

An ALM model with Downside risk and cVaR constraints

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Contents

✓ Overview

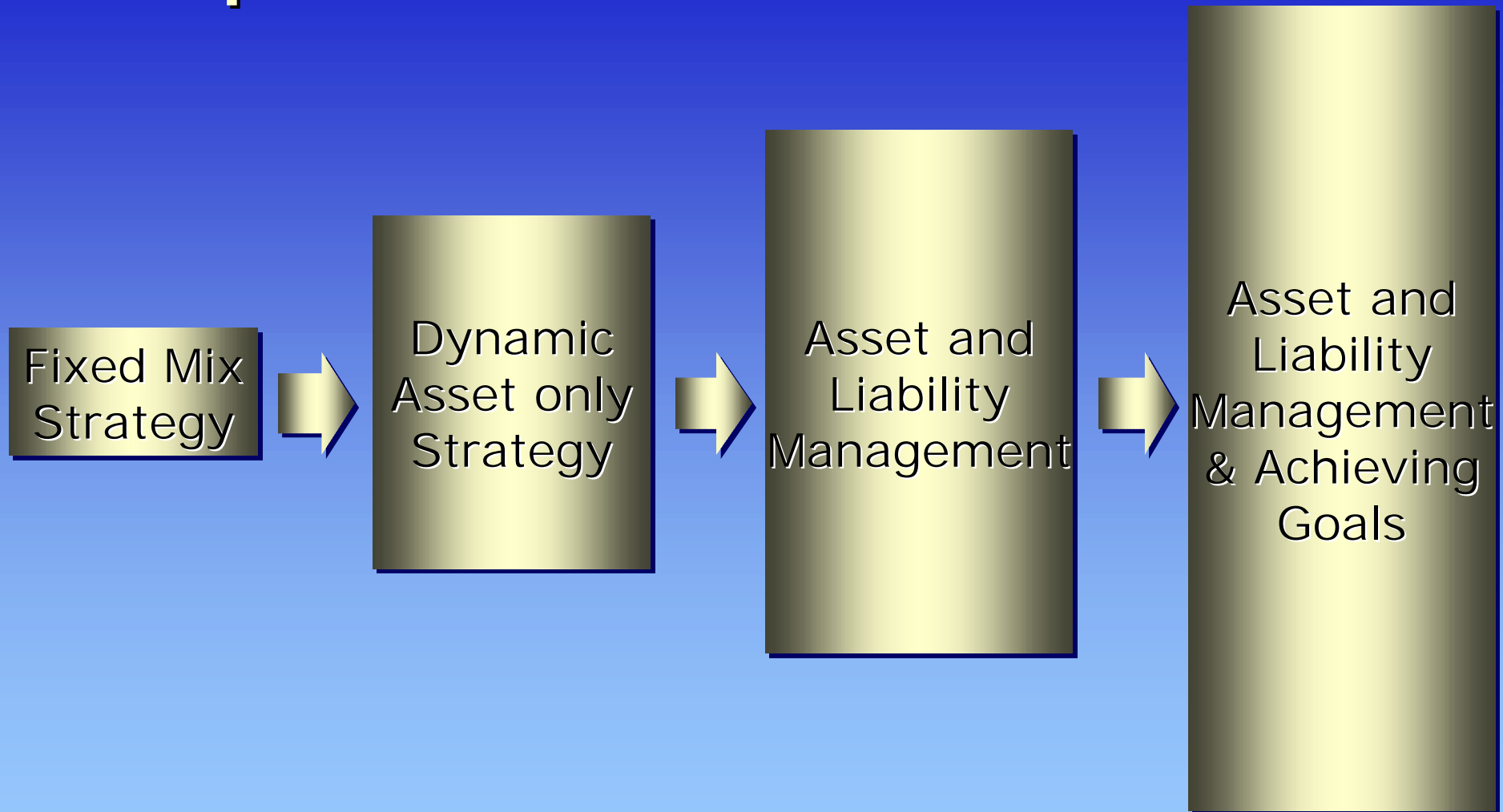
➤ Our investigation

➤ The Models

➤ Consideration of Risk

➤ Experimental results and discussions

Optimal Allocation Models



Asset and Liability Models under Uncertainty

- The basic concepts were developed by:
 - Kallberg, White, and Ziemba (1982)
 - Kusy and Ziemba (1986)
- Large Scale Applications include:
 - Mulvey, Gould, and Morgan (2000) "An Asset and Liability management system for the Towers Perrin-Tillinghast"
 - Carino and Ziemba, & Carino, Meyers, and Ziemba (1998) "Russel-Yasuda Kasai model"
 - Consigli and Dempster (1998) "The CALM stochastic programming model for dynamic ALM"
 - Dert (1995) "A dynamic model for ALM for defined benefit pension funds"
 - Zenios (1995) "Asset and Liability management under uncertainty"

ALM and SP Integration

Optimum Decision
Model and
Constraints

Models of Randomness

Liability
Models

Asset
Classes/
Asset Models

Asset and
Liability
Management
under
Uncertainty
...SP

Constraint Classes

Institution Specific Constraints

- Asset Classes
- Planning Horizon
- Threshold Constraints
- Cardinality Constraints
- Transaction Costs
- ...

