RECOGNITION ASSET MANAGEMENT SOLUTIONS

Client Customized Profile

Client Definition	Initial Asset Allocation	Dynamic Asset Allocation	Fund Selection	Performance and Risk Reporting
Classifying risk levels • Aversion / Tolerance to losses • Demand for income and capital growth • Geographic preferences • Allocation limits • Investment universe	**Bespoke Portfolio** • Adherence to Mandate • Adherence to Compliance • Adherence to Regulation • Target on loss minimization	**Dynamic Management** • Optimal rebalancing with respect to risk group definition • Identify market trends using Expert Opinions and AI-based Pattern Recognition	**Top Managers** • Multiple criteria • Multiple experts • Best choice • Ad-hoc Fund universe	**Full Information** • Constant reporting and monitoring • Audit trail for all decision making • Absolute control

CLIENT PROFILE

○ Target Portfolio: Client Profile

- **Risk Tolerance**: A key element in defining this profile is the investor's ability to assume a certain level of expected loss under exceptional market circumstances. When speaking of exceptionality, we refer to those situations whose probability of future occurrence is not greater than **5%**, but whose impact may generate a fall in equity (within 1 year) greater than **10%.**

- **Investment Universe**: The investment universe set with the different assets, their strategic reference weights, and the maximum and minimum limits for each of them are detailed in the table on next page, under the heading Strategic Portfolio. The aim is for the investor to have access to a sufficient variety of assets in order to obtain the best return-risk ratio in his/her portfolio thanks to proper diversification.

- **Investment Limits**: To ensure that we do not exceed this possible loss with that level of probability, maximum and minimum investment limits have been assigned for each of the assets and groups of assets that are part of the investment universe in the portfolio, so that under no circumstances these limits can be exceeded. In turn, **market stress scenarios have been analyzed** allowing us to consolidate, for the investment universe and defined limits, the stability and coherence of the proposed risk objective.

- **Market Views Choice**: The decision-making process based on human experts and/or artificial intelligence is applied to all levels of granularity that the assets in which it is going to invest. This way, the process initially generates overweight or underweight decisions for the large groups of assets (Equities, Government Bonds, Credit, Alternative Funds, and Liquidity). Later and within each of these groups, this is when the management decisions for each individual asset are also obtained through the process. For example, in the case of Credit Assets, the process will indicate which markets are the most recommended within the USA Investment Grade, Eurozone Investment Grade, USA Speculative Grade, Europe Speculative Grade and Emerging Countries Credit).

- **Active Tactical Management**: The process achieves a permanent surveillance of new market scenarios, necessary for agility in decision-making. The time horizon for these decisions is 6 weeks. After these 6 weeks, the entire process is carried out again, incorporating the most recent information to, in this way, allow continuous decision-making appropriate to the current macroeconomic and financial environment.

RAMS

Client Customized Profile

○ Strategic Asset Allocation

	Mínima	Neutral	Máxima
Equities	18.0%	36.0%	50.0%
Equity US	8.0%	14.0%	25.0%
Equity Europe	8.0%	14.0%	25.0%
Equity Japan	1.0%	3.5%	6.0%
Equity GEM	1.0%	4.5%	8.0%
Government	9.0%	20.5%	32.0%
US Treasury	3.0%	7.5%	12.0%
Eurozone Government	6.0%	13.0%	20.0%
Credit	16.0%	34.0%	52.0%
Investment Grade US	6.0%	10.5%	15.0%
Investment Grade Eurozone	8.0%	11.5%	15.0%
High Yield US	1.0%	4.5%	8.0%
High Yield Europe	1.0%	4.5%	8.0%
GEM Credit	0.0%	3.0%	6.0%
Alternative	0.0%	8.0%	21.0%
Cash	0.0%	1.5%	3.0%

MARKET ANALYSIS

RAMS

Dynamic Allocation – Professional Experts Opinions

- Analyst: Global Asset Allocation Expert A
- Focus: Top Asset Classes
- Granularity: Level 1

Decision survey

Global Assets

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium_High	High	Medium	Medium_Low
EQUITIES	Overweight	Overweight	Overweight	Neutral	Mild_Overweight	Mild_Underweight
GOVERNMENT	Underweight	Underweight	Neutral	Strong_Underweight	Underweight	Mild_Overweight
CREDIT	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Overweight	Mild_Overweight
ALTERNATIVE	Mild_Overweight	Overweight	Overweight	Overweight	Mild_Underweight	Neutral
CASH	Mild_Overweight	Mild_Underweight	Neutral	Underweight	Mild_Overweight	Mild_Overweight

Dynamic Allocation – Professional Experts Opinions

- Analyst: Global Equity Allocation Expert A
- Focus: Equity Classes
- Granularity: Level 2

Equity Regions

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	Medium_High	High	Medium	Medium_High	Low
USAEQLOC	Neutral	Mild_Overweight	Mild_Overweight	Mild_Underweight	Underweight	Mild_Overweight
EUREQLOC	Mild_Underweight	Neutral	Underweight	Mild_Underweight	Mild_Underweight	Mild_Underweight
JPNEQLOC	Underweight	Underweight	Underweight	Underweight	Mild_Underweight	Neutral
GEMEQLOC	Overweight	Neutral	Overweight	Overweight	Overweight	Mild_Underweight

RAMS

Dynamic Allocation – Professional Experts Opinions

- Analyst: Global Government Allocation Expert A
- Focus: Government Bond Classes
- Granularity: Level 2

Developed Government Areas

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	High	Medium	Low	Medium	Low
USAGOVLOC	Neutral	Neutral	Neutral	Neutral	Underweight	Overweight
EMUGOVLOC	Mild_Underweight	Neutral	Neutral	Mild_Underweight	Neutral	Neutral

Dynamic Allocation – Professional Experts Opinions

- Analyst: Global Credit Allocation Expert A
- Focus: Corporate Bond Classes
- Granularity: Level 2

Global Credit

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	Medium	Medium	High	Medium_High	Medium_Low
USAIGLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Overweight
EMUIGLOC	Neutral	Mild_Underweight	Neutral	Underweight	Mild_Underweight	Mild_Underweight
USAHYLOC	Mild_Underweight	Mild_Underweight	Mild_Underweight	Underweight	Mild_Underweight	Mild_Underweight
EURHYLOC	Mild_Underweight	Mild_Underweight	Mild_Underweight	Underweight	Mild_Underweight	Underweight
GEMGOCO	Strong_Overweight	Overweight	Mild_Overweight	Overweight	Overweight	Mild_Overweight

RAMS

Dynamic Allocation – Professional Experts Opinions

- Analyst: Emerging Markets Credit Expert A
- Focus: Emerging Markets Corporate Bonds
- Granularity: Level 3

Global Emerging Markets Government and Corporates

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium	Medium_High	Medium	Medium_High
GEMGOCOLC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Mild_Overweight
GEMGOCOHC	Mild_Underweight	Mild_Underweight	Neutral	Neutral	Neutral	Mild_Underweight

Dynamic Allocation – Professional Experts Opinions

- Analyst: Alternative Assets Expert A
- Focus: Alternative Assets Classes
- Granularity: Level 2

Alternative Assets

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium	Medium_High	Low	Low
COMPABSRLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Underweight
MKTNEULOC	Mild_Overweight	Overweight	Mild_Overweight	Neutral	Neutral	Mild_Overweight
COMMLOC	Underweight	Mild_Overweight	Mild_Underweight	Neutral	Mild_Overweight	Mild_Underweight

- Analyst: Currencies Expert A
- Focus: FX
- Granularity: Level 1

Global FX (all currencies against EUR)

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium_High	Medium_High	Medium	Medium_Low
USD	Mild_Underweight	Mild_Overweight	Strong_Overweight	Mild_Underweight	Neutral	Neutral
GBP	Mild_Underweight	Neutral	Neutral	Underweight	Neutral	Mild_Overweight
JPY	Strong_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Underweight
CHF	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Mild_Underweight
GEM	Underweight	Underweight	Neutral	Strong_Underweight	Neutral	Overweight

RAMS

Dynamic Allocation – Professional Experts Opinions

- Investment Committe, 5 Analysts
- Focus: Top Asset Classes
- Granularity: Level 1

Global Assets

- Analyst: Global Asset Allocation Expert A
- Focus: Top Asset Classes
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium_High	High	Medium	Medium_Low
EQUITIES	Overweight	Overweight	Overweight	Neutral	Mild_Overweight	Mild_Underweight
GOVERNMENT	Underweight	Underweight	Neutral	Strong_Underweight	Underweight	Mild_Overweight
CREDIT	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Overweight	Mild_Overweight
ALTERNATIVE	Mild_Overweight	Overweight	Overweight	Overweight	Mild_Underweight	Neutral
CASH	Mild_Overweight	Mild_Underweight	Neutral	Underweight	Mild_Overweight	Mild_Overweight

- Analyst: Global Asset Allocation Expert B
- Focus: Top Asset Classes
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium	Medium_High	Medium	Medium_Low
EQUITIES	Mild_Overweight	Overweight	Overweight	Mild_Underweight	Mild_Overweight	Mild_Underweight
GOVERNMENT	Underweight	Underweight	Neutral	Underweight	Underweight	Mild_Overweight
CREDIT	Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Mild_Overweight	Neutral
ALTERNATIVE	Mild_Overweight	Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Neutral
CASH	Mild_Overweight	Mild_Underweight	Neutral	Underweight	Mild_Overweight	Mild_Overweight

- Analyst: Global Asset Allocation Expert C
- Focus: Top Asset Classes
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_Low	High	Medium_High	High	Medium	Medium_Low
EQUITIES	Overweight	Strong_Overweight	Strong_Overweight	Neutral	Neutral	Neutral
GOVERNMENT	Mild_Underweight	Underweight	Mild_Underweight	Strong_Underweight	Underweight	Mild_Overweight
CREDIT	Strong_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Underweight
ALTERNATIVE	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Mild_Underweight
CASH	Underweight	Underweight	Neutral	Strong_Underweight	Neutral	Overweight

- Analyst: Global Asset Allocation Expert D
- Focus: Top Asset Classes
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	High	Medium_High	Medium_High	Medium	Medium_Low
EQUITIES	Overweight	Strong_Overweight	Mild_Overweight	Mild_Underweight	Neutral	Mild_Underweight
GOVERNMENT	Underweight	Underweight	Neutral	Underweight	Mild_Underweight	Mild_Overweight
CREDIT	Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Overweight	Neutral
ALTERNATIVE	Overweight	Mild_Overweight	Overweight	Mild_Overweight	Mild_Underweight	Neutral
CASH	Mild_Overweight	Mild_Underweight	Neutral	Underweight	Mild_Overweight	Mild_Overweight

- Analyst: Global Asset Allocation Expert E
- Focus: Top Asset Classes
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	High	High	Very_High	Low	Very_High
EQUITIES	Underweight	Overweight	Underweight	Strong_Underweight	Overweight	Strong_Underweight
GOVERNMENT	Strong_Underweight	Underweight	Strong_Underweight	Underweight	Mild_Overweight	Neutral
CREDIT	Underweight	Neutral	Underweight	Underweight	Neutral	Underweight
ALTERNATIVE	Strong_Overweight	Mild_Overweight	Strong_Overweight	Strong_Overweight	Mild_Overweight	Strong_Overweight
CASH	Overweight	Neutral	Overweight	Mild_Overweight	Underweight	Overweight

RAMS

Dynamic Allocation – Professional Experts Opinions

- Investment Committe, 5 Analysts
- Focus: Equity Classes
- Granularity: Level 2

Equity Regions

- Analyst: Global Equity Allocation Expert A
- Focus: Equity Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	Medium_High	High	Medium	Medium_High	Low
USAEQLOC	Neutral	Mild_Overweight	Mild_Overweight	Mild_Underweight	Underweight	Mild_Overweight
EUREQLOC	Mild_Underweight	Neutral	Underweight	Mild_Underweight	Mild_Underweight	Mild_Underweight
JPNEQLOC	Underweight	Underweight	Underweight	Underweight	Mild_Underweight	Neutral
GEMEQLOC	Overweight	Neutral	Overweight	Overweight	Overweight	Mild_Underweight

- Analyst: Global Equity Allocation Expert B
- Focus: Equity Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	Medium_High	High	Medium	Medium_High	Low
USAEQLOC	Neutral	Mild_Overweight	Mild_Overweight	Mild_Underweight	Underweight	Mild_Overweight
EUREQLOC	Mild_Underweight	Neutral	Mild_Overweight	Mild_Underweight	Mild_Underweight	Mild_Underweight
JPNEQLOC	Underweight	Underweight	Mild_Underweight	Underweight	Neutral	Neutral
GEMEQLOC	Overweight	Overweight	Mild_Underweight	Overweight	Overweight	Mild_Underweight

