Incorporating Liquidity Risk and Machine Learning within ERM and ALM to drive Risk-aware Business Decision-Making

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SS&C Algorithmics

ERM Enterprise Risk Management Symposium

Agenda

- New challenges for risk management in the insurance sector
- 5-step journey to a sophisticated ERM solution
- Liquidity risk management at L&G: a case study
- Machine Learning for Replicating Portfolios: a case study

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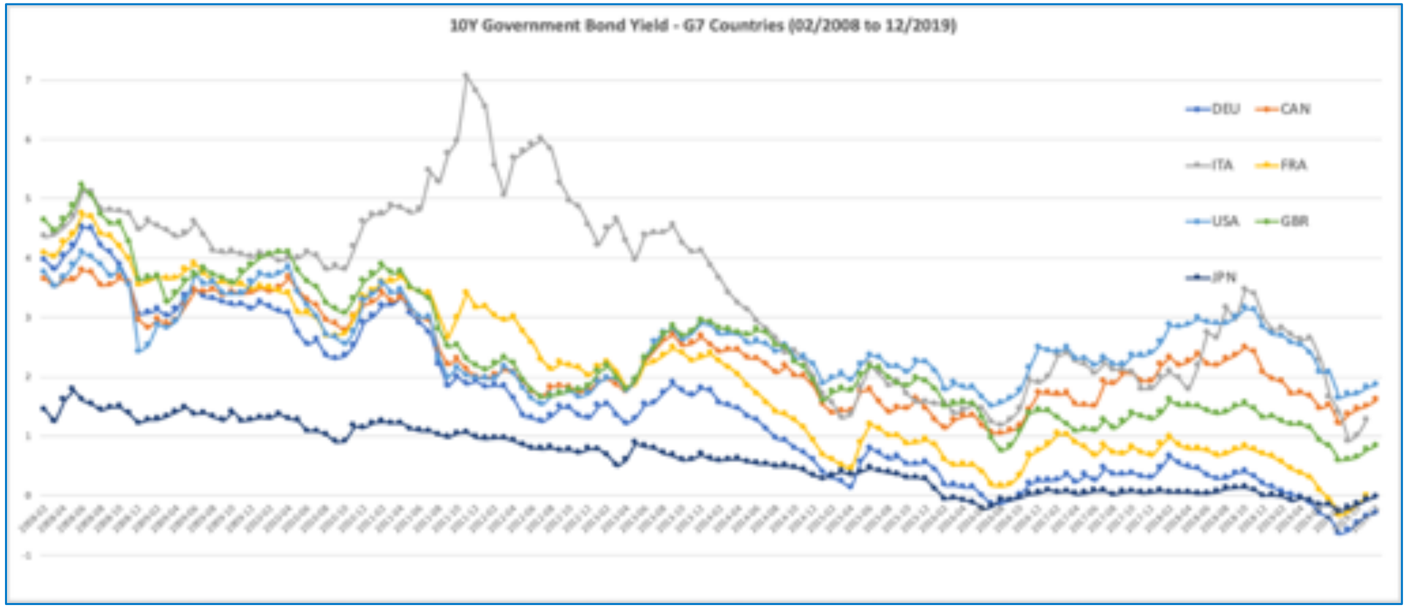
A challenging market landscape

Low to negative yields



10Y Government rate history across G7 countries (OECD)

Market challenges

- Low interest rates across core developed markets
- High long term guarantees in life or retirement products
- Limited premium rise due to client pressure and competition

Need to rethink investments and ERM in the insurance sector

New challenges call for new strategies

Markets, regulations, IT

Market and regulatory challenges…		…drive new business requirements
Complex and credit-intensive securities considered because of low market yields	→	Native asset modelling accounting for consistent **market and credit risk** management
Options and guarantees are often met with dynamic hedging strategies	→	Improved ALM with **liability proxying,** risk-aware investment strategies, **liquidity risk** management
Risk management under scrutiny of regulatory authorities and stakeholders	→	Compliance must be accompanied by business benefits and improved ALM
Demand for trustworthy data, renewed skill sets and IT infrastructures	→	Reduce TCO with cured data, **cloud** computing, managed services and **cognitive** technologies

Global shift to sophisticated ERM

Regulations and business needs drive the change

- Actuarial funding
- Long-term guarantees
- Prescriptive models

- Market-consistent balance sheet
- Stochastic projections
- Solvency II, Principles-based approaches
- ORSA
- Internal models

- Integrated modelling of **market and credit** risks
- **Liquidity risk** management
- **Liability Driven Investment**
- Innovation: **Machine Learning** and **Cloud**

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5 Step journey to a sophisticated ERM solution

5. Improve process with cloud and cognitive technologies
4. Expand ERM solution to include Liquidity risk, as well as ALM and LDI processes
3. Integrated Monte-Carlo analysis of market and credit risks
2. Calibrate proxies for liabilities (loss functions or Replicating Portfolios) using sample data sets
1. Devise a three step process: scenario generation, simulation of assets and liabilities, risk aggregation

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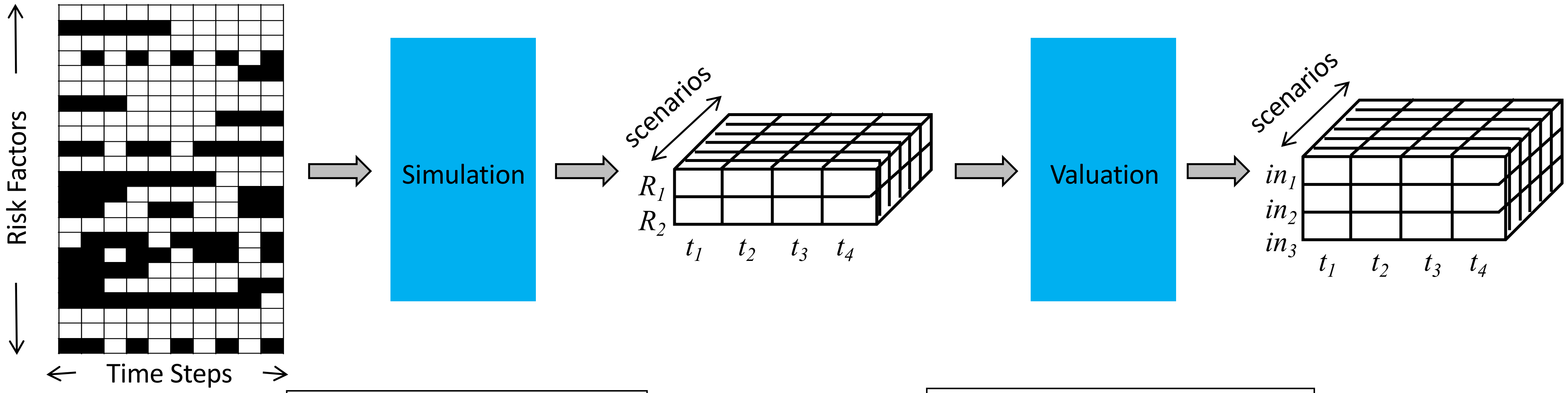
1 Market-Consistent Modelling of the Balance Sheet