Country Specific Constraints

- Tax
- Regulatory Requirements
- Minimum Asset Reserve
- ...

Risk Measures Constraints

- Downside
- VaR
- cVaR
- Variance
- Semi-variance
- Mean Absolute Deviation
- ...

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Our Investigation

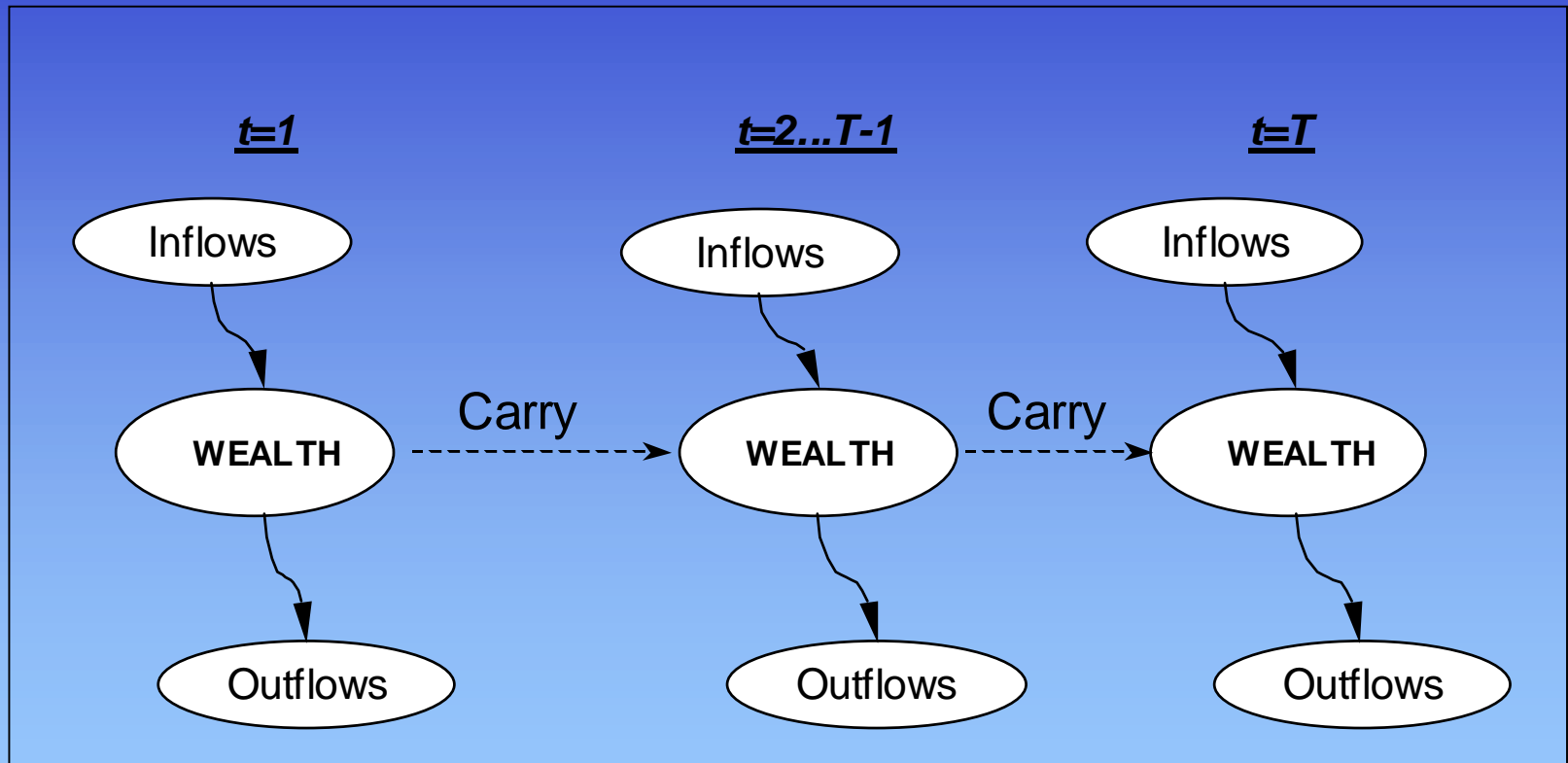
Model	Objective	Risk	Methodology
Two-stage multi-time period SP	Maximise Terminal Wealth	Downside	Rolling & Backtesting
		VaR	
Mean Variance	Maximise Single Period Wealth	Variance	Rolling & Backtesting