- Analyst: Global Equity Allocation Expert C
- Focus: Equity Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	Medium_High	High	Medium	Medium_High	Low
USAEQLOC	Neutral	Neutral	Underweight	Mild_Underweight	Underweight	Overweight
EUREQLOC	Mild_Underweight	Neutral	Underweight	Mild_Overweight	Mild_Underweight	Mild_Underweight
JPNEQLOC	Mild_Underweight	Mild_Underweight	Neutral	Underweight	Neutral	Neutral
GEMEQLOC	Overweight	Overweight	Mild_Overweight	Overweight	Overweight	Mild_Underweight

- Analyst: Global Equity Allocation Expert D
- Focus: Equity Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	Medium_High	High	Medium	Medium_High	Low
USAEQLOC	Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Underweight	Mild_Overweight
EUREQLOC	Mild_Underweight	Neutral	Mild_Overweight	Mild_Underweight	Mild_Underweight	Mild_Underweight
JPNEQLOC	Underweight	Underweight	Mild_Underweight	Strong_Underweight	Neutral	Neutral
GEMEQLOC	Overweight	Overweight	Neutral	Overweight	Neutral	Mild_Underweight

- Analyst: Global Equity Allocation Expert E
- Focus: Equity Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Very_High	Medium	Very_High	Low	High
USAEQLOC	Neutral	Mild_Overweight	Overweight	Mild_Underweight	Neutral	Mild_Overweight
EUREQLOC	Underweight	Overweight	Strong_Underweight	Underweight	Neutral	Strong_Underweight
JPNEQLOC	Neutral	Mild_Underweight	Neutral	Neutral	Neutral	Neutral
GEMEQLOC	Strong_Overweight	Underweight	Mild_Underweight	Strong_Overweight	Neutral	Mild_Underweight

RAMS

Dynamic Allocation – Professional Experts Opinions

- Investment Committe, 5 Analysts
- Focus: Government Bonds
- Granularity: Level 2

- Analyst: Global Government Allocation Expert A
- Focus: Government Bond Classes
- Granularity: Level 2

Developed Government Areas

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	High	Medium	Low	Medium	Low
USAGOVLOC	Neutral	Neutral	Neutral	Neutral	Underweight	Overweight
EMUGOVLOC	Mild_Underweight	Neutral	Neutral	Mild_Underweight	Neutral	Neutral

- Analyst: Global Government Allocation Expert B
- Focus: Government Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	High	Medium	Low	Medium	Low
USAGOVLOC	Neutral	Neutral	Overweight	Neutral	Underweight	Overweight
EMUGOVLOC	Mild_Underweight	Mild_Underweight	Neutral	Mild_Underweight	Neutral	Neutral

- Analyst: Global Government Allocation Expert C
- Focus: Government Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	High	Medium	Low	Medium	Low
USAGOVLOC	Neutral	Neutral	Neutral	Neutral	Underweight	Overweight
EMUGOVLOC	Mild_Underweight	Neutral	Neutral	Mild_Underweight	Neutral	Neutral

- Analyst: Global Government Allocation Expert D
- Focus: Government Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	High	Medium	Low	Medium	Low
USAGOVLOC	Mild_Underweight	Neutral	Mild_Overweight	Neutral	Underweight	Overweight
EMUGOVLOC	Mild_Overweight	Mild_Underweight	Neutral	Mild_Underweight	Neutral	Neutral

- Analyst: Global Government Allocation Expert E
- Focus: Government Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Very_High	High	Medium	Very_High	Low	High
USAGOVLOC	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral
EMUGOVLOC	Underweight	Underweight	Underweight	Underweight	Neutral	Underweight

RAMS

Dynamic Allocation – Professional Experts Opinions

- Investment Committe, 5 Analysts
- Focus: Corporate Bonds
- Granularity: Level 2

Global Credit

- Analyst: Global Credit Allocation Expert A
- Focus: Corporate Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	Medium	Medium	High	Medium_High	Medium_Low
USAIGLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Overweight
EMUIGLOC	Neutral	Mild_Underweight	Neutral	Underweight	Mild_Underweight	Mild_Underweight
USAHYLOC	Mild_Underweight	Mild_Underweight	Mild_Underweight	Underweight	Mild_Underweight	Mild_Underweight
EURHYLOC	Mild_Underweight	Mild_Underweight	Mild_Underweight	Underweight	Mild_Underweight	Underweight
GEMGOCO	Strong_Overweight	Overweight	Mild_Overweight	Overweight	Overweight	Mild_Overweight

- Analyst: Global Credit Allocation Expert B
- Focus: Corporate Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	Medium	Medium	Medium_High	Medium_High	Medium_Low
USAIGLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Overweight
EMUIGLOC	Neutral	Mild_Underweight	Neutral	Underweight	Mild_Underweight	Mild_Underweight
USAHYLOC	Mild_Underweight	Mild_Underweight	Mild_Underweight	Underweight	Mild_Underweight	Mild_Underweight
EURHYLOC	Mild_Underweight	Underweight	Neutral	Strong_Underweight	Mild_Overweight	Underweight
GEMGOCO	Overweight	Overweight	Neutral	Strong_Overweight	Mild_Overweight	Mild_Overweight

- Analyst: Global Credit Allocation Expert C
- Focus: Corporate Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_Low	Medium	Medium	Low	Medium_High	Medium_Low
USAIGLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Overweight
EMUIGLOC	Neutral	Mild_Underweight	Neutral	Underweight	Mild_Underweight	Mild_Underweight
USAHYLOC	Mild_Underweight	Underweight	Mild_Underweight	Mild_Underweight	Mild_Underweight	Mild_Underweight
EURHYLOC	Underweight	Underweight	Mild_Underweight	Underweight	Neutral	Underweight
GEMGOCO	Overweight	Overweight	Neutral	Overweight	Overweight	Mild_Overweight

- Analyst: Global Credit Allocation Expert D
- Focus: Corporate Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium_High	Medium	Medium	Low	Medium_High	Medium_Low
USAIGLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Overweight
EMUIGLOC	Neutral	Mild_Underweight	Neutral	Underweight	Mild_Underweight	Mild_Underweight
USAHYLOC	Neutral	Mild_Overweight	Mild_Underweight	Mild_Underweight	Mild_Underweight	Mild_Underweight
EURHYLOC	Mild_Underweight	Mild_Underweight	Mild_Underweight	Neutral	Underweight	Underweight
GEMGOCO	Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight

- Analyst: Global Credit Allocation Expert E
- Focus: Corporate Bond Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium_High	Very_High	Medium_High	Medium_Low
USAIGLOC	Mild_Underweight	Mild_Overweight	Neutral	Underweight	Neutral	Neutral
EMUIGLOC	Strong_Underweight	Mild_Underweight	Neutral	Strong_Underweight	Underweight	Mild_Underweight
USAHYLOC	Neutral	Mild_Overweight	Neutral	Neutral	Mild_Underweight	Underweight
EURHYLOC	Underweight	Neutral	Neutral	Mild_Underweight	Mild_Overweight	Strong_Underweight
GEMGOCO	Mild_Overweight	Mild_Overweight	Neutral	Mild_Overweight	Strong_Overweight	Mild_Overweight

RAMS

Dynamic Allocation – Professional Experts Opinions

- Investment Committe, 5 Analysts
- Focus: GEM Corporate Bonds
- Granularity: Level 3

Global Emerging Markets Government and Corporates

- Analyst: GEM Credit Expert A
- Focus: GEM Corporate Bonds
- Granularity: Level 3

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium	Medium_High	Medium	Medium_High
GEMGOCOLC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Mild_Overweight
GEMGOCOHC	Mild_Underweight	Mild_Underweight	Neutral	Neutral	Neutral	Mild_Underweight

- Analyst: GEM Credit Expert B
- Focus: GEM Corporate Bonds
- Granularity: Level 3

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium	Medium_High	Medium	Medium_High
GEMGOCOLC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Mild_Overweight
GEMGOCOHC	Mild_Underweight	Mild_Underweight	Neutral	Neutral	Neutral	Mild_Underweight

- Analyst: GEM Credit Expert C
- Focus: GEM Corporate Bonds
- Granularity: Level 3

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium	Medium_High	Medium	Medium_High
GEMGOCOLC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Mild_Overweight
GEMGOCOHC	Mild_Underweight	Mild_Underweight	Neutral	Neutral	Neutral	Mild_Underweight

- Analyst: GEM Credit Expert D
- Focus: GEM Corporate Bonds
- Granularity: Level 3

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium	Medium_High	Medium	Medium_High
GEMGOCOLC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Mild_Overweight
GEMGOCOHC	Mild_Underweight	Mild_Underweight	Neutral	Neutral	Neutral	Mild_Underweight

- Analyst: GEM Credit Expert E
- Focus: GEM Corporate Bonds
- Granularity: Level 3

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	Medium	Medium_High	High	Medium	Medium_High
GEMGOCOLC	Neutral	Mild_Underweight	Neutral	Mild_Overweight	Neutral	Underweight
GEMGOCOHC	Mild_Underweight	Neutral	Mild_Overweight	Neutral	Neutral	Neutral

RAMS

Dynamic Allocation – Professional Experts Opinions

- Investment Committe, 5 Analysts
- Focus: Alternative Assets Classes
- Granularity: Level 2

Alternative Assets

- Analyst: Alternative Assets Expert A
- Focus: Alternative Assets Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium	Medium_High	Low	Low
COMPABSRLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Underweight
MKTNEULOC	Mild_Overweight	Overweight	Mild_Overweight	Neutral	Neutral	Mild_Overweight
COMMLOC	Underweight	Mild_Overweight	Mild_Underweight	Neutral	Mild_Overweight	Mild_Underweight

- Analyst: Alternative Assets Expert **B**
- Focus: Alternative Assets Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium	Medium_High	Low	Low
COMPABSRLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Underweight
MKTNEULOC	Mild_Overweight	Overweight	Mild_Overweight	Neutral	Neutral	Mild_Overweight
COMMLOC	Underweight	Mild_Overweight	Mild_Underweight	Neutral	Mild_Overweight	Mild_Underweight

- Analyst: Alternative Assets Expert C
- Focus: Alternative Assets Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium	Medium_High	Low	Low
COMPABSRLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Underweight
MKTNEULOC	Mild_Overweight	Overweight	Mild_Overweight	Neutral	Neutral	Mild_Overweight
COMMLOC	Underweight	Mild_Underweight	Mild_Underweight	Overweight	Mild_Overweight	Mild_Underweight

- Analyst: Alternative Assets Expert **D**
- Focus: Alternative Assets Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium	Medium_High	Low	Low
COMPABSRLOC	Mild_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Neutral	Underweight
MKTNEULOC	Mild_Overweight	Overweight	Mild_Overweight	Neutral	Neutral	Mild_Overweight
COMMLOC	Underweight	Mild_Overweight	Mild_Underweight	Neutral	Mild_Overweight	Mild_Underweight

- Analyst: Alternative Assets Expert **E**
- Focus: Alternative Assets Classes
- Granularity: Level 2

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	High	Medium	High	Medium	High
COMPABSRLOC	Mild_Overweight	Mild_Overweight	Neutral	Overweight	Neutral	Mild_Overweight
MKTNEULOC	Overweight	Overweight	Strong_Overweight	Strong_Overweight	Neutral	Overweight
COMMLOC	Neutral	Neutral	Neutral	Mild_Underweight	Neutral	Strong_Underweight

RAMS

Dynamic Allocation – Professional Experts Opinions

- Investment Committe, 5 Analysts
- Focus: FX
- Granularity: Level 1

Global FX (all currencies against EUR)

- Analyst: Currencies Expert A
- Focus: FX
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium_High	Medium_High	Medium	Medium_Low
USD	Mild_Underweight	Mild_Overweight	Strong_Overweight	Mild_Underweight	Neutral	Neutral
GBP	Mild_Underweight	Neutral	Neutral	Underweight	Neutral	Mild_Overweight
JPY	Strong_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Underweight
CHF	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Mild_Underweight
GEM	Underweight	Underweight	Neutral	Strong_Underweight	Neutral	Overweight

- Analyst: Currencies Expert B
- Focus: FX
- Granularity: Level 1

Importance:	Medium	High	Medium_High	Medium_High	Medium	Medium_Low
USD	Mild_Underweight	Mild_Overweight	Strong_Overweight	Mild_Underweight	Neutral	Neutral
GBP	Mild_Underweight	Neutral	Neutral	Underweight	Neutral	Mild_Overweight
JPY	Strong_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Underweight
CHF	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Mild_Underweight
GEM	Underweight	Underweight	Neutral	Strong_Underweight	Neutral	Overweight

- Analyst: Currencies Expert C
- Focus: FX
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium_High	Medium_High	Medium	Medium_Low
USD	Mild_Underweight	Mild_Overweight	Strong_Overweight	Mild_Underweight	Neutral	Neutral
GBP	Mild_Underweight	Neutral	Neutral	Underweight	Neutral	Mild_Overweight
JPY	Strong_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Underweight
CHF	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Mild_Underweight
GEM	Underweight	Underweight	Neutral	Strong_Underweight	Neutral	Overweight