Historical Time Series
- Interest rates
- Exchange rates
- Equity indexes
- Commodities
- Individual securities

Risk Factor Scenarios
- Consistent paths of risk factor changes
- Copula codependent structures widely used

Instrument Scenarios
- Consistent paths of instrument values
- Mark-to-Future cube



Simulation Methods
- Historical sampling
- Stochastic models
- Calibration
- Codependence
- Transformations (PCA)

Valuation Methods
- Linear factor models
- Analytic
- Numerical methods
- Proxies

Portfolio level aggregation

Mark-To-Future decouples the simulation and aggregation

A portfolio is a set of positions, $\boldsymbol{x}$, where x_j is the number of units of instrument j, j = 1, …, N

From the instrument values in the MtF cube, the portfolio value at time t in scenario i is

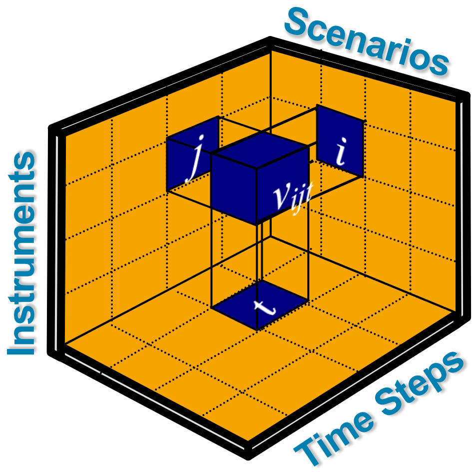
$$V_{it}(\boldsymbol{x}) = \sum_{j=1}^{N} v_{ijt} \cdot x_j$$

Given the initial portfolio value, it is straightforward to compute changes in value (profits and losses) and returns in each scenario

loss $\longrightarrow$ $\ell_{it}(\boldsymbol{x}) = V_0(\boldsymbol{x}) - V_{it}(\boldsymbol{x})$

An MtF cube can be used to value portfolios that hold any subset of its instruments

- No need to re-simulate when positions change
- x are decision variables in portfolio optimization



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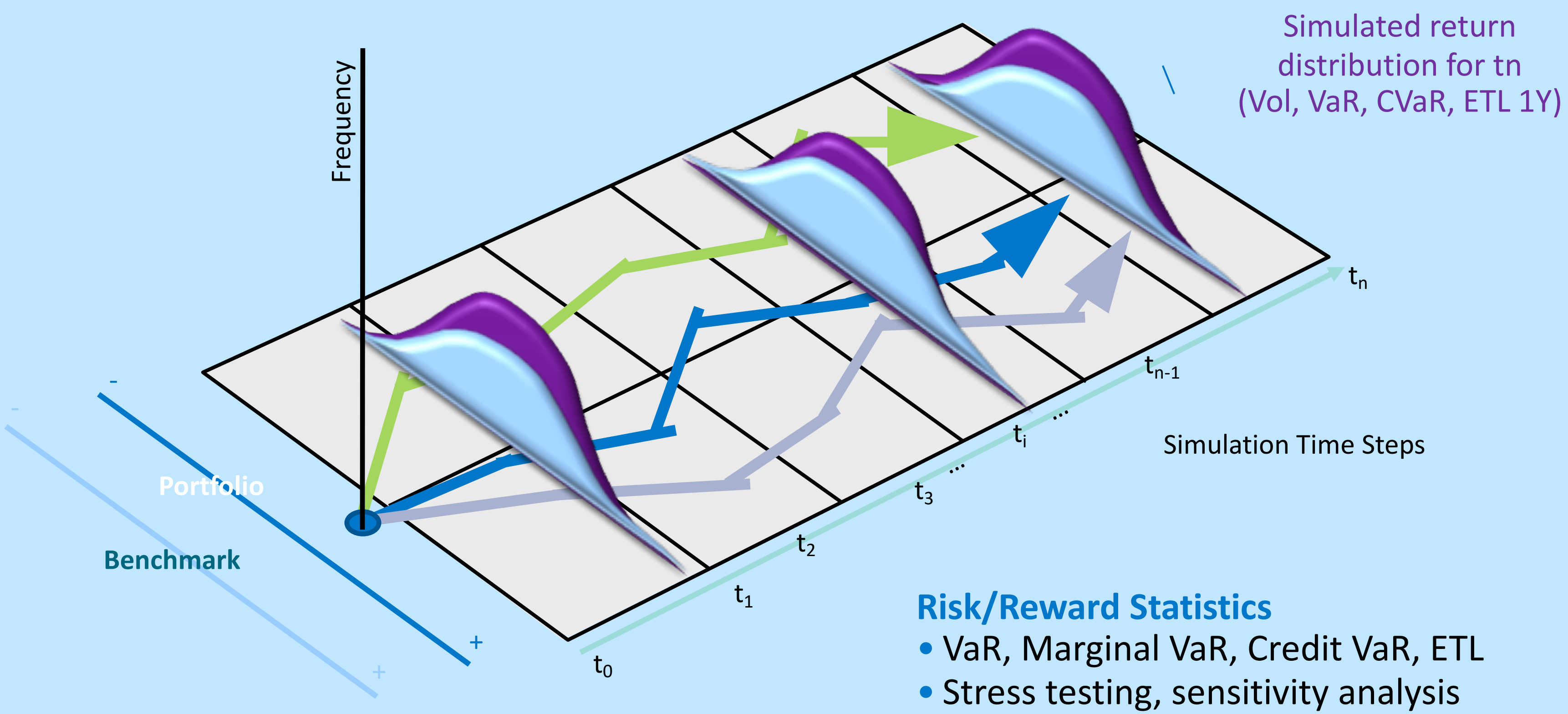
Full Monte Carlo Simulation

Mark-To-Future For A Multiple Horizon Risk Perspective



Risk/Reward Statistics

- VaR, Marginal VaR, Credit VaR, ETL
- Stress testing, sensitivity analysis

Relative Risk Indicators

- Tracking error, Marginal TE, Attribution
- LDI, ALM, capital projections

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How to proxy liability portfolios

Enhance the ALM process

Why do we need liability proxying?