Overview

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An ALM Stochastic Programming Model

Surplus Wealth = assets – PV(liabilities) – PV(goals)

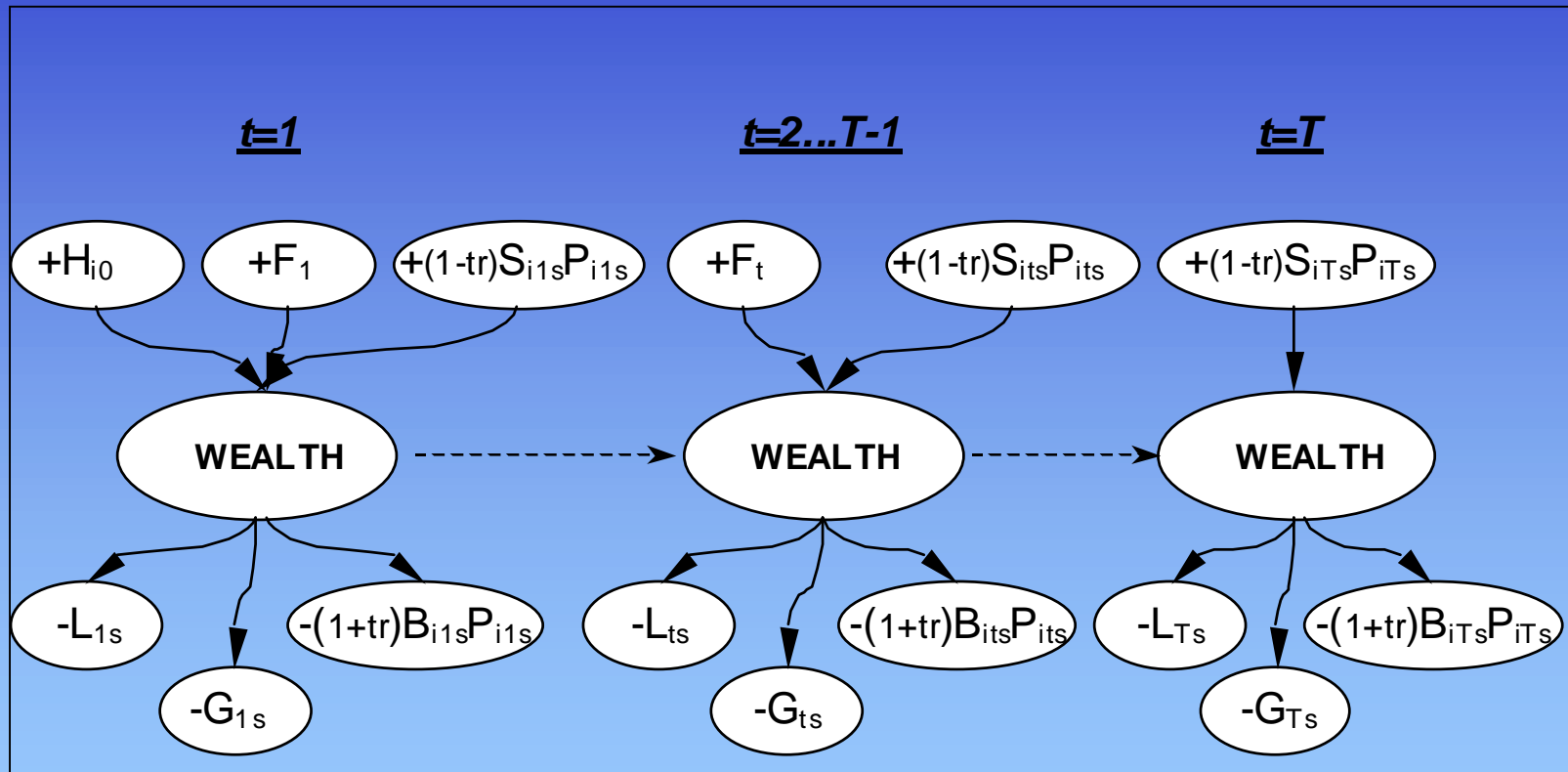


Model Components

	NOTATION	EXPLANATION	
INDEX	i	Assets	$i=1..n$
	s	Scenarios	$s=1..S$
	t	Timeperiod	$t=1..T$
	k	RiskGroup	$k=1..K$
DATA PARAMETERS	P_{ist}	Prices [assets,scenarios,timeperiod]	
	L_{ts}	Liability [timeperiod,scenario]	
	π_s	Probability [scenario]	
	H_{i0}	Initial_Holdings [assets, timeperiod=0]	
	F_t	Funding [timeperiod]	
	$1+tr$	Transaction_Buy	
	$1- tr$	Transaction_Sell	
	ρ_k	RiskGroup_Holdings	
DECISION VARIABLES	H_{ist}	Amounthold [assets, scenarios,timeperiod]	
	B_{ist}	Amountbuy [assets, scenarios,timeperiod]	
	S_{ist}	Amountsell [assets, scenarios,timeperiod]	

An ALM Stochastic Programming Model

Surplus Wealth = assets – PV(liabilities) – PV(goals)



Model Constraints

➤ *Asset holdings constraint:*

- C1. $H_{ist} = H_{i0} + B_{ist} - S_{ist}$, $t = 1, i=1\dots n, s=1\dots S$