- Analyst: Currencies Expert D
- Focus: FX
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	Medium	High	Medium_High	Medium_High	Medium	Medium_Low
USD	Mild_Underweight	Mild_Overweight	Strong_Overweight	Mild_Underweight	Neutral	Neutral
GBP	Mild_Underweight	Neutral	Neutral	Underweight	Neutral	Mild_Overweight
JPY	Strong_Overweight	Mild_Overweight	Neutral	Mild_Underweight	Mild_Underweight	Mild_Underweight
CHF	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Overweight	Mild_Underweight	Mild_Underweight
GEM	Underweight	Underweight	Neutral	Strong_Underweight	Neutral	Overweight

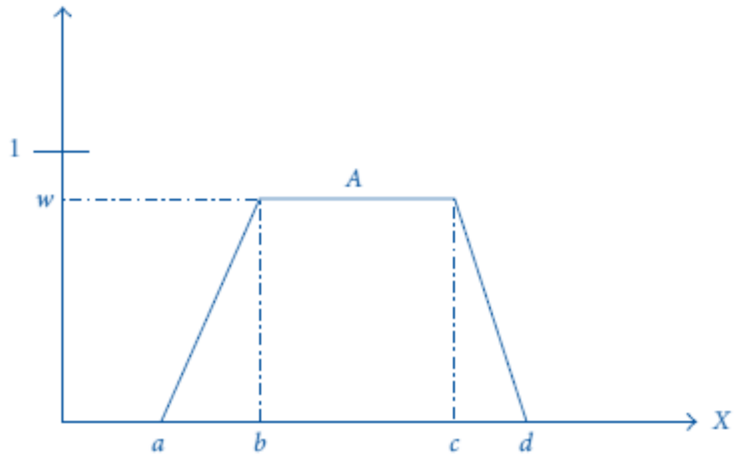
- Analyst: Currencies Expert E
- Focus: FX
- Granularity: Level 1

Criteria:	Macroeconomics	Sentiment	Policy	Value	Technical	Systemic_Risk
Importance:	High	High	Very_High	High	Medium	High
USD	Mild_Overweight	Mild_Overweight	Strong_Overweight	Neutral	Neutral	Mild_Overweight
GBP	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral
JPY	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral
CHF	Neutral	Neutral	Mild_Overweight	Neutral	Neutral	Overweight
GEM	Neutral	Neutral	Neutral	Mild_Overweight	Neutral	Underweight

○ FUZZY LOGIC

- Fuzzy logic is a logic that allows vagueness, imprecision, and uncertainty. The concept of fuzzy sets and the respective theory that can be regarded as the extension of the classical set theory. One of the fundamental mathematical constructs is the similarity measure. In the same way as the notion of the fuzzy subset generalizes that of the classical subset, the concept of similarity can be considered as being a multivalued generalization of the classical notion of equivalence.

- We can represent a generalized trapezoidal fuzzy number A as A = (a, b, c, d; w), where a, b, c, and d are real values and $0 < w \leq 1$ as shown below.

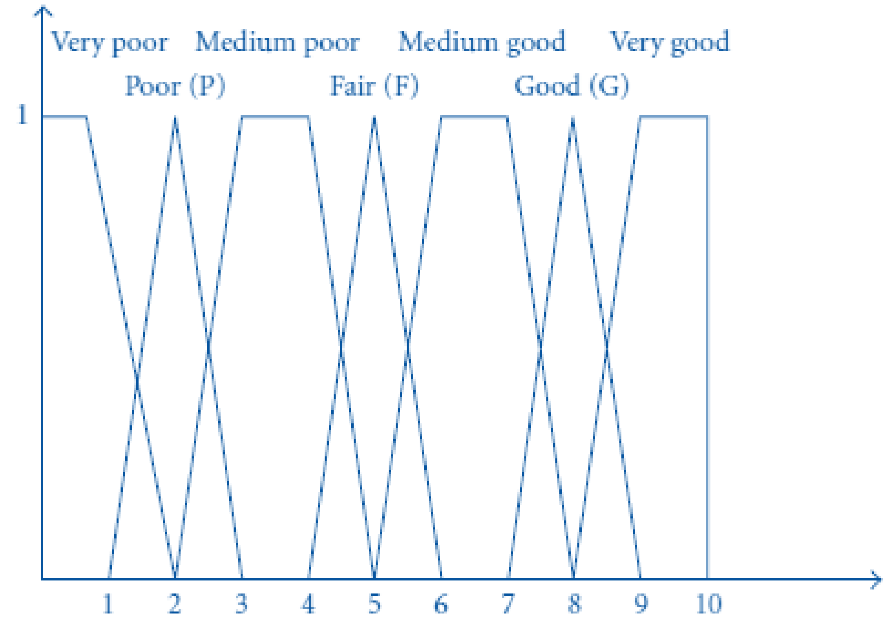


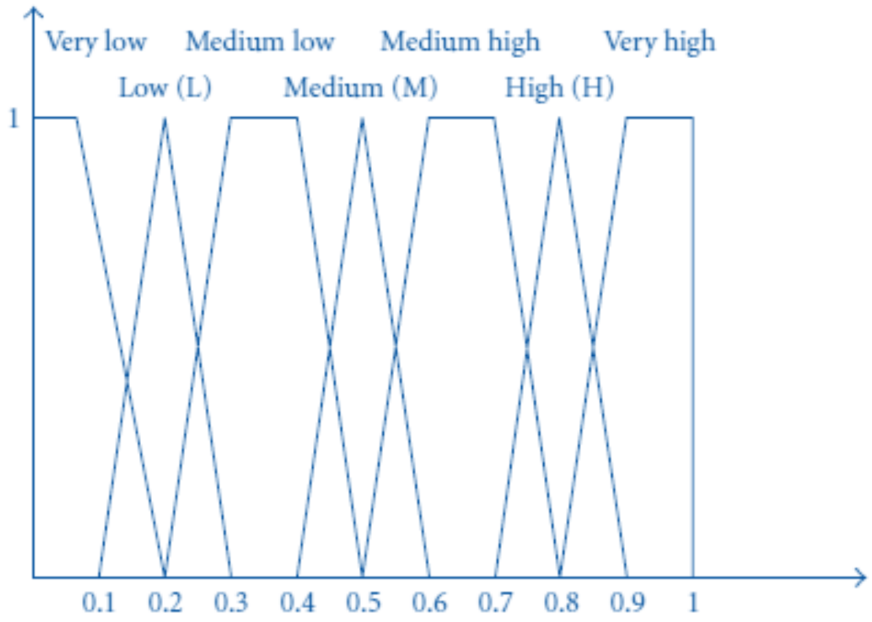
- Assume that we have two generalized trapezoidal fuzzy numbers A and B, where A = (a1, a2, a3, a4,wa) and B = (b1, b2, b3, b4,wb). The degree of similarity between two generalized fuzzy numbers can be computed as:

$$S(\tilde{A},\tilde{B}) = \left(1 - \frac{\sum_{i=1}^{4}|a_i - b_i|}{4}\right) \times \frac{\min\left(P(\tilde{A}),P(\tilde{B})\right) + \min(w_a, w_b)}{\max\left(P(\tilde{A}),P(\tilde{B})\right) + \max(w_a, w_b)}$$

Dynamic Allocation – Professional Experts Opinions

- In this case we consider the importance weights of various criteria and the ratings of qualitative criteria as linguistic variables. Because linguistic assessments approximate the subjective judgement of decision-maker, we are using linear trapezoidal membership functions to capture the vagueness of these linguistic assessments. These linguistic variables (that we define as opinions and convictions on those opinions) can be expressed in positive trapezoidal fuzzy numbers, as shown in the figures below.





- The importance weight of each criterion can be either directly assigning or indirectly using pairwise comparison. In this project linguistic variables shown are used to evaluate the importance of the criteria and the ratings of alternatives with respect to qualitative criteria. For example, the linguistic variable “Medium Good” can be represented as (5, 6, 7, 8) and “Good” as (7, 8, 8, 9).

o TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution

- A tactical approach towards asset selection often involves multiple criteria and several decision makers, and decision-making is often influenced by uncertainty in practice.

- Asset selection may involve several and different types of criteria, combination of different decision models, group decision-making, and various forms of uncertainty. The technique for order of preference by similarity to ideal solution (TOPSIS), which is one of the known classical MCDM (Multi Criteria Decision Making) methods, may provide the basis for developing asset selection models that can effectively deal with these properties. It bases upon the concept that the chosen alternative should have the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS).

- TOPSIS is extended to fuzzy environment where linguistic assessments can be used instead of numerical values. This method allows to consider the fuzziness in the decision data and group decision-making process, where linguistic variables are used to assess the weights of all criteria and the ratings of each alternative with respect to each criterion.

Dynamic Allocation – Professional Experts Opinions

The proposed method is applied to solve the problem, and its computational procedure is summarized as follows:

- Step 1. Decision-makers use the linguistic weighting variables to assess the importance of the criteria and relevance of their opinions.
- Step 2. Decision-makers use the linguistic rating variables to evaluate the ratings of suppliers with respect to each criterion.
- Step 3. Convert the linguistic evaluations into trapezoidal fuzzy numbers and determine the fuzzy weight of each criterion.
- Step 4. Normalize the fuzzy-decision matrix.
- Step 5. Build the weighted normalized fuzzy-decision matrix.
- Step 6. Determine the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS).
- Step 7. Calculate the similarity of each asset class by using weighted normalized fuzzy decision matrix and FPIS by calculating the similarity matrix, and then average similarity value for each asset.

```
% linguistic variables for importance weight of each criterion as generalized fuzzy numbers:
VL=[0 0 0.1 0.2 1];      %Very low
L=[0.1 0.2 0.2 0.3 1];   %Low
ML=[0.2 0.3 0.4 0.5 1];  %Medium low
M=[0.4 0.5 0.5 0.6 1];   %Medium
MH=[0.5 0.6 0.7 0.8 1];  %Medium high
H=[0.7 0.8 0.8 0.9 1];   %High
VH=[0.8 0.9 1.0 1.0 1];  %Very High
% linguistic variables for ratings as fuzzy numbers:
VP=[0,0,1,2, 1];     % Very Poor
P=[1,2,2,3, 1];      % Poor
MP=[2,3,4,5, 1];     % Medium Poor
F=[4,5,5,6, 1];      % Fair
MG=[5,6,7,8, 1];     % Medium Good
G=[7,8,8,9, 1];      % Good
VG=[8,9,10,10,1];    % Very Good
```

Dynamic Allocation – Professional Experts Opinions

```
% Number of decision makers k
numberExperts = size(WDL1Global,1);
k = numberExperts;

% Number of criterias to be evaluated n
numberCriteria = size(WDL1Global,2);
n = numberCriteria;

% Number of attributes to be ranked (assets, sub-assets, etc...) m
numberAssets = size(FDML1Global,1)/numberExperts;
m = numberAssets;

% Information about if the given criteria is a cost or benefit
criteria:
% Benefit=1, Cost=2, should be given as a vector of length n, i.e., if
n =
% 6, then criteria=[1 1 1 1 1 1];
criteria = ones(1,numberCriteria);

% Criteria for selecting Fuzzy Positive Ideal Solution FPIS and Fuzzy
Negative Ideal Solution FNIS.
% Three possible option are now implemented.
ideal = idealglobal; % "3" is the best ideal

% Chosen similarity measure: Integer number within {1,2,3,4}
simi = simiglobal; % "2" is the value that generates higher dispersion
in the ranking
```

```
% Construct Relevance_+_Conviction matrix
WDL1Globalstr = cellstr(WDL1Global);
WDL1Globalfuz = cellfun(@eval,WDL1Globalstr,'UniformOutput',false);
rowDist = ones(1,numberExperts);
WDL1Globalfltopsis = mat2cell(WDL1Globalfuz,rowDist);

% Construct Recommendation matrix
FDML1Globalstr = cellstr(FDML1Global);
FDML1Globalfuz = cellfun(@eval,FDML1Globalstr,'UniformOutput',false);
FDML1Globalfltopsis = mat2cell(FDML1Globalfuz,
size(FDML1Globalfuz,1)/numberExperts.*ones(numberExperts,1),
numberCriteria);

% Calculate Closeness Coefficients and Similarity values
[CCSL1Global,SstarL1Global,SnegL1Global,OrderL1Global]=Stopsis(WDL1Glob
alfltopsis,FDML1Globalfltopsis,k,m,n,ideal,criteria,simi);
```

RAMS

Dynamic Allocation – Professional Experts Opinions: Ranking

- Investment Committee, TAA Ranking
- Focus: All Asset Classes
- Granularity: Level 1, 2, 3

Equities	**0.571**	Neutral-Overweight				
			Equity US		0.507	Neutral
			Equity Europe		0.429	Neutral-Negative
			Equity Japan		0.404	Neutral-Negative
			Equity GEM		0.614	Positive
Government	**0.349**	Underweight				
			US Treasury		0.524	Neutral-Positive
			Eurozone Government		0.476	Neutral-Negative
Credit	**0.512**	Neutral				
			Investment Grade US		0.504	Neutral
			Investment Grade Eurozone		0.412	Neutral-Negative
			High Yield US		0.410	Neutral-Negative
			High Yield Europe		0.390	Negative
			GEM Credit		0.644	Positive
			GEM Credit HC		0.544	Neutral-Positive
			GEM Credit LC		0.457	Neutral-Negative
Alternative	**0.617**	Overweight				
			HF Equally Weighted		0.492	Neutral
			Market Neutral		0.575	Neutral-Positive
			Commodities		0.440	Neutral-Negative
Cash	**0.482**	Neutral-Underweight				

Dynamic Allocation – Machine Learning

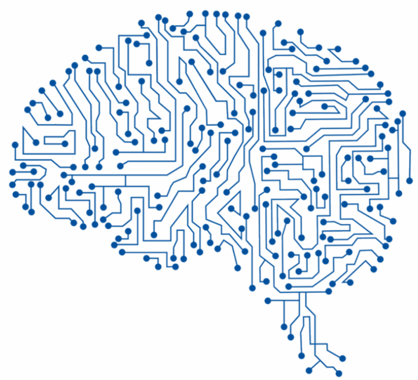
Experienced managers are those who confronted different business cycles.