- Actuarial projection systems unable to handle large simulation runs
- Leverage cash flows generated from existing actuarial solutions
- Consistent valuation and simulation of assets and liabilities
- Replicating Portfolios allows to generate cash-flows projecting at any horizon

Main techniques to proxy the liabilities

Zero bonds

Replicate static cash-flows with zero bonds (or sensitivity instruments.)

The stochastic simulation shall apply stochastic discounting under each scenario.

Distributions

The actuarial ALM system outputs the entire marginal distribution (analytical or empirical.)

This can be interpolated and re-sampled in the calculation engine from a correlated risk driver.

LSMC/Curve Fitting

The actuarial ALM system outputs a sample of values, using a nested real-world + risk neutral scenario set.

A (linear) regression is run to find the best fitting polynomial.

Portfolio Replication

The actuarial ALM system outputs a sample of cash-flows.

Find a portfolio of securities (real or synthetic) that matches liability cash-flows over time and scenarios.

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Manage market and credit risk

An integrated view of all risk types

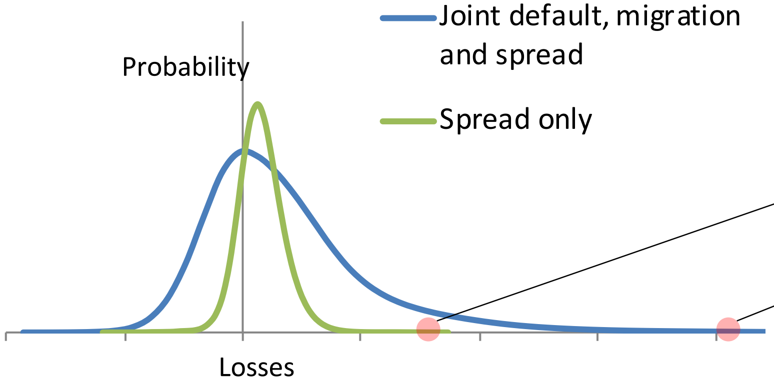
Integrated modeling of market and credit risk allows to decompose loss distributions by

- spread,
- default and
- migration risk

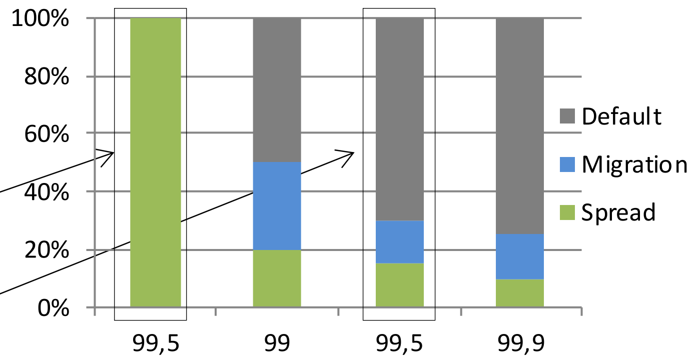
Credit events are correlated to market movements

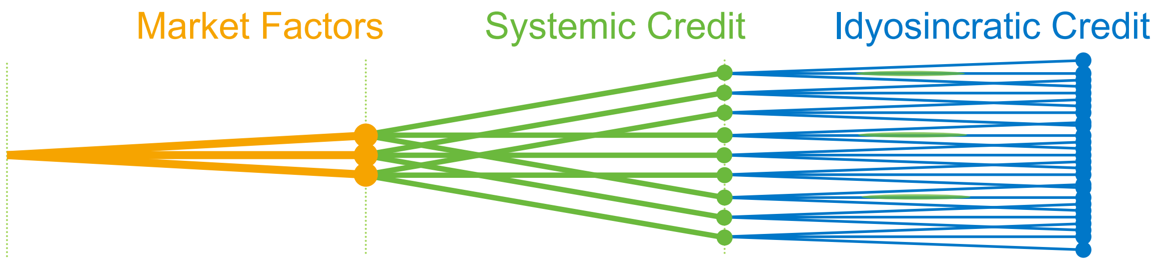
- Each issuer is mapped to an equity risk driver
- Equity level drives issue Credit Worthiness Index (CWI)
- CWI level determines rating