- C2. $H_{ist} = H_{ist-1} + B_{ist} - S_{ist}$, $t = 2\dots T, i=1\dots n, s=1\dots S$

➤ *Fund balance constraint*

- C3.
$$\sum_{i=1}^n P_{ist} (1 + tr_i) B_{ist} = \sum_{i=1}^n P_{ist} (1 - tr_i) S_{ist} - L_{ts} + F_t,$$

$$t = 1\dots T, s=1\dots S$$

Model Constraints

➤ *RiskGrades™ (JPMorgan - RiskMetrics) based classification of risk groups...partitions asset set $N = \{1 \dots n\}$*

- $g_k \subseteq N, k = 1 \dots K$

➤ *Risk Groups constraint:*

- $\bigcup_k g_k = N, g_j \cap g_k = 0 \quad \forall (j, k)$

- C4. $\sum_{i \in g_k} H_{ist} \leq \rho_k * \sum_{i=1}^n H_{ist}, t=1 \dots T, s=1 \dots S$

- $\sum_{k=1}^K \rho_k = 1$

➤ *S&P100 is the benchmark*

Model Constraints

➤ *Non-anticipativity Constraints*

- C5.1 Amount of asset classes/stocks the investor holds

$$H_{ist} - H_{is't} = 0, \quad t=1, s=1, \forall i=1\dots n, s'=2\dots S$$

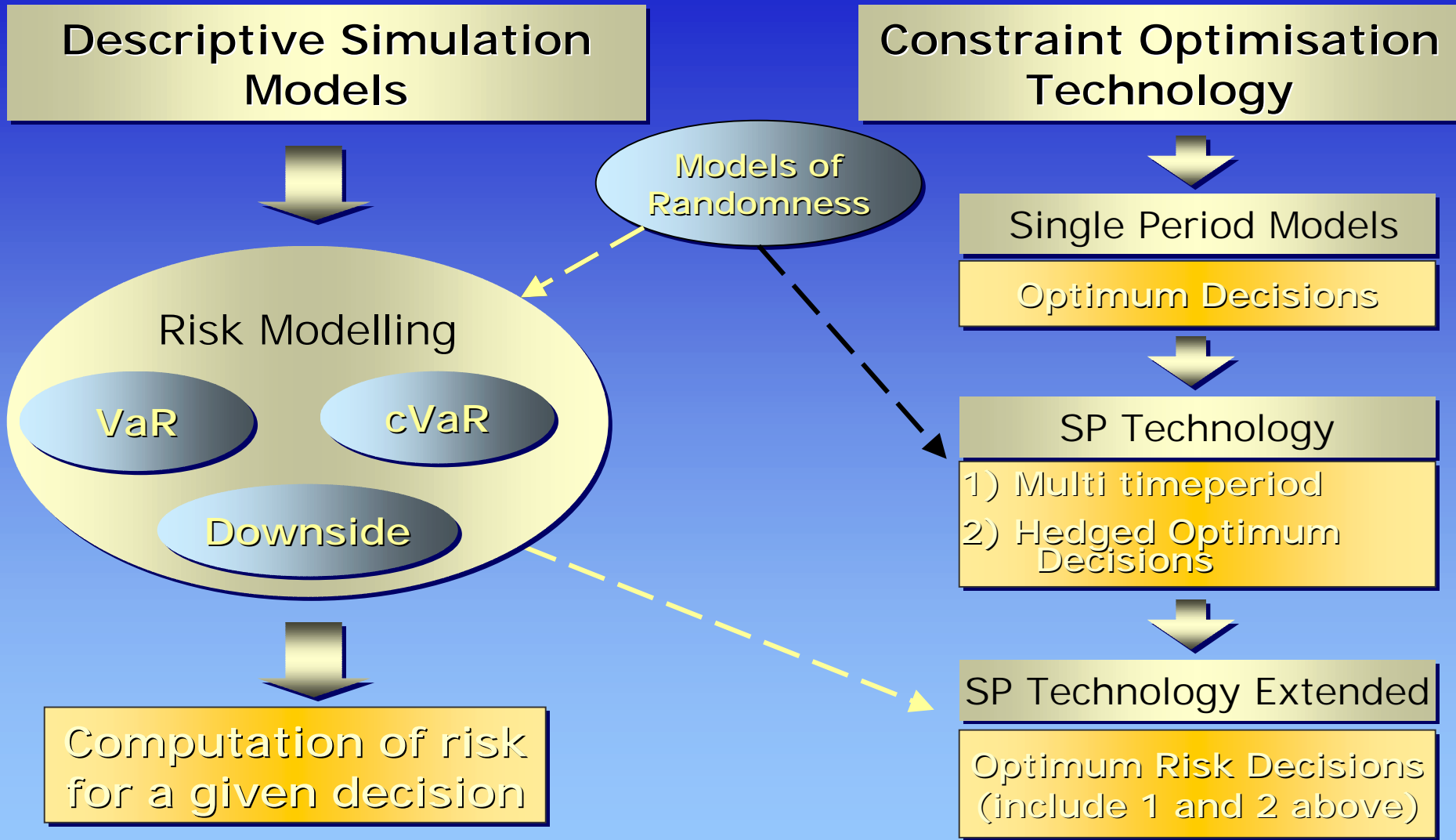
- C5.2 Amount of asset classes/stocks the investor buys

