredit shortened their decision process from days to hours and significantly improved their productivity. [» Read the story](#)



Nykredit's tool for calculating and visualizing risk statistics.

UniCredit Bank Austria developed and rapidly deployed an enterprise-wide market data engine to improve their risk management operation. In addition to improving their risk management operation, they lowered their operating cost as well. [» Read the story](#)



Zero-coupon yield curve plot in UniCredit Bank Austria's UMD environment.

# Fraud Detection

Fraud is a common problem in every type of business, and a major source of operational risk. There are many types of fraudulent activities, including credit card fraud, cybercrime, and identity theft. Fraudulent activities exist not only on the consumer level, but also on the corporate level. The Madoff Ponzi scheme is one high-profile scandal that affected many financial institutions as well as individual investors.

A general principle for preventing fraudulent activities is to have effective policies and codes of conduct, including an anti-fraud policy, whistleblower policy, conflict-of-interest policy, and code of ethics. Given the fact that fraud is a billion-dollar crime, fraudsters will quickly adapt themselves to new technologies and exploit any physical or technical loopholes. Therefore, financial institutions were among the early adopters of advanced data analytics for fraud detection. Mathematical and computational techniques commonly used for fraud detection include:

- Statistical analysis
- Machine learning
- Deep learning
- Text analytics
- Graph theory
- Big data computing

**Read more about fraud detection:**

- [Systematic Fraud Detection Through Automated Data Analytics in MATLAB](#)

	Gateway Fund	Growth Fund of America	Fairfield Sentry (Madoff)
Discontinuity at zero			•
Low correlation with other assets			•
Unconditional serial correlation			•
Conditional serial correlation			•
Numbr of returns equal to zero			•
Number of negative returns	•		•
Number of unique returns			
Number of consecutive identical returns	•	•	•
Uniform distribution of the last digit		•	•
Benford's law on the first digit		•	•

*Suspicious patterns of hedge funds.*

# Real-World Examples

As a part of European Commission (EC), Joint Research Centre (JRC) was founded to provide independent scientific advice and support on issues related to European Union (EU) policies. One of the primary interests in finance and economics is to protect the financial interests of the EU through antifraud. Thus, JRC developed statistical tools for analyzing trade data, including FSDA Toolbox, a MATLAB based toolbox for forward search data analysis. These tools target various fraudulent activities such as customs fraud, trade-related infringements, money laundering, and regulatory circumventions of EU trading policies.

» [View presentation](#)

» [Download the toolbox](#)



## Learn More

*Ready for a deeper dive? Explore these resources to learn more about operational risk modeling, examples, and tools.*

### Watch

[Wolters Kluwer Delivers Operational Risk Capital Modeling Tool \(2:34\)](#)

### Read

[Financial Risk Management: Improving Model Governance with MATLAB](#)

[Developing and Implementing Scenario Analysis Models to Measure Operational Risk at Intesa Sanpaolo](#)

### Explore

[Deep Learning](#)

[Text Analytics Toolbox](#)