Simulate credit loss distributions



Analyze risk contributions





Scenarios are generated simultaneously for market factors and credit drivers

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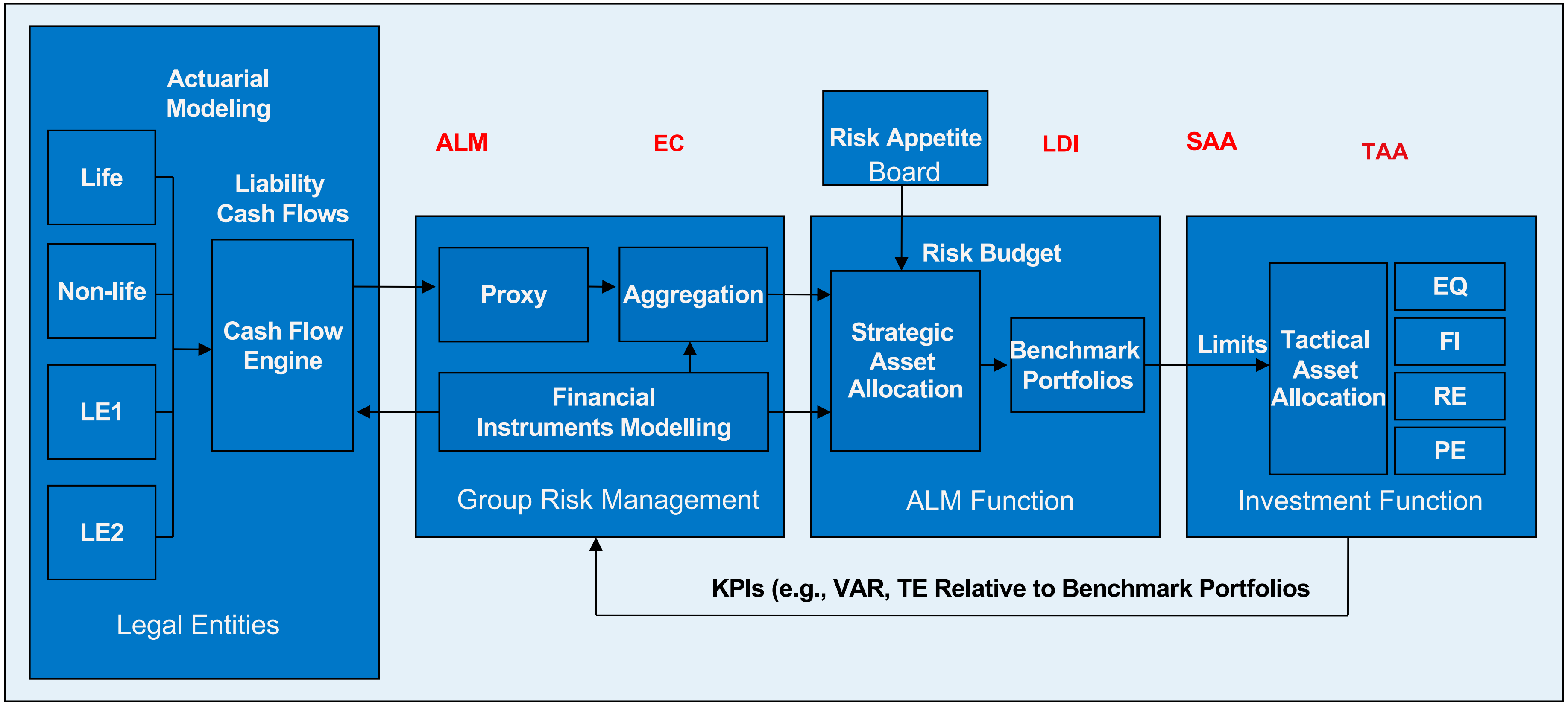
4 Advantages of an integrated ALM platform



- Consistent modeling of assets and liabilities, simulated under a joint scenario set
- Link together enterprise risk management, asset liability management and investment management
- Use what-if and optimization for strategic asset allocation, with liabilities as a benchmark
- Adopt risk-based limits to monitor portfolio managers relative to asset allocations

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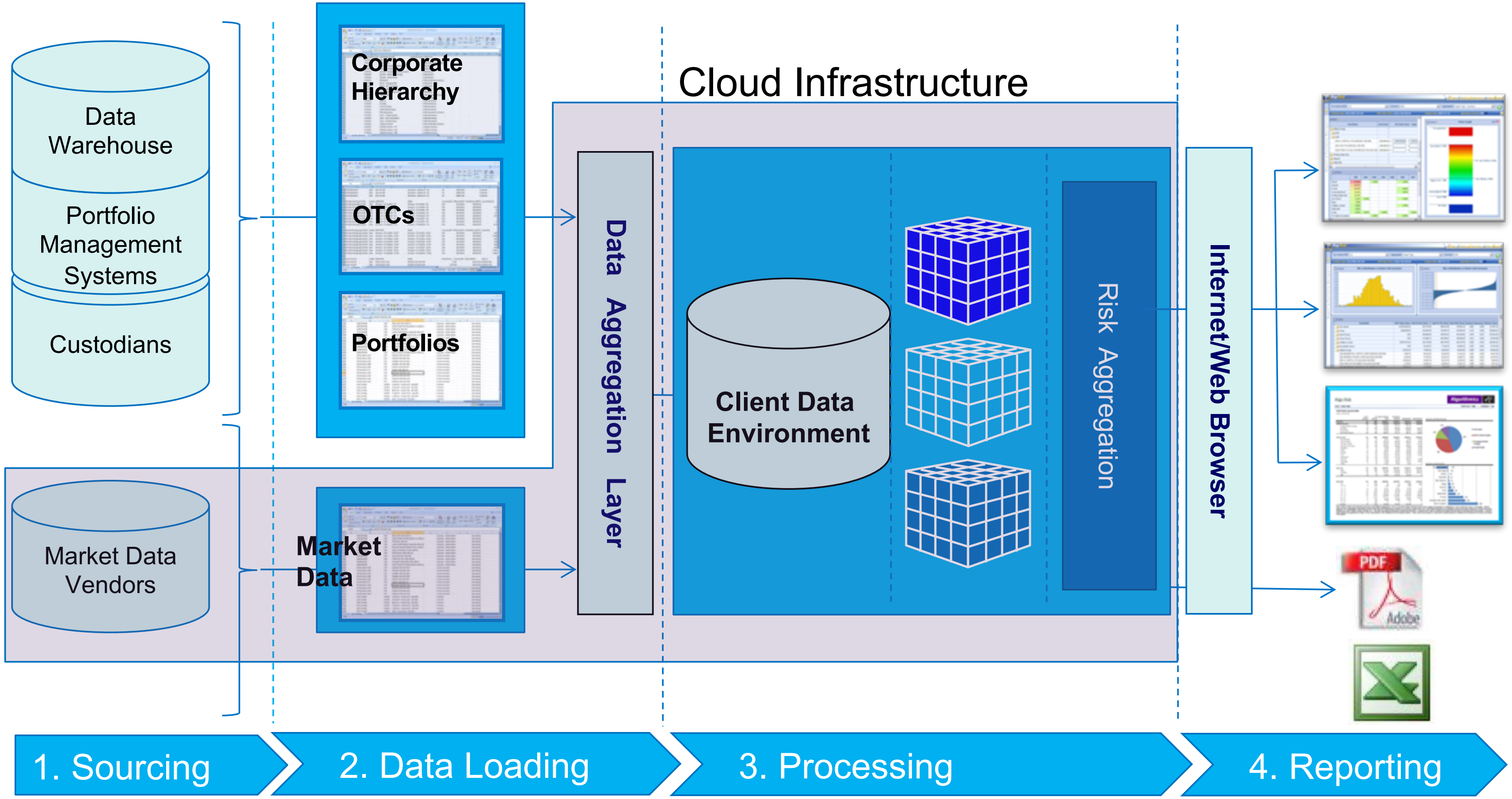
Move to Cloud

Manage simulation bursts and reduce TCO



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Liquidity Management and Planning

How it is becoming a regulatory requirement

'*Liquidity risk*' means the risk that insurance and reinsurance undertakings are unable to realise investments and other assets in order to settle their financial obligations when they fall due

Solvency II Directive, Art. 13(34)

Increasing regulatory pressure:

G-SII Liquidity Management Plan is being applied by an increasing number of local authorities

IAIS issued a *holistic framework* for systemic risk to be applied in 2020 with liquidity requirements

Local initiatives, e.g. PRA's CP4/19

Liquidity Risk is becoming material for insurance

Insurers increasingly move market risks into liquidity risk

Why are insurance firms exposed to Liquidity Risk?