$$B_{ist} - B_{is't} = 0, \quad s=1, t=1 \forall i=1\dots n, s'=2\dots S$$

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Risk Decisions



Downside Risk

- The definition was introduced by Bawa (1975) and Fishburn (1977)
- Penalise only negative returns relative to a given benchmark – target θ
- $R_\gamma = E([\max\{\theta - x, 0\}]^\alpha) = \int_{-\infty}^{\theta} (\theta - x)^\alpha dF(x), \alpha \geq 0$
 - $F(x)$: the probability distribution function over portfolio returns x
 - $\alpha = 0$: Shortfall Probability
 - $\alpha = 1$: Expected Shortfall
 - $\alpha = 2$: Downside Variance

Downside Risk

➤ *Downside Risk Constraint*

- C6.1 $A_t - \left(\sum_{i=1}^n P_{ist} H_{ist} - L_{ist} + F_{ist} \right) \leq R_{ts}$,
 $t=2..T, s=1..S$.

- C6.2 $\sum_{s=1}^S \pi_s R_{ts} \leq (1-\gamma) * R_t^{\max}$

$$0 \leq \gamma \leq 1, i = 1..n, t = 2..T \text{ and } s = 1..S$$

- R_t^{\max} : maximum amount of downside risk the portfolio can have each time period
- R_{ts} : the downside risk for each scenario
- A_t : target level
- γ : parameter representing the risk aversion of the investor.

Value at Risk

➤ JP Morgan (1994), Uryasev et al. (1999), Bucay et al. (1999), Rockafellar & Uryasev (2000)

➤ VaR: The level of underperformance for a given portfolio with probability β

- $\Psi(x, \alpha) = \int_{f(x,y) \leq \alpha} p(x,y) dy$

- The probability that the loss function $f(x,y)$ does not exceed some threshold value α

- $\text{VaR}(x, \beta) = \min \{ \alpha \in \mathbb{R} \mid \Psi(x, \alpha) \geq \beta \}$

Value at Risk

- cVaR: The mean of the level of under performance for a given portfolio with probability β

- $$\text{cVaR}(x, \beta) = (1 - \beta)^{-1} \int_{f(x, y) \geq \text{VaR}(x, \beta)} f(x, y) p(y) d(y)$$

- $\text{cVaR} \geq \text{VaR}$
- cVaR can be minimised for discrete scenarios within the linear programming framework and we extend it to the SP setting

cVaR

➤ cVaR Risk Constraint (C7)

- $$\sum_{i=1}^n \{ (F_0 + H_{i,0} * P_{i,0}) - (F_t - L_{t,s} + H_{i,t-1,s} * P_{i,t,s}) \} - \alpha_t \leq z_{s,t} ,$$

 $t = 1, s=1...S$
- $$\sum_{i=1}^n \{ (F_{t-1} - L_{t-1,s} + H_{i,t-1,s} * P_{i,t-1,s}) - (F_t - L_{t,s} + H_{i,t-1,s} * P_{i,t,s}) \} - \alpha_t \leq z_{s,t} ,$$