They will use this knowledge when, in future situations, conditions will resemble those that they previously faced.

Altogether they exhibit behavioural patterns when managing their portfolios, reflecting those in markets performance.

Our main purpose is to find those patterns in the information available from decades of markets history.

Machine Learning is the cognitive technology that will allow us for the extraction of these patterns.



When strong patterns are found, they will likely generalize to make good forecasts.

- Uncertainty is the reason for trading. Probability Theory is the most complete body of knowledge created by experts during decades to understand and master uncertainty. This source of knowledge improves its accuracy when both the quality and the quantity of data increase.

- The professional investor's job is to make sense of these data, to discover the patterns that govern how markets behave and encapsulate them in theories that can be used for predicting what will happen in new situations.

- The solution to this challenge has to be based on:

  1. a science that can explain how the great variety, volume and velocity of data can affect the behaviour of asset prices, and

  2. a technology that can incorporate this new data in an efficient manner to create real- time investment decisions, guaranteeing unstopped surveillance on markets.

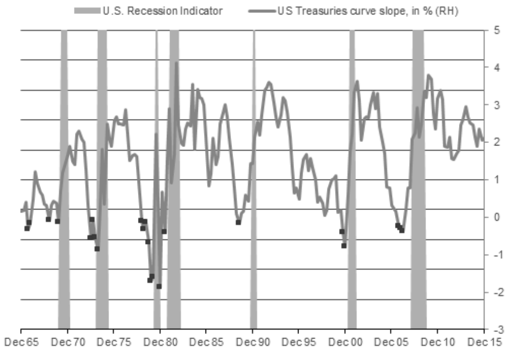
RAMS

- The framework follows a logical mindset:

Fundamental Research

- Macroeconomy
- Behavioural
- Risk
- Value

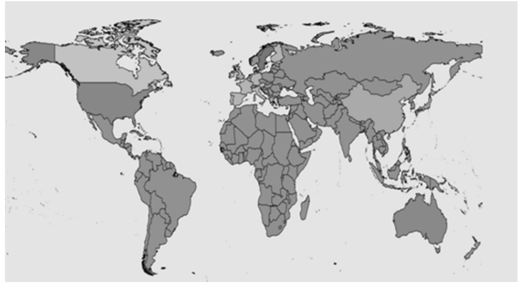
Leveraging industry and academic research for factor selection



Data into Information

- Transform Big Data into Smart Data
- Formulate the right Question

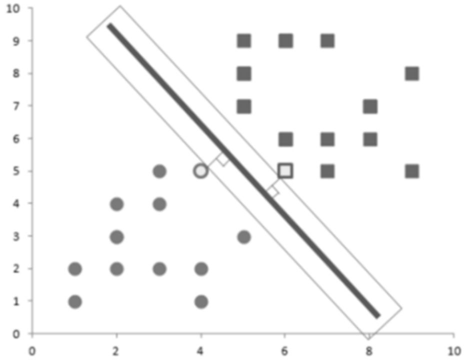
Data transformation for interpretability



Machine Learning

- Classification
- Confidence level

Defining the problem



Asset Classes Ranking

Achieving the solution

Dynamic Allocation – Machine Learning : Fundamental Factors

Comprehensive

Includes all necessary factors to discriminate amongst different market regimes

Explainable

Based on solid research foundations

Factors presence and influence is observed during different market cycles

Persistent

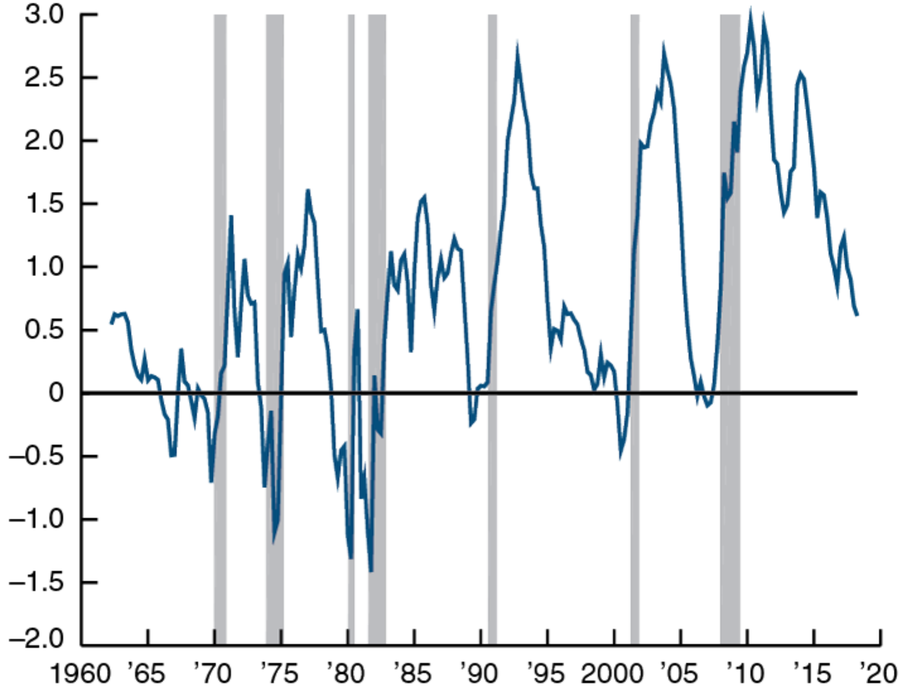
Easily available to make the process reactive to new information

Accessible

Yield Curve slope

Many studies document the predictive power of the slope of the Treasury yield curve for forecasting recessions. This factors is motivated, for example, by the empirical evidence in the figure, which shows the term-structure slope, measured by the spread between the yields on ten-year and two-year U.S. Treasury securities, and shading that denotes U.S. recessions (dated by the National Bureau of Economic Research).

Note that the yield-curve slope becomes negative before each economic recession since the 1970s. That is, an “inversion” of the yield curve, in which short-maturity interest rates exceed long-maturity rates, is typically associated with a recession in the near future.



Source: FED, Bloomberg

“The 3m vs 10y T-Bill spread is a valuable forecasting tool, that significantly outperforms other macroeconomic indicators in predicting recessions two to six quarters ahead.”
–Arturo Estrella and Frederic S. Mishkin, Federal Reserve Bank of New York

RAMS

Dynamic Allocation – Machine Learning : Fundamental Factors

					tickers1	names1		tickers2	names2	names
Australia	Developed Markets	Developed Markets Asia Pacific ex Japan	Australia		ADSWAP10 Curncy	G10Y_Australia		ADSWAP2Q BGN Curncy	G02Y_Australia	YCS_Australia
Austria	Developed Markets	Developed Markets EMU	Austria		GAGB10YR Index	G10Y_Austria		GAGB2YR Index	G02Y_Austria	YCS_Austria
Belgium	Developed Markets	Developed Markets EMU	Belgium		GBGB10YR Index	G10Y_Belgium		GBGB2YR Index	G02Y_Belgium	YCS_Belgium
Brazil	Emerging Markets	Emerging Markets Latin America	Brazil		GEBU10Y Curncy	G10Y_Brazil		GEBU2Y Curncy	G02Y_Brazil	YCS_Brazil
Canada	Developed Markets	Developed Markets North America	Canada		CDSW10 Curncy	G10Y_Canada		CDSW2 BGN Curncy	G02Y_Canada	YCS_Canada
China	Emerging Markets	Emerging Markets Asia	China		GCNY10YR Index	G10Y_China		GCNY2YR Index	G02Y_China	YCS_China
CzechRepublic	Emerging Markets	Emerging Markets Europe	CzechRepublic		CZGB10YR Index	G10Y_CzechRepublic		CZGB2YR Index	G02Y_CzechRepublic	YCS_CzechRepublic
Denmark	Developed Markets	Developed Markets Nordic Countries	Denmark		GDGB10YR Index	G10Y_Denmark		GDGB2YR Index	G02Y_Denmark	YCS_Denmark
France	Developed Markets	Developed Markets EMU	France		GFRN10 Index	G10Y_France		GFRN2 Index	G02Y_France	YCS_France
Germany	Developed Markets	Developed Markets EMU	Germany		GDBR10 Index	G10Y_Germany		GDBR2 Index	G02Y_Germany	YCS_Germany
HongKong	Developed Markets	Developed Markets Asia Pacific ex Japan	HongKong		HDSW10 Curncy	G10Y_HongKong		HDSW2 CMPN Curncy	G02Y_HongKong	YCS_HongKong
Hungary	Emerging Markets	Emerging Markets Europe	Hungary		GHGB10YR Index	G10Y_Hungary		GHTB1Y Index	G02Y_Hungary	YCS_Hungary
India	Emerging Markets	Emerging Markets Asia	India		IRSWO10 Curncy	G10Y_India		IRSWO2 CMPN Curncy	G02Y_India	YCS_India
Indonesia	Emerging Markets	Emerging Markets Asia	Indonesia		GIDN10YR Index	G10Y_Indonesia		GIDN2YR Index	G02Y_Indonesia	YCS_Indonesia
Ireland	Developed Markets	Developed Markets EMU	Ireland		GIGB10YR Index	G10Y_Ireland		GIGB2YR Index	G02Y_Ireland	YCS_Ireland
Italy	Developed Markets	Developed Markets EMU	Italy		GBTPGR10 Index	G10Y_Italy		GBTPGR2 Index	G02Y_Italy	YCS_Italy
Japan	Developed Markets	Developed Markets Japan	Japan		GJGC10 Index	G10Y_Japan		GJGC2 Index	G02Y_Japan	YCS_Japan
Korea	Emerging Markets	Emerging Markets Asia	Korea		GVSK10YR Index	G10Y_Korea		GVSK2YR Index	G02Y_Korea	YCS_Korea
Malaysia	Emerging Markets	Emerging Markets Asia	Malaysia		MGIY10Y Index	G10Y_Malaysia		MGIY2Y Index	G02Y_Malaysia	YCS_Malaysia
Mexico	Emerging Markets	Emerging Markets Latin America	Mexico		GMXN10YR Index	G10Y_Mexico		GMXN02YR Index	G02Y_Mexico	YCS_Mexico
Netherlands	Developed Markets	Developed Markets EMU	Netherlands		GNTH10YR Index	G10Y_Netherlands		GNTH2YR Index	G02Y_Netherlands	YCS_Netherlands
NewZealand	Developed Markets	Developed Markets Asia Pacific ex Japan	NewZealand		NDSWAP10 Curncy	G10Y_NewZealand		NDSWAP2 BGN Curncy	G02Y_NewZealand	YCS_NewZealand
Norway	Developed Markets	Developed Markets Nordic Countries	Norway		NKSW10 Curncy	G10Y_Norway		NKSW2 CMPL Curncy	G02Y_Norway	YCS_Norway
Poland	Emerging Markets	Emerging Markets Europe	Poland		POGB10YR Index	G10Y_Poland		POGB2YR Index	G02Y_Poland	YCS_Poland
Portugal	Developed Markets	Developed Markets EMU	Portugal		GSPT10YR Index	G10Y_Portugal		GSPT2YR Index	G02Y_Portugal	YCS_Portugal
Russia	Emerging Markets	Emerging Markets Europe	Russia		RRSWM10 Curncy	G10Y_Russia		RRSWM2 Curncy	G02Y_Russia	YCS_Russia
Singapore	Developed Markets	Developed Markets Asia Pacific ex Japan	Singapore		MASB10Y Index	G10Y_Singapore		MASB2Y Index	G02Y_Singapore	YCS_Singapore
Spain	Developed Markets	Developed Markets EMU	Spain		GSPG10YR Index	G10Y_Spain		GSPG2YR Index	G02Y_Spain	YCS_Spain
Sweden	Developed Markets	Developed Markets Nordic Countries	Sweden		GSGB10YR Index	G10Y_Sweden		GSGB2YR Index	G02Y_Sweden	YCS_Sweden
Thailand	Emerging Markets	Emerging Markets Asia	Thailand		GVTL10YR Index	G10Y_Thailand		GVTL2YR Index	G02Y_Thailand	YCS_Thailand
Turkey	Emerging Markets	Emerging Markets Europe	Turkey		TYSW10V3 Curncy	G10Y_Turkey		TYSW2V3 CMPN Curncy	G02Y_Turkey	YCS_Turkey
UnitedKingdom	Developed Markets	Developed Markets United Kingdom	UnitedKingdom		GUKG10 Index	G10Y_UnitedKingdom		GUKG2 Index	G02Y_UnitedKingdom	YCS_UnitedKingdom
UnitedStates	Developed Markets	Developed Markets North America	UnitedStates		USSWAP10 Curncy	G10Y_UnitedStates		USSWAP2 BGN Curncy	G02Y_UnitedStates	YCS_UnitedStates

```
% Read from file:
[tickerToNamesLong] = readcell(fullfile('C:\Users\emili\Documents\Recognition\CoraL1TA\BBG_Inputs','CODA_Inputs_World_Map.xlsx'),...
                  'Sheet','YCS_Country','Range','J13:K54');
>>

% blp creates a Bloomberg connection object and returns its properties
bloomberg = blp;

>>

bloomberg.DataReturnFormat = 'table';
LastPrice = {'PX_LAST'};

>>

[DataSecuritiesMultipleLong,SymbolSecuritiesMultipleLong] = ...
        history(bloomberg, SymbolLong, LastPrice, fromdate, todate, ...
        {'daily','all_calendar_days','previous_value'});

[DataSecuritiesMultipleShort,SymbolSecuritiesMultipleShort] = ...
        history(bloomberg, SymbolShort, LastPrice, fromdate, todate, ...
        {'daily','all_calendar_days','previous_value'});

>>

% Save to current directory folder
save('TableAggregateYCSInputs.mat','TableAggregateYCSInputs')
```