–

- Investments in illiquid assets
- Higher market volatility
- Surrenders (no compulsory annuitisation)
- Increased derivative hedging

Source: PRA's CP4/19

Sources of liquidity risks incurred under stressed market conditions

Liability Side: Increase in lapse rates, surrender of life insurance policies.

–

Some insurance products contain options to withdraw cash.

When insurers do not adequately match such liabilities with sufficiently liquid assets, this may lead to a liquidity shortage and ultimately trigger fire sales.

Asset Side: Monetising assets, market depth, access and size.

–

Sudden demands for collateral could force the lender to sell illiquid assets.

In a stressed market, these sales could impact the insurer's creditworthiness, triggering more collateral demands and leading to a price spiral

Off balance Sheet: Collateral and margin obligations.

–

When derivatives are used to hedge market risk, **margin requirements transform capital risk into liquidity risk**.

A macroeconomic shock could trigger calls for additional margin, forcing insurers to raise liquidity

Liquidity risk solution at Legal & General

Case Study of Algorithmics solution at L&G

Highlights:

–

Produce metrics used to measure liquidity requirements for derivatives hedging

–

Provide business users the required self-service capabilities

–

Source curated data from the Algo Market Data Service

Business problem

–

Monitor liquidity under stress in order to improve the asset allocation in an autonomous manner.

Solution

–

AWA for Liquidity risk, fueled by MDS data, provides liquidity analytics to business users including VaR, what-if and biting scenarios

Functional Scope:

Collateralize derivative portfolio while managing risks and ensuring:

1. To forecast liquidity impacts of market events
2. To have sufficient eligible assets to post as derivative collateral in stress scenarios
3. To hold enough cash and gilts to cover risk

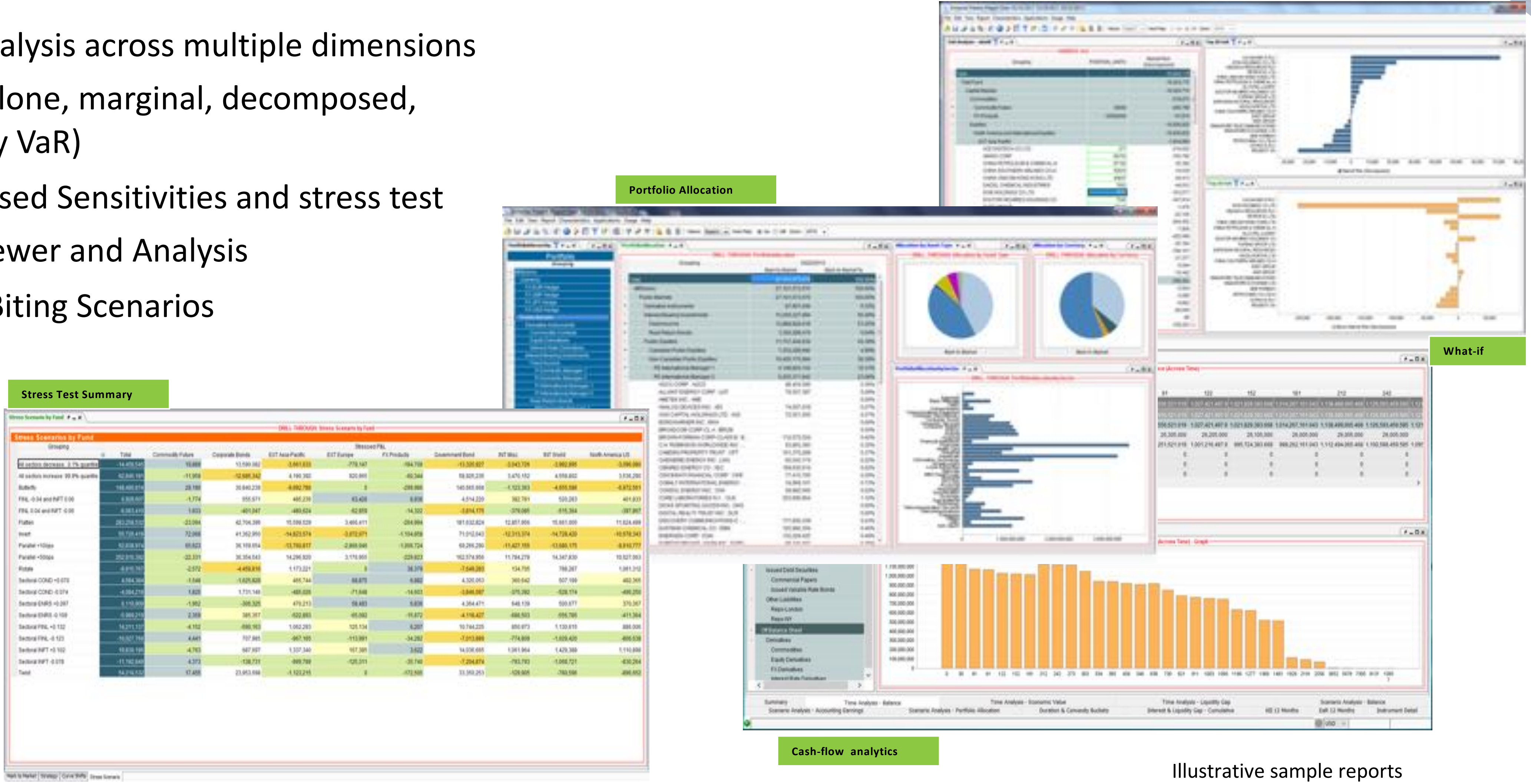
Calculation Methodology:

- Monte Carlo + Historical random sampling + Deterministic scenarios
- Granularity of standalone/diversified VaR e.g. eligible assets, counterparty, product type.
- Daily MDS market data feed

L&G Algo solution reports

The ERM framework now serves liquidity and ALM departements

- Portfolio Analysis across multiple dimensions
- VaR (standalone, marginal, decomposed, contributory VaR)
- Scenario-based Sensitivities and stress test
- Scenario Viewer and Analysis
- Smoothed Biting Scenarios