 $t = 2...T, s=1...S$
- $$\alpha_t + S^{-1} * (1-\beta)^{-1} * \sum_{s=1}^S z_{st} \leq \bar{\omega}_t$$

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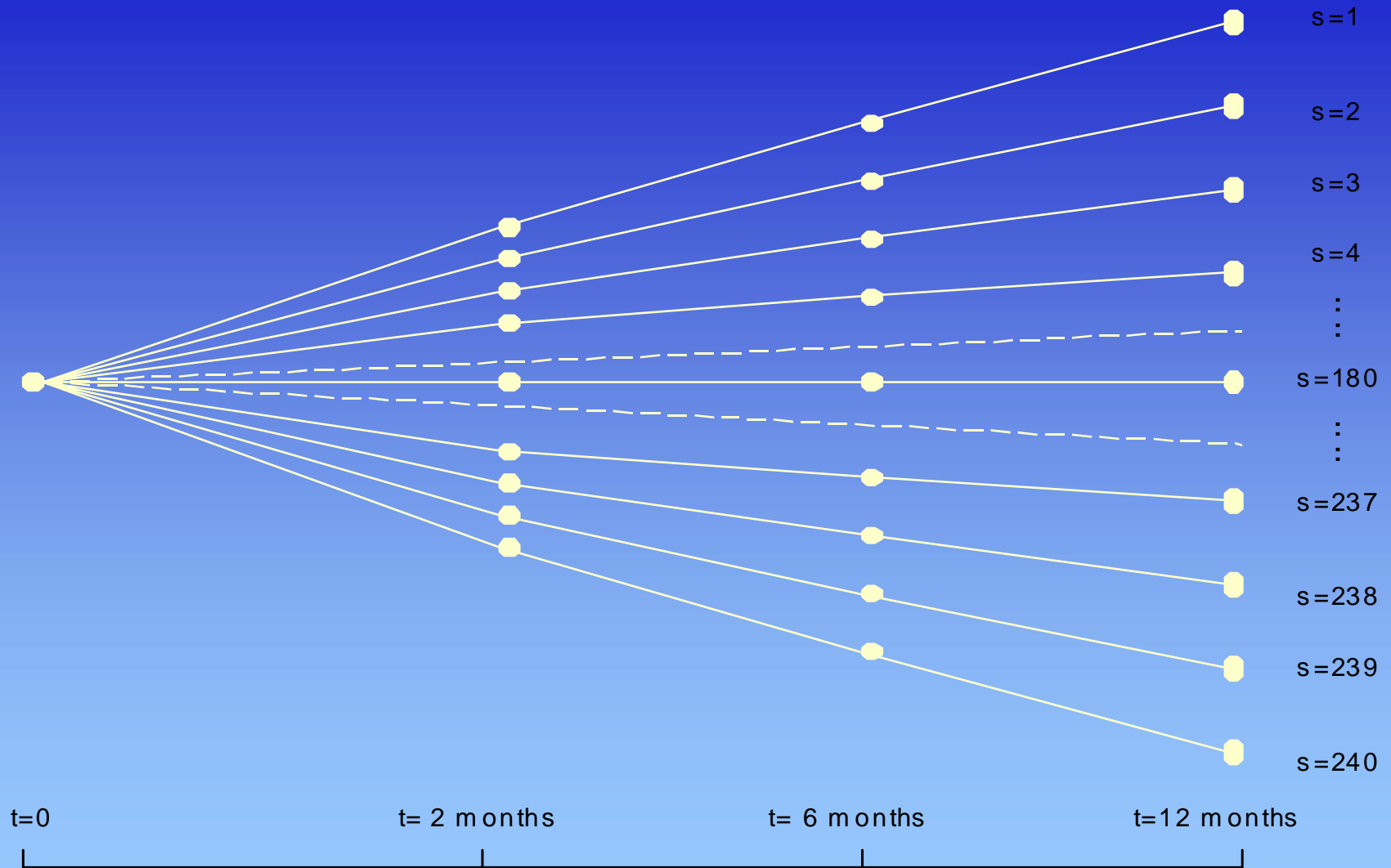
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Model specific characteristics and data

- 59 stocks constituting the S&P100
- 12 months planning horizon
- Rebalancing in months 2 and 6 The level of underperformance for a given portfolio with probability β
- 240 scenarios
- Classification of stocks into 5 Risk Groups
- 5 risk profiles:
 - Minimum, Medium Low, Medium, Medium High, and High risk

➤ 10 years backtesting

Two Stage Scenario Tree



Rolling Decisions

➤ Why rolling ?