Default Risk Factor”

- Data is obtained from 5 economic regions, in more than 1000 different individual companies, during the last 15 years, for about 7 different values and market ratios.
- The level of information is expanded to maximum detail combining fundamental and behavioural elements: this factor is based on the Merton distance-to-default (DD) measure

Source: Bloomberg; own calculations

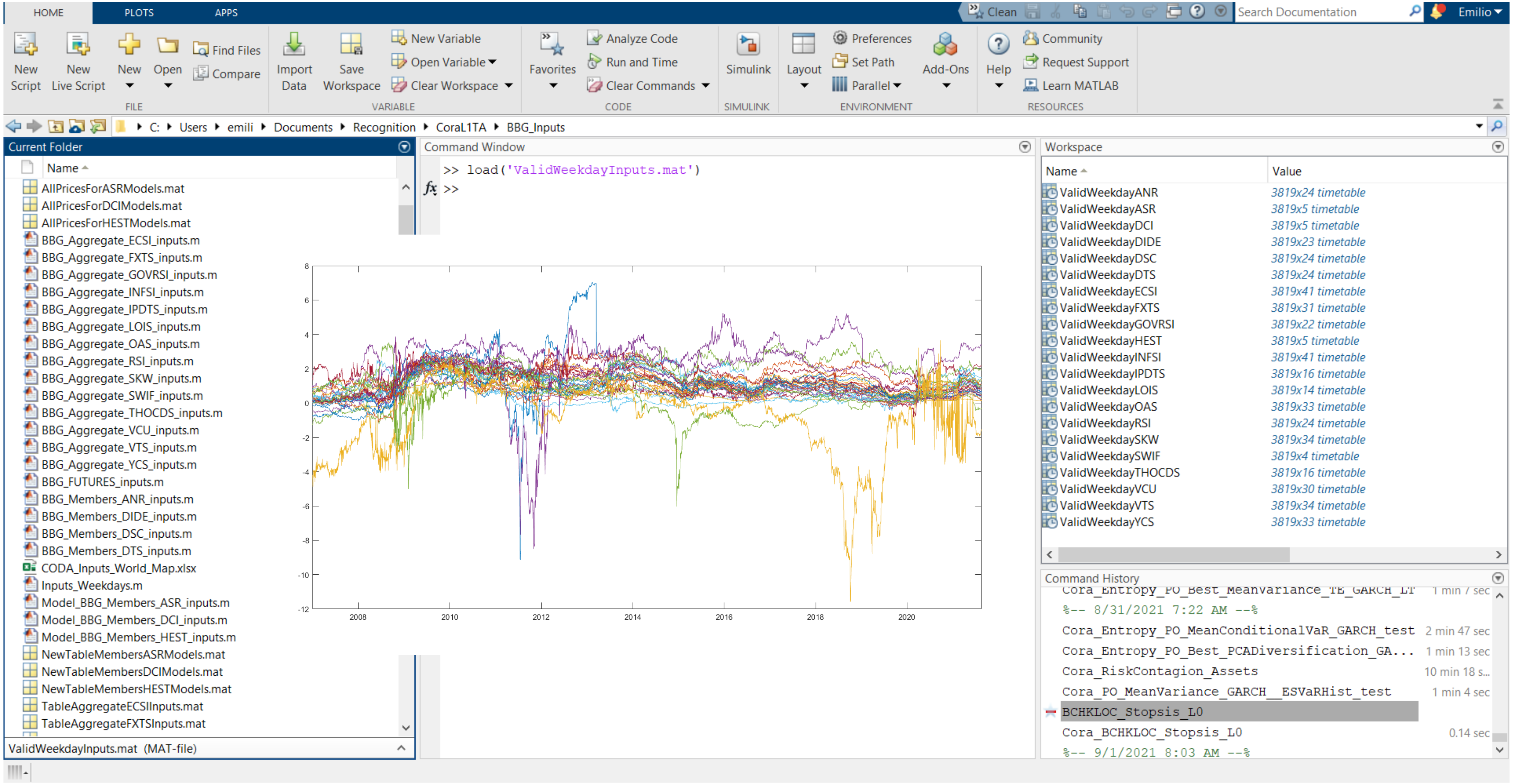
- The key insight of the Merton framework is that the equity of the firm can be viewed as a call option on the total assets of the firm where the strike price is equal to its liabilities.
- It is capable of defining logic and interpretable scenarios: market implied default probabilities are cyclical and highly correlated to realised default rates, rising during periods of overall economic distress and falling during expansions.

Dynamic Allocation – Machine Learning : Fundamental Factors

Australia	Developed Markets	Developed Markets Asia Pacific ex Japan	Australia		AS31 Index	DSC_Australia
Brazil	Emerging Markets	Emerging Markets Latin America	Brazil		IBOV Index	DSC_Brazil
Chile	Emerging Markets	Emerging Markets Latin America	Chile		IPSA Index	DSC_Chile
China	Emerging Markets	Emerging Markets Asia	China		SHCSI100 Index	DSC_China
Colombia	Emerging Markets	Emerging Markets Latin America	Colombia		COLCAP Index	DSC_Colombia
France	Developed Markets	Developed Markets EMU	France		CAC Index	DSC_France
Germany	Developed Markets	Developed Markets EMU	Germany		DAX Index	DSC_Germany
Greece	Developed Markets	Developed Markets EMU	Greece		ASE Index	DSC_Greece
India	Emerging Markets	Emerging Markets Asia	India		SENSEX Index	DSC_India
Italy	Developed Markets	Developed Markets EMU	Italy		IT30 Index	DSC_Italy
Japan	Developed Markets	Developed Markets Japan	Japan		TPXC30 Index	DSC_Japan
Korea	Emerging Markets	Emerging Markets Asia	Korea		KOSPI50 Index	DSC_Korea
Mexico	Emerging Markets	Emerging Markets Latin America	Mexico		MEXBOL Index	DSC_Mexico
Netherlands	Developed Markets	Developed Markets EMU	Netherlands		AEX Index	DSC_Netherlands
Norway	Developed Markets	Developed Markets Nordic Countries	Norway		OBX Index	DSC_Norway
Poland	Emerging Markets	Emerging Markets Europe	Poland		WIG20 Index	DSC_Poland
Portugal	Developed Markets	Developed Markets EMU	Portugal		PSI20 Index	DSC_Portugal
Russia	Emerging Markets	Emerging Markets Europe	Russia		RTSI$ Index	DSC_Russia
Singapore	Developed Markets	Developed Markets Asia Pacific ex Japan	Singapore		STI Index	DSC_Singapore
Spain	Developed Markets	Developed Markets EMU	Spain		IBEX Index	DSC_Spain
Sweden	Developed Markets	Developed Markets Nordic Countries	Sweden		OMX Index	DSC_Sweden
Turkey	Emerging Markets	Emerging Markets Europe	Turkey		TR20I Index	DSC_Turkey
UnitedKingdom	Developed Markets	Developed Markets United Kingdom	UnitedKingdom		UKX Index	DSC_UnitedKingdom
UnitedStates	Developed Markets	Developed Markets North America	UnitedStates		OEX Index	DSC_UnitedStates

```
% For each Country or Region Equity Index we need to obtain the tickers
% of the members (i.e., single Equities) that are included in that Index,
% so we obtain index members for all indices in "tickers"

[IndexMembers,BBGTickers] = getdata(bloomberg,symbol,'INDX_MEMBERS’);

>>

for History = 1:SizeIndexMembersListSample

    [DataSecuritiesMultiple,SymbolSecuritiesMultiple] = ...
        history(bloomberg,IndexMembersListSample{History,1},...
        DefaultScore,fromdate,todate,{'daily','all_calendar_days','previous_value'});

     DataSecuritiesMultipleHistory {History} = DataSecuritiesMultiple;

end

>>

save('TableMembersDSCInputs.mat','TableMembersDSCInputs')
```

Dynamic Allocation – Machine Learning : Fundamental Factors



RAMS

Dynamic Allocation – Machine Learning : Signals

- Analyst: Global Asset Allocation Machine Learning
- Focus: Top Asset Classes
- Granularity: Level 1

From	Until	Equities	Government Bonds	Credit	Alternative	Cash
December 29, 2006	February 9, 2007	1	-1	-1	1	-1
January 1, 2007	February 12, 2007	1	-1	-1	1	-1
January 2, 2007	February 13, 2007	1	-1	-1	1	-1
January 3, 2007	February 14, 2007	1	-1	-1	1	-1
January 4, 2007	February 15, 2007	1	-1	-1	1	-1
January 5, 2007	February 16, 2007	1	-1	-1	1	-1
January 8, 2007	February 19, 2007	1	-1	-1	1	-1
January 9, 2007	February 20, 2007	1	-1	-1	1	-1
January 10, 2007	February 21, 2007	1	-1	-1	1	-1
January 11, 2007	February 22, 2007	1	-1	-1	1	-1
January 12, 2007	February 23, 2007	1	-1	1	1	-1
January 15, 2007	February 26, 2007	1	-1	1	1	-1
January 16, 2007	February 27, 2007	1	-1	1	1	-1
January 17, 2007	February 28, 2007	-1	1	1	1	-1
>>						
November 23, 2007	January 4, 2008	-1	1	1	1	-1
November 26, 2007	January 7, 2008	-1	1	-1	1	1
November 27, 2007	January 8, 2008	-1	1	1	-1	1
November 28, 2007	January 9, 2008	-1	1	-1	1	1
November 29, 2007	January 10, 2008	-1	1	-1	-1	1
November 30, 2007	January 11, 2008	-1	1	1	-1	1
December 3, 2007	January 14, 2008	-1	1	-1	-1	1
December 4, 2007	January 15, 2008	-1	1	1	-1	1
December 5, 2007	January 16, 2008	-1	1	1	-1	1
December 6, 2007	January 17, 2008	-1	1	1	-1	1
December 7, 2007	January 18, 2008	-1	1	1	-1	1
December 10, 2007	January 21, 2008	-1	1	1	-1	1
>>						
June 18, 2021	July 30, 2021	1	1	1	-1	-1
June 21, 2021	August 2, 2021	1	1	1	-1	-1
June 22, 2021	August 3, 2021	1	1	1	-1	-1
June 23, 2021	August 4, 2021	1	1	1	-1	-1
June 24, 2021	August 5, 2021	1	1	1	-1	-1
June 25, 2021	August 6, 2021	1	1	1	-1	-1
June 28, 2021	August 9, 2021	1	1	1	-1	-1
June 29, 2021	August 10, 2021	1	1	-1	-1	-1
June 30, 2021	August 11, 2021	1	1	-1	-1	-1
July 1, 2021	August 12, 2021	1	1	-1	-1	-1
July 2, 2021	August 13, 2021	1	1	1	-1	-1
July 5, 2021	August 16, 2021	1	1	1	-1	-1
July 6, 2021	August 17, 2021	-1	1	1	-1	-1
July 7, 2021	August 18, 2021	-1	1	1	-1	-1

Multilable Ranking Support Vector Machines

- Multi-label learning is concerned with learning from examples, where each example is associated with multiple labels
- A multi-label problem has the following settings:
  - The set of labels is predefined, meaningful and human-interpretable.
  - Each training example is associated with several labels of the labelset.
  - Labels may be correlated. These relationships between labels represent additional knowledge that can be explored during the training of the learners to facilitate the learning process
- Depending on the goal, we can distinguish two types of tasks: multi-label classification and multi-label ranking. In the case of multi-label classification, the goal is to construct a predictive model that will provide a list of relevant labels for a given, previously unseen example.
- On the other hand, the goal in the task of multi-label ranking is to construct a predictive model that will provide, for each unseen example, a degree of confidence (i.e., a ranking) of the labels from the set of possible labels.