Illustrative sample reports

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Machine Learning in Insurance

Increasing application span

- Understanding data. ML can be effectively applied across structured, semi-structured or unstructured datasets.
- Process automation, including chatbots, claims registration and settlement
- Fraud detection to identify fraudulent claims more accurately and timely
- Underwriting and credit scoring, i.e. checking datasets to understand if a person qualifies for an insurance
- Recommender systems to provide insurance advice
- Risk Management:
  - ✓ Modeling complex contracts
  - ✓ Calculating Economic Capital
  - ✓ Proxy liabilities

Advantages of Replicating Portfolios

RP's make excellent proxies for insurance liabilities

- Replication error approaches zero (no projection error)
- Reproduces values and cash-flows of the liabilities, thus allowing ALM and AA
- Provides immediate indication of risk composition, facilitating hedging strategies
- Automatically updates with new market data and time horizons

Use Cases:

- Pricing (e.g. Black-Sholes)
- Risk and Portfolio Management (e.g. modeling a portfolio of alternatives)
- Liability Proxying for insurance asset-liability and capital management

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The difference between LSMC and replicating portfolio in insurance liability modeling

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Open Access | Original Research Paper
First Online: 04 November 2016

Abstract

Solvency II requires insurers to calculate the 1-year value at risk of their balance sheet. This involves the valuation of the balance sheet in 1 year's time. As for insurance liabilities, closed-form solutions to their value are generally not available, insurers turn to estimation procedures. While pure Monte Carlo simulation set-ups are theoretically sound, they are often infeasible in practice. Therefore, approximation methods are exploited. Among these, least squares Monte Carlo (LSMC) and portfolio replication are prominent and widely applied in practice. In this paper, we show that, while both are variants of regression-based Monte Carlo methods, they differ in one significant aspect. While the replicating portfolio approach only contains an approximation error, which converges to zero in the limit, in LSMC a projection error is additionally present, which cannot be eliminated. It is revealed that the replicating portfolio technique enjoys numerous advantages and is therefore an attractive model choice.

ML makes Replicating Portfolios easy

In ML/AI terms, Portfolio Replication is a **regression problem** with advanced constraints, bucketing and other enhancements.

Problem: train the model precisely avoiding underfitting and overfitting.

An L1 regularized regression or **LASSO** can be implemented via the trading budget constraint. Efficient frontiers of objective function values vs. trading budget help solving the "**bias-variance tradeoff**"

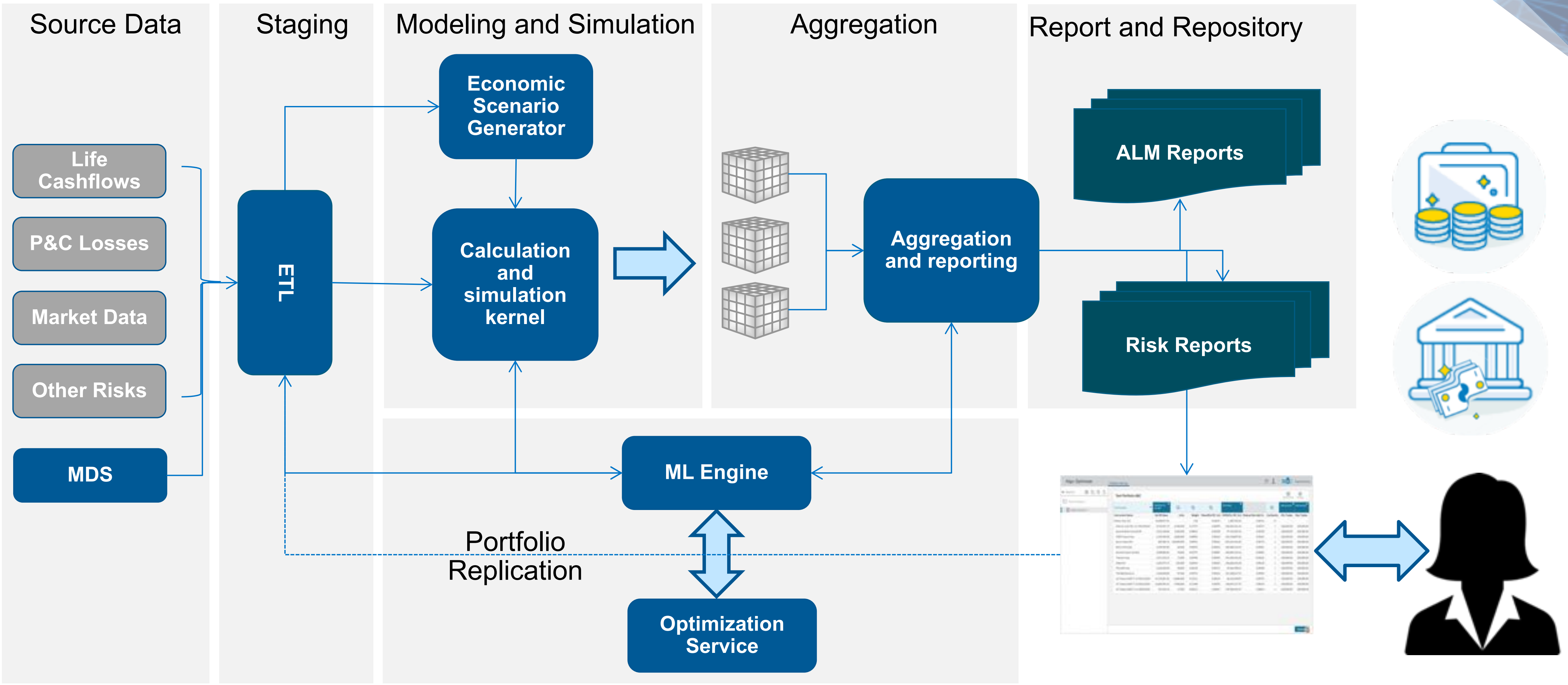
To this end we shall combine two ML methodologies:

- **hyperparameter tuning** and
- **cross validation**

Note: this requires a solution and optimization architecture granting a high the level of automation and visualization functionalities

Hybrid Software Architecture for RP Automation

Machine learning can be enabled by a high performance modular approach



ML-enhanced Replicating Portfolio: a case study

1000 simulated scenarios, equal probabilities

- Risk factors include interest rates, equity indexes
- Each scenario contains annual cash flows for a 30-year time horizon
- 500 scenarios are used for optimization, 500 scenarios are used to evaluate the replicating portfolios out-of-sample. The pptimization tries to match 500 × 30 = 15000 liability cash flows