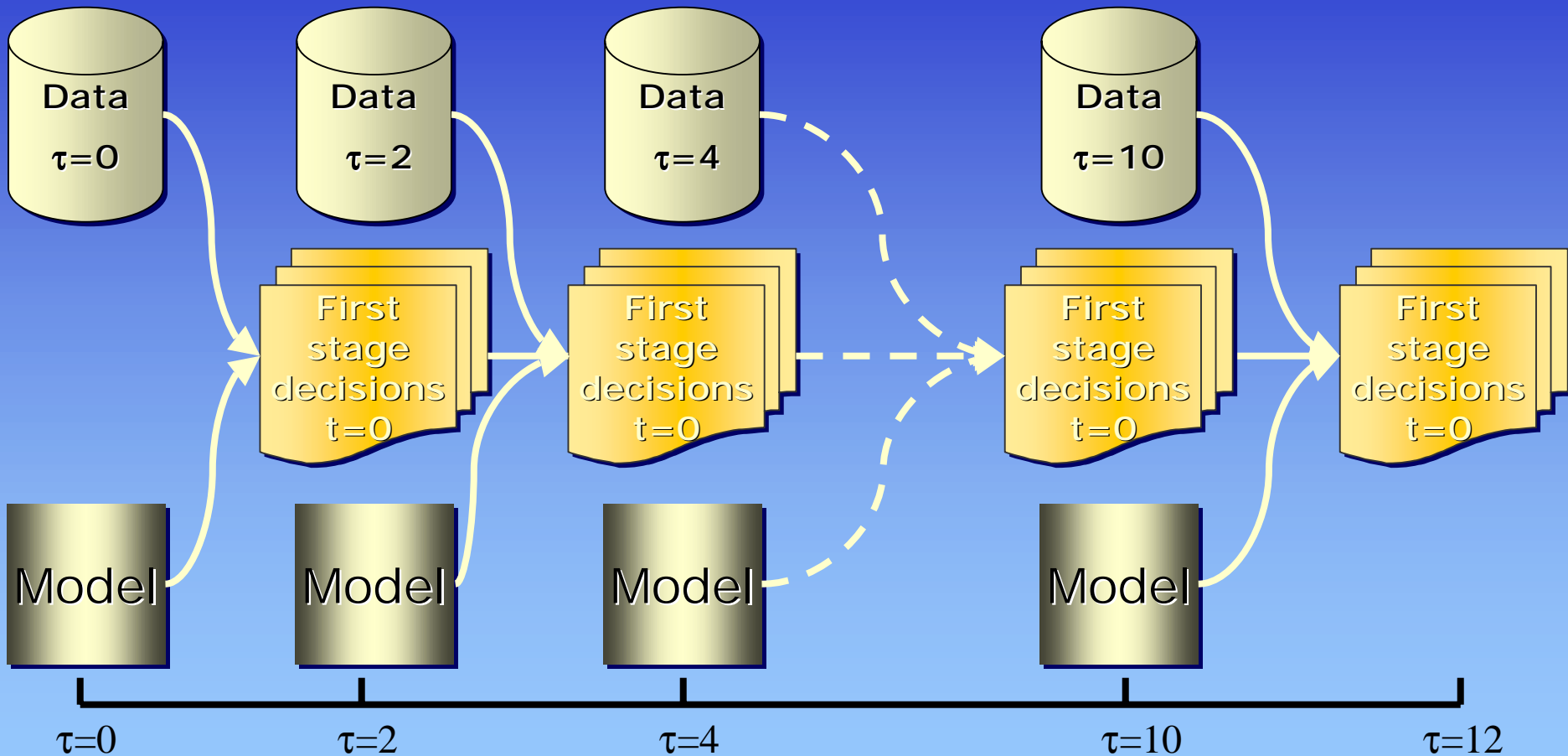
- Data and information in the financial markets is continuously updated
- In real life applications only the first stage decisions are followed

➤ What do we achieve ?