Dynamic Allocation – Machine Learning : Ranking

- Machine Learning, TAA Ranking
- Focus: All Asset Classes
- Granularity: Level 1, 2, 3

Equities	**0.646**	**Overweight**		
		Equity US	0.805	Very Positive
		Equity Europe	0.458	Neutral-Negative
		Equity Japan	0.538	Neutral-Positive
		Equity GEM	0.462	Neutral-Negative
Government	**0.024**	**Strong Underweight**		
		US Treasury	0.532	Neutral-Positive
		Eurozone Government	0.468	Neutral-Negative
Credit	**0.718**	**Overweight**		
		Investment Grade US	0.045	Very Negative
		Investment Grade Eurozone	0.238	Negative
		High Yield US	0.950	Very Positive
		High Yield Europe	0.950	Very Positive
		GEM Credit	0.388	Negative
		GEM Credit HC	0.812	Very Positive
		GEM Credit LC	0.345	Negative
Alternative	**0.745**	**Overweight**		
		HF Equally Weighted	0.424	Neutral-Negative
		Market Neutral	0.680	Positive
		Commodities	0.356	Negative
Cash	**0.379**	**Underweight**		

RAMS

Dynamic Allocation – Human and Machines: Ranking

- Human experts Investment Committee, TAA Ranking
- Focus: All Asset Classes
- Granularity: Level 1, 2, 3

Equities	0.571	Neutral-Overweight			
		Equity US	0.507	Neutral	
		Equity Europe	0.429	Neutral-Negative	
		Equity Japan	0.404	Neutral-Negative	
		Equity GEM	0.614	Positive	
Government	0.349	Underweight			
		US Treasury	0.524	Neutral-Positive	
		Eurozone Government	0.476	Neutral-Negative	
Credit	0.512	Neutral			
		Investment Grade US	0.504	Neutral	
		Investment Grade Eurozone	0.412	Neutral-Negative	
		High Yield US	0.410	Neutral-Negative	
		High Yield Europe	0.390	Negative	
		GEM Credit	0.644	Positive	
		GEM Credit HC	0.544	Neutral-Positive	
		GEM Credit LC	0.457	Neutral-Negative	
Alternative	0.617	Overweight			
		HF Equally Weighted	0.492	Neutral	
		Market Neutral	0.575	Neutral-Positive	
		Commodities	0.440	Neutral-Negative	
Cash	0.482	Neutral-Underweight			

- Machine Learning, TAA Ranking
- Focus: All Asset Classes
- Granularity: Level 1, 2, 3

Equities	0.646	Overweight			
		Equity US	0.805	Very Positive	
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		Market Neutral	0.680	Positive	
		Commodities	0.356	Negative	
Cash	0.379	Underweight			

PORTFOLIO CONSTRUCTION

○ Entropy Pooling

- The Ranking is the result of a probabilistic approach to a possible scenario of out and underperformance in relative terms between all asset classes.

- Traditionally, investment managers are bound to express views in terms of expected returns and covariances to measure risk, which is a difficult task and as a consequence penalizes the use of appropriate portfolio optimization techniques.

- Through the Entropy Pooling methodology (“Fully Flexible Views: Theory and Practice”, Attilio Meucci, December 4 2010) we manage to obtain the necessary portfolio optimization parameters implied by the Ranking.

- This means that from now on the asset allocator can, through the opinions expressed by the Investment Committee, “extract” from the output of those the expected distribution function for each asset class, as simultaneously the expected covariance matrix.

- **This is a great advantage as it is not necessary to “hard code” any expected returns that can contradict what is agreed by the Investment Committee, and we will not use only past history as the input to measure the assets correlation matrix, as this one is itself modified implicitly when we make market recommendations that do not match with past prior performance.**

○ Entropy Pooling

- Human experts Investment Committee, TAA Ranking
- Focus: All Asset Classes
- Granularity: Level 1, 2, 3

Equities	0.571	Neutral-Overweight			
		Equity US	0.507	Neutral
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Alternative	0.617	Overweight			
		HF Equally Weighted	0.492	Neutral
		Market Neutral	0.575	Neutral-Positive
		Commodities	0.440	Neutral-Negative
Cash	0.482	Neutral-Underweight			

- Final aggregated ranking by investable Asset class

MSCI USA Net Total Return Local Index	1.076
MSCI Europe Net Total Return Local Index	0.990
MSCI Japan Net Total Return Local Index	0.961
MSCI Emerging Net Total Return Local Index	1.184
Bloomberg Barclays US Treasury Total Return Unhedged USD	0.855
Bloomberg Barclays EuroAgg Treasury Total Return Index Value Unhedged EUR	0.815
Bloomberg US Corporate Total Return Value Unhedged USD	1.015
Bloomberg Euro Aggregate Corporate Total Return Index Value Unhedged EU	0.918
Bloomberg US Corporate High Yield Total Return Index Value Unhedged USD	0.916
Bloomberg Pan-European High Yield (Euro) TR Index Value Unhedged EUR	0.893
Bloomberg EM Hard Currency Aggregate TR Index Value Unhedged USD	1.128
Bloomberg EM Local Currency Core Net Ret Total Return Unhedged USD	1.064
Hedge Fund Research HFRX Equal Weighted Strategies Index	1.102
Hedge Fund Research HFRX EH Equity Market Neutral Index	1.192
Bloomberg Commodity Index Total Return	1.042
EONIA Total Return Index	0.982
Bloomberg Euro Treasury Bills Index TR Index Value Unhedged EUR	0.982

○ Entropy Pooling

- Ranking distance matrix by Asset class

	USAEQEH	EUREQEUR	JPNEQEH	GEMEQEH	USAGOVEH	EMUGOVEUR	USAIGEH	EMUIGEUR	USAHYEH	EURHYEUR	GEMHCGOCOEH	GEMLCGOCOEH	COMPABSREH	MNEUEH	COMMEH	EMUDEPOLOC	EMUTBILLLOC
USAEQEH	0.000	-0.086	-0.115	0.108	-0.221	-0.261	-0.060	-0.157	-0.159	-0.182	0.052	-0.012	0.026	0.116	-0.033	-0.094	-0.094
EUREQEUR	0.086	0.000	-0.029	0.194	-0.135	-0.175	0.026	-0.071	-0.073	-0.097	0.138	0.074	0.112	0.202	0.053	-0.008	-0.008
JPNEQEH	0.115	0.029	0.000	0.223	-0.106	-0.146	0.055	-0.043	-0.044	-0.068	0.167	0.103	0.141	0.231	0.081	0.021	0.021
GEMEQEH	-0.108	-0.194	-0.223	0.000	-0.328	-0.369	-0.168	-0.265	-0.267	-0.290	-0.056	-0.120	-0.081	0.008	-0.141	-0.201	-0.201
USAGOVEH	0.221	0.135	0.106	0.328	0.000	-0.040	0.160	0.063	0.061	0.038	0.273	0.209	0.247	0.337	0.187	0.127	0.127
EMUGOVEUR	0.261	0.175	0.146	0.369	0.040	0.000	0.201	0.103	0.101	0.078	0.313	0.249	0.287	0.377	0.227	0.167	0.167
USAIGEH	0.060	-0.026	-0.055	0.168	-0.160	-0.201	0.000	-0.097	-0.099	-0.122	0.113	0.048	0.087	0.176	0.027	-0.033	-0.033
EMUIGEUR	0.157	0.071	0.043	0.265	-0.063	-0.103	0.097	0.000	-0.002	-0.025	0.210	0.145	0.184	0.273	0.124	0.064	0.064
USAHYEH	0.159	0.073	0.044	0.267	-0.061	-0.101	0.099	0.002	0.000	-0.023	0.212	0.147	0.186	0.275	0.126	0.066	0.066
EURHYEUR	0.182	0.097	0.068	0.290	-0.038	-0.078	0.122	0.025	0.023	0.000	0.235	0.171	0.209	0.298	0.149	0.089	0.089
GEMHCGOCOEH	-0.052	-0.138	-0.167	0.056	-0.273	-0.313	-0.113	-0.210	-0.212	-0.235	0.000	-0.064	-0.026	0.064	-0.086	-0.146	-0.146
GEMLCGOCOEH	0.012	-0.074	-0.103	0.120	-0.209	-0.249	-0.048	-0.145	-0.147	-0.171	0.064	0.000	0.038	0.128	-0.021	-0.082	-0.082
COMPABSREH	-0.026	-0.112	-0.141	0.081	-0.247	-0.287	-0.087	-0.184	-0.186	-0.209	0.026	-0.038	0.000	0.090	-0.060	-0.120	-0.120
MNEUEH	-0.116	-0.202	-0.231	-0.008	-0.337	-0.377	-0.176	-0.273	-0.275	-0.298	-0.064	-0.128	-0.090	0.000	-0.149	-0.210	-0.210
COMMEH	0.033	-0.053	-0.081	0.141	-0.187	-0.227	-0.027	-0.124	-0.126	-0.149	0.086	0.021	0.060	0.149	0.000	-0.060	-0.060
EMUDEPOLOC	0.094	0.008	-0.021	0.201	-0.127	-0.167	0.033	-0.064	-0.066	-0.089	0.146	0.082	0.120	0.210	0.060	0.000	0.000
EMUTBILLLOC	0.094	0.008	-0.021	0.201	-0.127	-0.167	0.033	-0.064	-0.066	-0.089	0.146	0.082	0.120	0.210	0.060	0.000	0.000

```
%% Ranking embedding step

% Calculate initial probability for each multivariate observation (we
% assume each instance is unique)

Probabilities = 1/size(InvestAssetsReturnsArray,1);
PriorProbabilitiesReturns =
Probabilities(ones(size(InvestAssetsReturnsArray,1), 1));

% Define number of assets

NumberAssets = size(RankingVector,2);

% Create array of #assets x #assets

RankingArray = repmat(RankingVector,NumberAssets,1);

% Calculate differences to create recommendation relative signal

RankingArrayDifference = bsxfun(@minus, RankingArray, RankingVector');
RankingArrayDistances = RankingArrayDifference;
DistanceMultiplier = (abs(reshape(RankingArrayDistances, [],
1))/(max(RankingVector)-min(RankingVector)))';

% Classify relative signals as negative recommendations (-1) or similar /
positive (0)

RankingArrayDifference(RankingArrayDifference <0) = (-1);
RankingArrayDifference(RankingArrayDifference >=0) = (0);

% If relative ranking is negative assign column asset index

IndexArrayColumn = repmat((1:1:NumberAssets),NumberAssets,1);

% If relative ranking is similar / positive assign row asset index

IndexArrayRow = repmat((1:1:NumberAssets),NumberAssets,1)';
```

```
% Create Lower group of relative recommendations

for idx = find(RankingArrayDifference == -1)

   RankingArrayDifference(idx) = IndexArrayColumn(idx);

end

for idx = find(RankingArrayDifference == 0)

   RankingArrayDifference(idx) = IndexArrayRow(idx);

end

Lower = RankingArrayDifference;

% Create Upper group of relative recommendations

Upper = IndexArrayRow;

% Compute and plot efficient frontier based on prior market distribution,
% using a simple example with Mean-Variance

Options.NumPortf=20; % number of portfolios in efficient frontier
Options.FrontierSpan=[.3 .9]; % range of normalized exp.vals. spanned by efficient
frontier

[preexpectedreturns,preexpectedvolatilities,preoptimalweights,PriorAverageReturns,PriorCov
ariance] = ...
    EfficientFrontier(InvestAssetsReturnsArray,PriorProbabilitiesReturns,Options);
PriorCorrelation = corrcov (PriorCovariance);
PlotResults(preexpectedreturns,preexpectedvolatilities,preoptimalweights,PriorAverageRetur
ns)

% Process ordering information (this is the core of the Entropy Pooling approach).
% The expected return of each entry of Lower is supposed to be smaller than
% the respective entry in Upper.

[PosteriorProbabilitiesReturns,InvestAssetsReturnsDifferences] = ...

ViewRankingDistance(InvestAssetsReturnsArray,DistanceMultiplier,PriorProbabilitiesReturns,
Lower,Upper);
```

```
%% Confidence step

% Specify confidence on ranking according to a dispersion measure (can be
related to difference in final combined ranking)

% ConfidenceRanking = 0.5; % if arbitrarily we assign a 50%
% ConfidenceRanking = std(RankingVector); % if dispersion is calculated as a
volatility of the ranking
ConfidenceRanking = range(RankingVector); % if dispersion is calculated as the
range of the ranking

PosteriorProbabilitiesReturns = (1-ConfidenceRanking) *
PriorProbabilitiesReturns + ...
                                 ConfidenceRanking *
PosteriorProbabilitiesReturns;

% Simulate historical returns sample according to the ranking influence in
% the entropy pooling method.

RatioPosteriorPrior = PosteriorProbabilitiesReturns./PriorProbabilitiesReturns;
ModifiedHistoricalReturns =
bsxfun(@times,RatioPosteriorPrior,InvestAssetsReturnsArray);

% Include trading limits accoring to market crisis scenarios (+/-15%)
TradingLimit = 0.15; % 15% limit before market closes
ModifiedHistoricalReturns (ModifiedHistoricalReturns < -TradingLimit) = -
TradingLimit;
ModifiedHistoricalReturns (ModifiedHistoricalReturns > TradingLimit) =
TradingLimit;

ModifiedHistoricalReturnsArray = [Dates(2:end) ModifiedHistoricalReturns];
cora_ModifiedHistoricalReturnsTable = array2table
(ModifiedHistoricalReturnsArray);
cora_ModifiedHistoricalReturnsTable.Properties.VariableNames = ['DATE'
InvestAssetsReturns.Properties.VariableNames];
```