■ 1157 possible replicating assets, including

- Interest rate sensitive instruments (bonds, swaps, caps and floors)
- Equity sensitive instruments in 3 markets (forward contracts, options)

■ Objective function

Cash flow of instrument j in scenario i at time t

Cash flow of liability in scenario i at time t

$$\min_x \sum_{t=1}^{30} \sum_{i=1}^{500} \left\| \sum_{j=1}^{1157} c_{ijt} \cdot x_j - l_{it} \right\|$$

Absolute or squared difference

■ Trading budget constraint

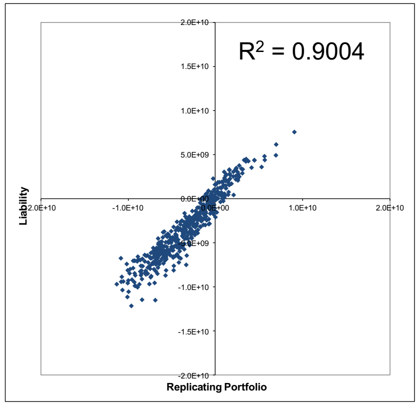
$$\sum_{j=1}^{1157} |x_j| \leq b$$

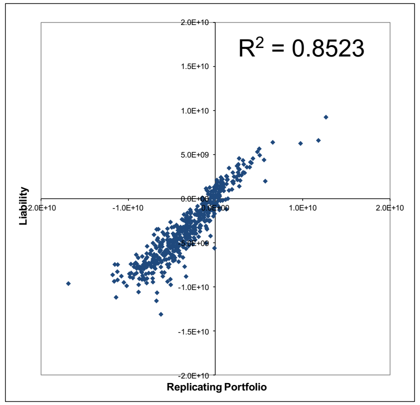
Authors: Oleksandr Romanko, Helmut Mausser

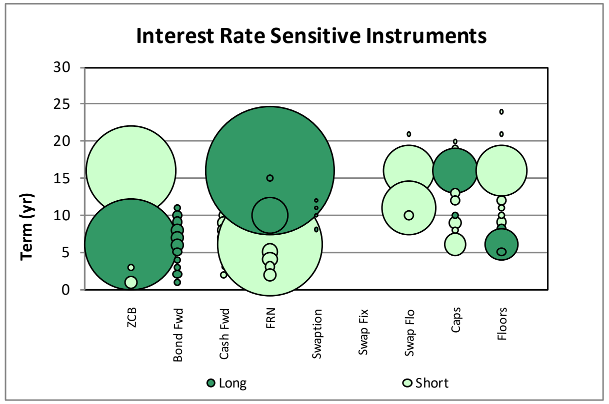
Hyperparameter tuning improves the quality of RPs