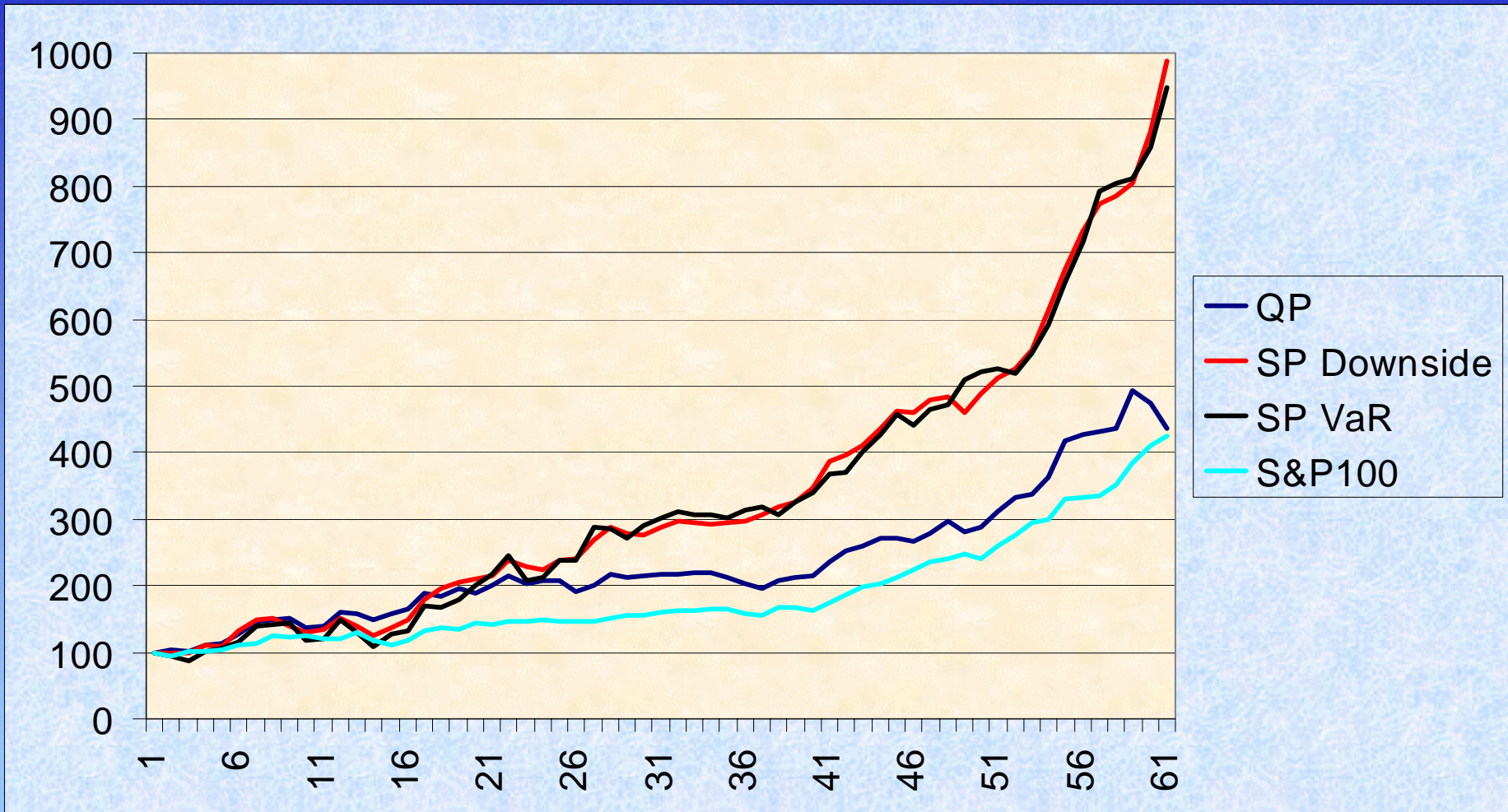
- We simulate the actions taken by the financial institution or the investor
- We simulate the impact that these actions have on the portfolio wealth
- We gain some insight into the behaviour of the models in respect of historical data

Rolling Decisions

➤ Explanation of the framework



Visual Demonstration of Results



Computational Results

Year	Risk Profile	SP Downside	SP VaR	QP
1989	Min	40.63%	39.74%	34.58%
	Medium Low	45.90%	41.58%	42.67%
	Medium	49.74%	52.52%	45.79%
	Medium High	49.11%	41.68%	41.53%
	High	40.55%	43.75%	33.46%
1990	Min	-8.27%	-7.14%	20.04%
	Medium Low	-6.50%	-4.09%	10.46%
	Medium	-6.36%	-9.54%	8.47%
	Medium High	-5.08%	-14.67%	8.91%
	High	1.06%	0.80%	10.59%
1993	Min	15.15%	20.20%	5.92%
	Medium Low	20.06%	20.16%	5.79%
	Medium	20.84%	21.90%	4.39%
	Medium High	21.61%	22.21%	4.68%
	High	26.30%	28.79%	6.39%
1998	Min	50.85%	50.41%	4.04%
	Medium Low	45.61%	50.32%	4.53%
	Medium	46.50%	39.65%	4.60%
	Medium High	46.92%	41.96%	3.32%
	High	46.50%	42.75%	10.27%

And in the end when it all gets too much...