Entropy Pooling

- Historical returns and correlation matrix

MSCI USA Net Total Return Local Index	14.1%
MSCI Europe Net Total Return Local Index	9.0%
MSCI Japan Net Total Return Local Index	10.0%
MSCI Emerging Net Total Return Local Index	6.4%
Bloomberg Barclays US Treasury Total Return Unhedged USD	2.0%
Bloomberg Barclays EuroAgg Treasury Total Return Index Value Unhedged EUR	4.2%
Bloomberg US Corporate Total Return Value Unhedged USD	4.1%
Bloomberg Euro Aggregate Corporate Total Return Index Value Unhedged EU	3.7%
Bloomberg US Corporate High Yield Total Return Index Value Unhedged USD	5.3%
Bloomberg Pan-European High Yield (Euro) TR Index Value Unhedged EUR	6.2%
Bloomberg EM Hard Currency Aggregate TR Index Value Unhedged USD	4.2%
Bloomberg EM Local Currency Core Net Ret Total Return Unhedged USD	1.6%
Hedge Fund Research HFRX Equal Weighted Strategies Index	0.7%
Hedge Fund Research HFRX EH Equity Market Neutral Index	-1.5%
Bloomberg Commodity Index Total Return	-5.0%
EONIA Total Return Index	-0.1%
Bloomberg Euro Treasury Bills Index TR Index Value Unhedged EUR	0.1%

	USAEQEH	EUREQEUR	JPNEQEH	GEMEQEH	USAGOVEH	EMUGOVEUR	USAIGEH	EMUIGEUR	USAHYEH	EURHYEUR	GEMHCGOCOEH	GEMLCGOCOEH	COMPABSREH	MNEUEH	COMMEH	EMUDEPOLOC	EMUTBILLLOC
USAEQEH		63.2%	17.7%	41.2%	-40.3%	0.2%	-14.6%	2.0%	47.7%	35.9%	28.5%	23.8%	24.6%	10.8%	36.0%	-1.7%	12.4%
EUREQEUR	63.2%		32.3%	56.4%	-37.3%	2.6%	-9.6%	5.4%	57.7%	51.9%	36.2%	28.4%	32.4%	18.6%	35.5%	-2.7%	18.4%
JPNEQEH	17.7%	32.3%		45.3%	-13.7%	-1.5%	3.7%	16.9%	29.3%	40.0%	24.1%	13.6%	19.9%	9.9%	12.8%	-3.0%	4.2%
GEMEQEH	41.2%	56.4%	45.3%		-24.6%	6.0%	1.6%	21.9%	53.4%	55.3%	47.6%	37.8%	64.2%	46.2%	32.4%	-3.1%	11.3%
USAGOVEH	-40.3%	-37.3%	-13.7%	-24.6%		38.4%	82.2%	36.5%	-20.0%	-17.8%	19.6%	13.0%	-15.8%	-11.7%	-20.4%	4.5%	-3.9%
EMUGOVEUR	0.2%	2.6%	-1.5%	6.0%	38.4%		38.1%	62.2%	7.6%	18.9%	29.2%	28.8%	10.6%	5.8%	-2.6%	2.8%	41.1%
USAIGEH	-14.6%	-9.6%	3.7%	1.6%	82.2%	38.1%		54.8%	27.2%	24.5%	52.7%	32.1%	0.7%	-2.2%	-6.5%	2.8%	3.8%
EMUIGEUR	2.0%	5.4%	16.9%	21.9%	36.5%	62.2%	54.8%		37.4%	54.1%	53.5%	36.3%	17.4%	8.4%	2.0%	4.0%	17.8%
USAHYEH	47.7%	57.7%	29.3%	53.4%	-20.0%	7.6%	27.2%	37.4%		76.6%	70.4%	43.4%	34.6%	15.0%	31.8%	0.1%	15.9%
EURHYEUR	35.9%	51.9%	40.0%	55.3%	-17.8%	18.9%	24.5%	54.1%	76.6%		64.4%	39.9%	33.9%	17.5%	25.3%	-0.7%	26.0%
GEMHCGOCOEH	28.5%	36.2%	24.1%	47.6%	19.6%	29.2%	52.7%	53.5%	70.4%	64.4%		64.8%	27.1%	11.7%	24.3%	2.9%	17.4%
GEMLCGOCOEH	23.8%	28.4%	13.6%	37.8%	13.0%	28.8%	32.1%	36.3%	43.4%	39.9%	64.8%		23.2%	10.5%	24.6%	3.5%	15.1%
COMPABSREH	24.6%	32.4%	19.9%	64.2%	-15.8%	10.6%	0.7%	17.4%	34.6%	33.9%	27.1%	23.2%		84.7%	19.3%	-2.7%	8.1%
MNEUEH	10.8%	18.6%	9.9%	46.2%	-11.7%	5.8%	-2.2%	8.4%	15.0%	17.5%	11.7%	10.5%	84.7%		8.6%	-0.5%	3.9%
COMMEH	36.0%	35.5%	12.8%	32.4%	-20.4%	-2.6%	-6.5%	2.0%	31.8%	25.3%	24.3%	24.6%	19.3%	8.6%		-2.2%	4.4%
EMUDEPOLOC	-1.7%	-2.7%	-3.0%	-3.1%	4.5%	2.8%	2.8%	4.0%	0.1%	-0.7%	2.9%	3.5%	-2.7%	-0.5%	-2.2%		19.0%
EMUTBILLLOC	12.4%	18.4%	4.2%	11.3%	-3.9%	41.1%	3.8%	17.8%	15.9%	26.0%	17.4%	15.1%	8.1%	3.9%	4.4%	19.0%	

- Ranking implied expected returns and correlation matrix

MSCI USA Net Total Return Local Index	8.6%
MSCI Europe Net Total Return Local Index	5.5%
MSCI Japan Net Total Return Local Index	6.1%
MSCI Emerging Net Total Return Local Index	4.1%
Bloomberg Barclays US Treasury Total Return Unhedged USD	1.2%
Bloomberg Barclays EuroAgg Treasury Total Return Index Value Unhedged EUR	2.6%
Bloomberg US Corporate Total Return Value Unhedged USD	2.5%
Bloomberg Euro Aggregate Corporate Total Return Index Value Unhedged EU	2.2%
Bloomberg US Corporate High Yield Total Return Index Value Unhedged USD	3.3%
Bloomberg Pan-European High Yield (Euro) TR Index Value Unhedged EUR	3.8%
Bloomberg EM Hard Currency Aggregate TR Index Value Unhedged USD	2.8%
Bloomberg EM Local Currency Core Net Ret Total Return Unhedged USD	1.1%
Hedge Fund Research HFRX Equal Weighted Strategies Index	0.5%
Hedge Fund Research HFRX EH Equity Market Neutral Index	-0.9%
Bloomberg Commodity Index Total Return	-3.2%
EONIA Total Return Index	-0.1%
Bloomberg Euro Treasury Bills Index TR Index Value Unhedged EUR	0.1%

	USAEQEH	EUREQEUR	JPNEQEH	GEMEQEH	USAGOVEH	EMUGOVEUR	USAIGEH	EMUIGEUR	USAHYEH	EURHYEUR	GEMHCGOCOEH	GEMLCGOCOEH	COMPABSREH	MNEUEH	COMMEH	EMUDEPOLOC	EMUTBILLLOC
USAEQEH		64.8%	19.1%	44.2%	-40.1%	4.2%	-11.1%	7.8%	51.1%	40.8%	33.0%	27.1%	27.5%	11.9%	38.0%	-0.5%	14.4%
EUREQEUR	64.8%		33.4%	58.0%	-36.6%	5.3%	-5.9%	9.5%	60.1%	53.9%	39.5%	31.4%	34.2%	19.7%	36.9%	-2.1%	19.4%
JPNEQEH	19.1%	33.4%		45.8%	-14.2%	-0.6%	4.2%	17.2%	29.9%	39.3%	24.4%	14.4%	20.7%	10.6%	13.6%	-3.1%	4.7%
GEMEQEH	44.2%	58.0%	45.8%		-24.5%	8.8%	4.8%	25.8%	56.5%	57.8%	50.1%	40.2%	65.4%	46.6%	34.2%	-2.4%	12.9%
USAGOVEH	-40.1%	-36.6%	-14.2%	-24.5%		36.6%	81.9%	35.5%	-18.6%	-16.6%	20.0%	13.6%	-15.0%	-9.9%	-19.8%	4.3%	-4.6%
EMUGOVEUR	4.2%	5.3%	-0.6%	8.8%	36.6%		39.3%	63.2%	12.1%	23.3%	32.3%	31.5%	13.0%	7.1%	-0.3%	3.5%	41.7%
USAIGEH	-11.1%	-5.9%	4.2%	4.8%	81.9%	39.3%		57.0%	30.1%	28.4%	55.7%	35.2%	4.5%	1.1%	-3.0%	3.0%	5.1%
EMUIGEUR	7.8%	9.5%	17.2%	25.8%	35.5%	63.2%	57.0%		42.7%	58.3%	57.9%	39.7%	22.0%	11.2%	6.3%	4.4%	19.5%
USAHYEH	51.1%	60.1%	29.9%	56.5%	-18.6%	12.1%	30.1%	42.7%		79.2%	73.3%	46.6%	38.4%	17.4%	35.2%	0.9%	18.3%
EURHYEUR	40.8%	53.9%	39.3%	57.8%	-16.6%	23.3%	28.4%	58.3%	79.2%		68.2%	43.4%	37.8%	19.7%	29.0%	0.0%	27.9%
GEMHCGOCOEH	33.0%	39.5%	24.4%	50.1%	20.0%	32.3%	55.7%	57.9%	73.3%	68.2%		66.8%	31.4%	14.9%	27.8%	3.5%	19.3%
GEMLCGOCOEH	27.1%	31.4%	14.4%	40.2%	13.6%	31.5%	35.2%	39.7%	46.6%	43.4%	66.8%		26.4%	13.1%	27.1%	4.1%	16.7%
COMPABSREH	27.5%	34.2%	20.7%	65.4%	-15.0%	13.0%	4.5%	22.0%	38.4%	37.8%	31.4%	26.4%		84.5%	21.6%	-1.9%	9.5%
MNEUEH	11.9%	19.7%	10.6%	46.6%	-9.9%	7.1%	1.1%	11.2%	17.4%	19.7%	14.9%	13.1%	84.5%		10.1%	-0.5%	4.3%
COMMEH	38.0%	36.9%	13.6%	34.2%	-19.8%	-0.3%	-3.0%	6.3%	35.2%	29.0%	27.8%	27.1%	21.6%	10.1%		-1.6%	6.0%
EMUDEPOLOC	-0.5%	-2.1%	-3.1%	-2.4%	4.3%	3.5%	3.0%	4.4%	0.9%	0.0%	3.5%	4.1%	-1.9%	-0.5%	-1.6%		18.4%
EMUTBILLLOC	14.4%	19.4%	4.7%	12.9%	-4.6%	41.7%	5.1%	19.5%	18.3%	27.9%	19.3%	16.7%	9.5%	4.3%	6.0%	18.4%	

○ Portfolio Optimization: Mean Variance

	Mínima	Neutral	Máxima
Equities	18.0%	36.0%	50.0%
Equity US	8.0%	14.0%	25.0%
Equity Europe	8.0%	14.0%	25.0%
Equity Japan	1.0%	3.5%	6.0%
Equity GEM	1.0%	4.5%	8.0%
Government	9.0%	20.5%	32.0%
US Treasury	3.0%	7.5%	12.0%
Eurozone Government	6.0%	13.0%	20.0%
Credit	16.0%	34.0%	52.0%
Investment Grade US	6.0%	10.5%	15.0%
Investment Grade Eurozone	8.0%	11.5%	15.0%
High Yield US	1.0%	4.5%	8.0%
High Yield Europe	1.0%	4.5%	8.0%
GEM Credit	0.0%	3.0%	6.0%
Alternative	0.0%	8.0%	21.0%
Cash	0.0%	1.5%	3.0%