In-sample | Out-of-sample

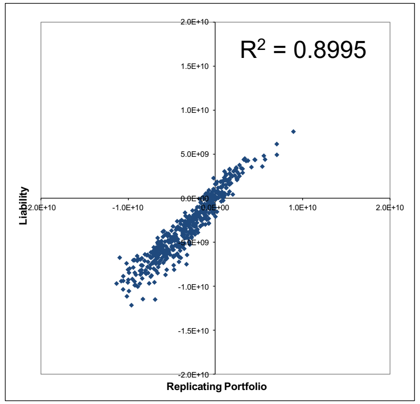
Budget = 7 B

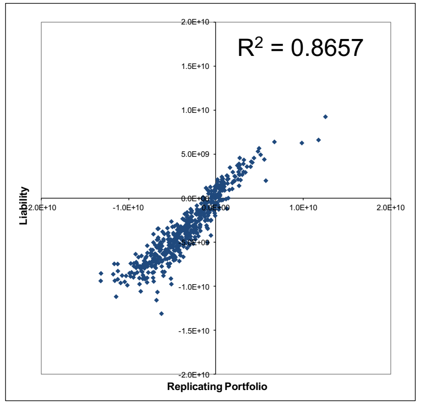


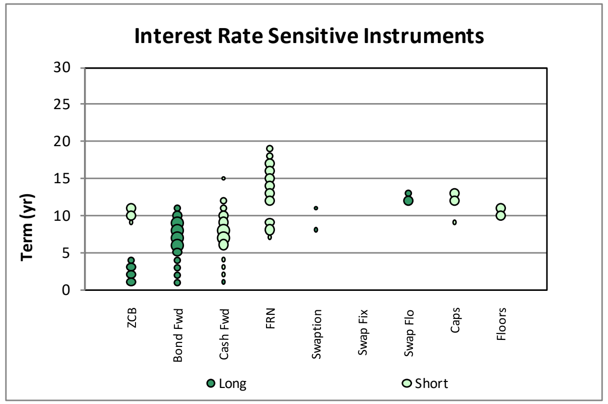




Budget = 626 M







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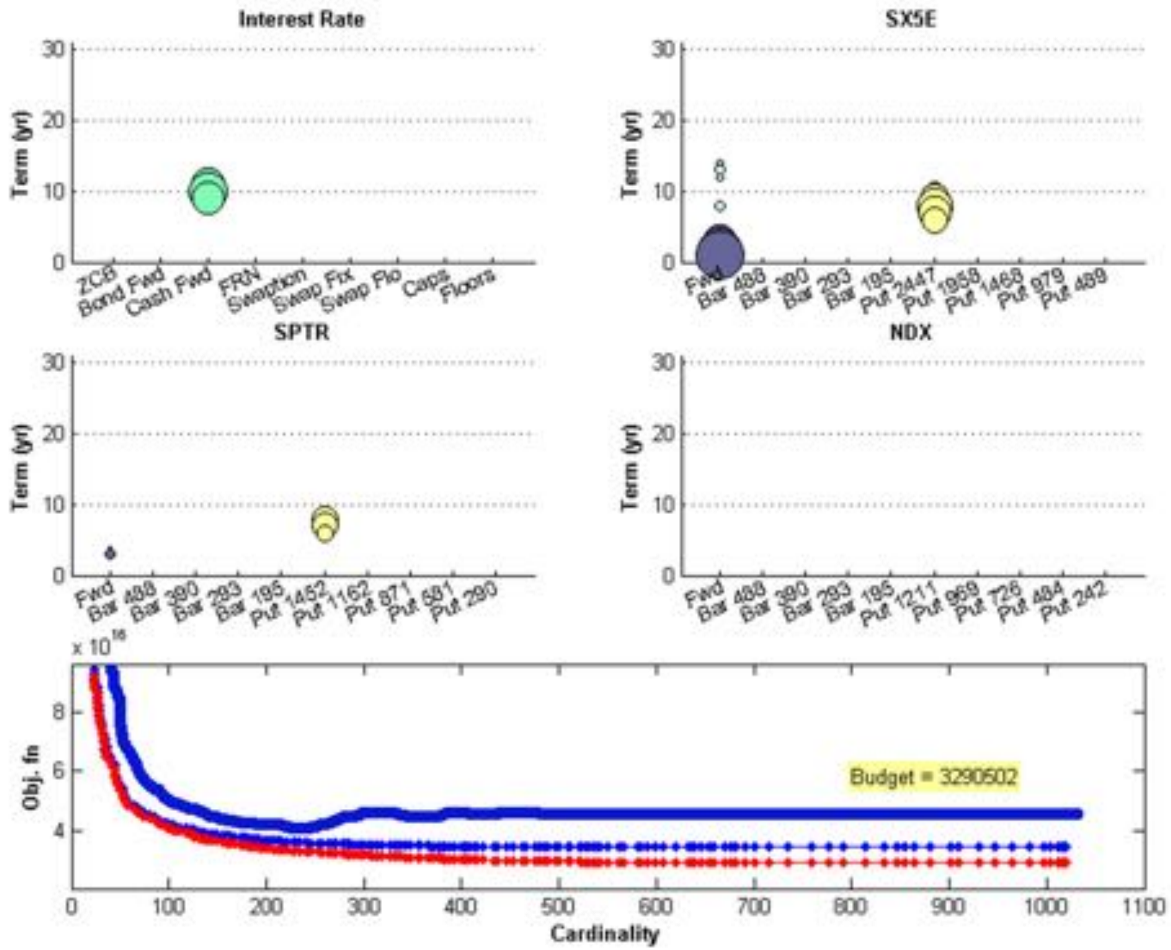
Machine Learning allows to choose the optimal and stable RP



The out-of-sample error has a point of minimum corresponding to cardinality 230.

Search the "ideal" trading budget by averaging out-of-sample frontiers across cross-validation folds and selecting the point of minimum.

The workflow should facilitate the automation of cross-validation to select the "ideal" trading budget that minimizes the out-of-sample error.

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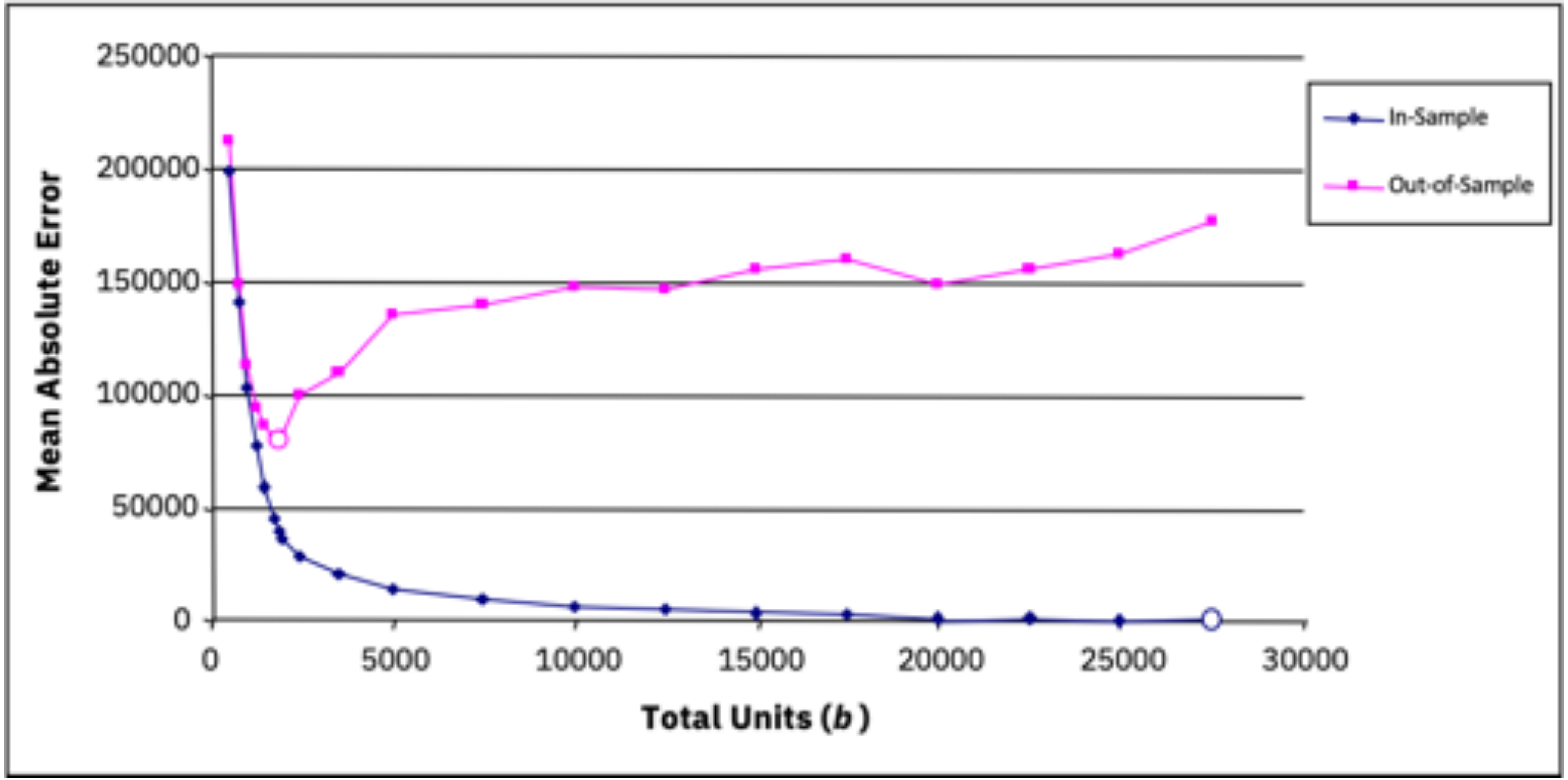
The minimum of the Out-of-Sample Efficient Frontier is the optimal Replicating Portfolio



Thanks

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