○ Portfolio Optimization: Mean Variance

Mean Variance Efficient Frontier

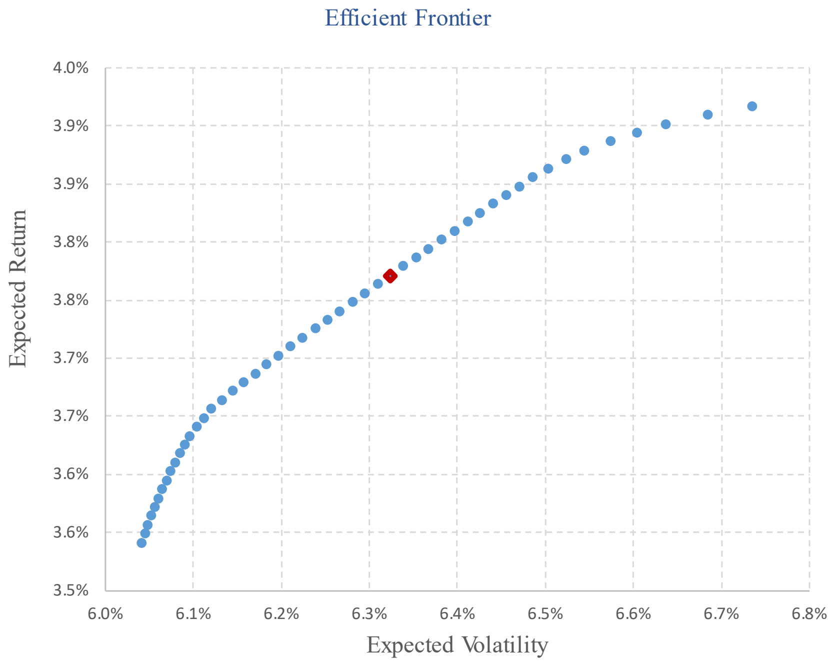
```
% Use Portfolio to create an instance of an object of the Portfolio class.

p_Neutral_mv = Portfolio;
p_Neutral_mv = Portfolio(p_Neutral_mv,'AssetList',AssetsList);

% Set assets moments
p_Neutral_mv = Portfolio(p_Neutral_mv, 'AssetMean', HistMeanRets,
'AssetCovar', HistCovRets);

>>

% Set budget bounds
p_Neutral_mv = Portfolio(p_Neutral_mv, 'LowerBudget', 1, 'UpperBudget',
1);

% Set assets bounds
p_Neutral_mv = Portfolio(p_Neutral_mv, 'LowerBound', LowerBoundLast,
'UpperBound', UpperBoundLast, 'BoundType', 'Simple');

% Set groups bounds
p_Neutral_mv = Portfolio(p_Neutral_mv, 'GroupMatrix', Groups,
'LowerGroup', LowerBoundGroups, 'UpperGroup', UpperBoundGroups);


% Estimate the efficient frontier with the methods |estimateFrontier| and
% |estimatePortMoments|, where |estimateFrontier| estimates efficient
portfolios and |estimatePortMoments| estimates risks and returns for
portfolios.

p_Neutral_mv_weights = p_Neutral_mv.estimateFrontier(50);
[p_Neutral_mv_Risk, p_Neutral_mv_Retn] = estimatePortMoments(p_Neutral_mv,
p_Neutral_mv_weights);
```

Best Omega Portfolio in M-V Efficient Frontier

```
% To pre-decide a "best" portfolio according to the corresponding Omega
ratio for the long term expected return (as obtained from the CDF), we
analyze this ratio for all portfolios in the efficient frontier.

OmegaAnchorAll = [];

for numports = 1:size(p_Neutral_mv_weights,2)

    weights = p_Neutral_mv_weights(:,numports);

    for i = 1:nTrials

    cumulativeReturns(i) = sum(log(1 + (exp(simulatedReturns(:,:,i)) - 1) *
weights));

    end

    OmegaAnchor = lpm(-cumulativeReturns, -prctile(cumulativeReturns,50),
1) / ...
        lpm(cumulativeReturns, prctile(cumulativeReturns,50), 1);

    OmegaAnchorAll = [OmegaAnchorAll OmegaAnchor];

end
```

○ Portfolio Optimization: Mean Variance

		Best Omega Portfolio	vs Benchmark
EQUITIES		37.4%	1.4%
	MSCI USA Net Total Return Local Index	15.7%	1.67%
	MSCI Europe Net Total Return Local Index	13.4%	-0.61%
	MSCI Japan Net Total Return Local Index	3.4%	-0.11%
	MSCI Emerging Net Total Return Local Index	4.9%	0.41%
GOVERNMENT		17.1%	-3.4%
	Bloomberg Barclays US Treasury Total Return Unhedged USD	7.2%	-0.35%
	Bloomberg Barclays EuroAgg Treasury Total Return Index Value Unhedged EUR	10.0%	-3.01%
CREDIT		33.7%	-0.3%
	Bloomberg Barclays US Corporate Total Return Value Unhedged USD	11.1%	0.56%
	Bloomberg Barclays Euro Aggregate Corporate Total Return Index Value Unhedged EU	11.3%	-0.20%
	Bloomberg Barclays US Corporate High Yield Total Return Index Value Unhedged USD	3.5%	-1.01%
	Bloomberg Barclays Pan-European High Yield (Euro) TR Index Value Unhedged EUR	4.2%	-0.26%
	Bloomberg Barclays EM Hard Currency Aggregate+ Local Currency	3.6%	0.63%
	Bloomberg Barclays EM Hard Currency Aggregate TR Index Value Unhedged USD	2.0%	0.49%
	Bloomberg Barclays EM Local Currency Core Net Ret Total Return Unhedged USD	1.6%	0.13%
ALTERNATIVE		10.5%	2.5%
	Hedge Fund Research HFRX Equal Weighted Strategies Index	3.2%	0.22%
	Hedge Fund Research HFRX EH Equity Market Neutral Index	7.2%	2.19%
	Bloomberg Commodity Index Total Return	0.1%	0.08%
CASH		1.3%	-0.2%



○ Portfolio Risk based on Extreme Value Theory

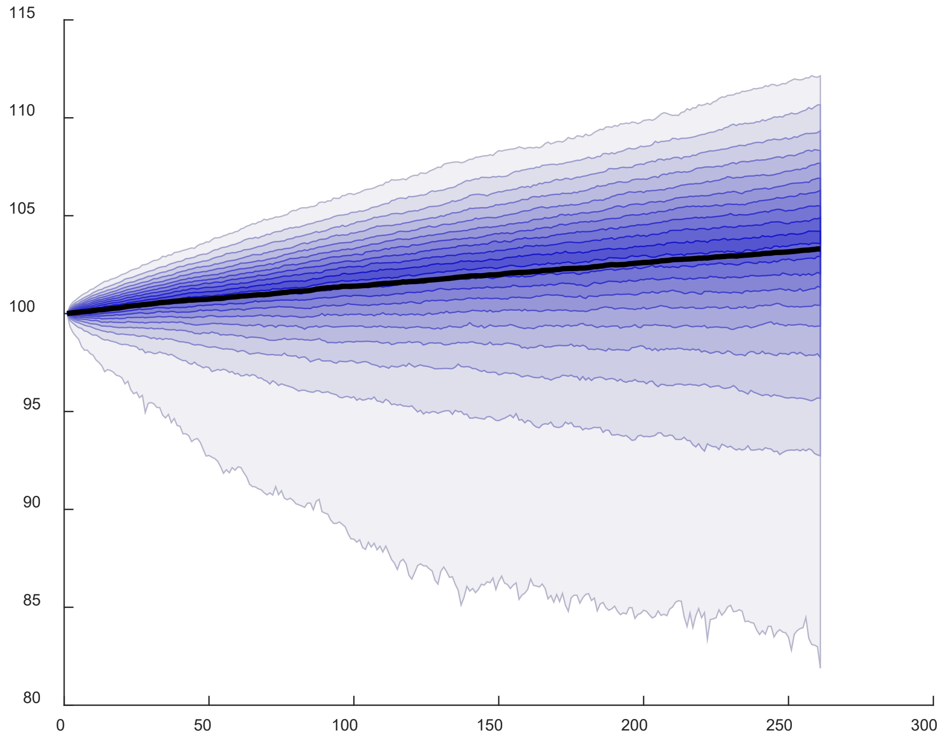
Best Omega Portfolio Expected Performance

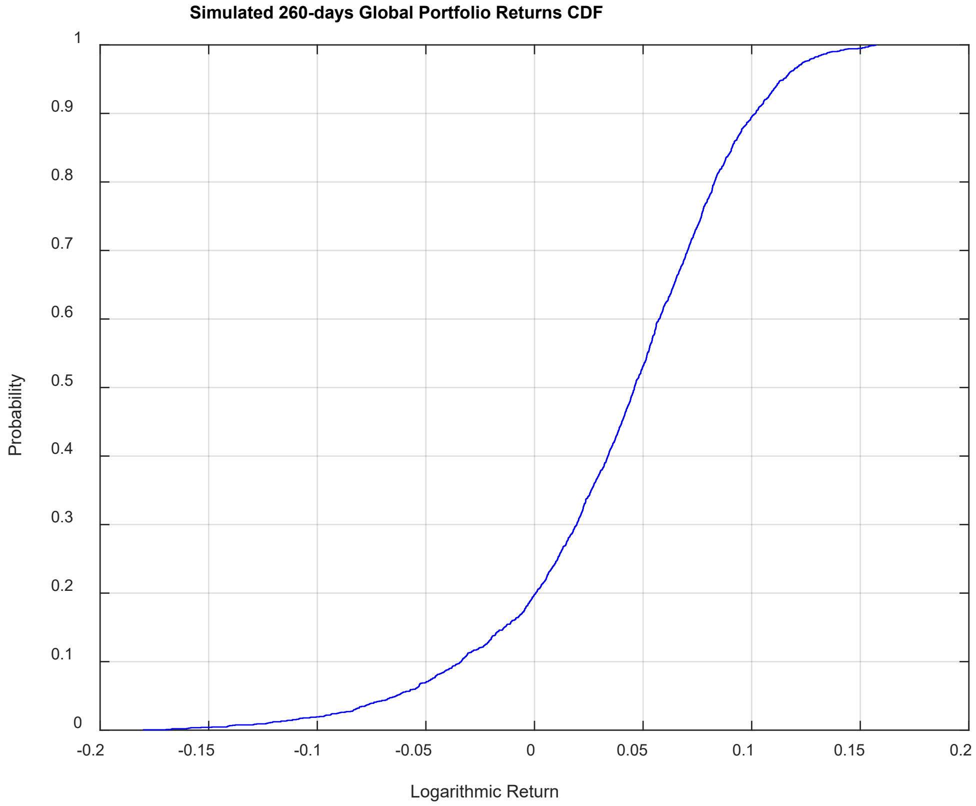
```
%% Simulate Global Index Portfolio Returns with a t Copula

s = RandStream.getGlobalStream();
reset(s)

nTrials = 2000;
horizon = 260;
Z = zeros(horizon, nTrials, nIndices);
U = copularnd('t', R, DoF, horizon * nTrials);  % t copula simulation

for j = 1:nIndices

    Z(:,:,j) = reshape(icdf(tails{j}, U(:,j)), horizon, nTrials);

end

Y0 = InvestAssetsReturnsArray(end,:);    % presample returns
Z0 = residuals(end,:);                   % presample standardized residuals
V0 = variances(end,:);                   % presample variances

simulatedReturns = zeros(horizon, nTrials, nIndices);

for i = 1:nIndices

    simulatedReturns(:,:,i) = filter(fit{i}, Z(:,:,i), ...
                                    'Y0', Y0(i), 'Z0', Z0(i), 'V0',
V0(i));

end
```

```
% Now reshape the simulated returns array such that each page represents a
% single trial of a multivariate return AssetsList, rather than multiple
trials of a univariate return AssetsList.

simulatedReturns = permute(simulatedReturns, [1 3 2]);

for DaysAssetsScenarios = 1:nIndices

    DaysScenariosPerAsset =
squeeze(simulatedReturns(:,DaysAssetsScenarios,:));
    THRetDaysScenariosPerAsset = prod((DaysScenariosPerAsset+1),1)-1;
    THRetDaysScenariosPerAssetSample{DaysAssetsScenarios} =
THRetDaysScenariosPerAsset;

end

% Obtain the cumulative final returns for each asset, for each simulation,
for the whole simulated period. This is a useful matrix for the
implementation of stochastic based optimisation models (i.e., CVaR,
Omega,...)

THRetDaysScenariosPerAssetSampleArray =
cell2mat(THRetDaysScenariosPerAssetSample(:));
THRetDaysScenariosPerAssetSampleArray =
THRetDaysScenariosPerAssetSampleArray';
```

RAMS

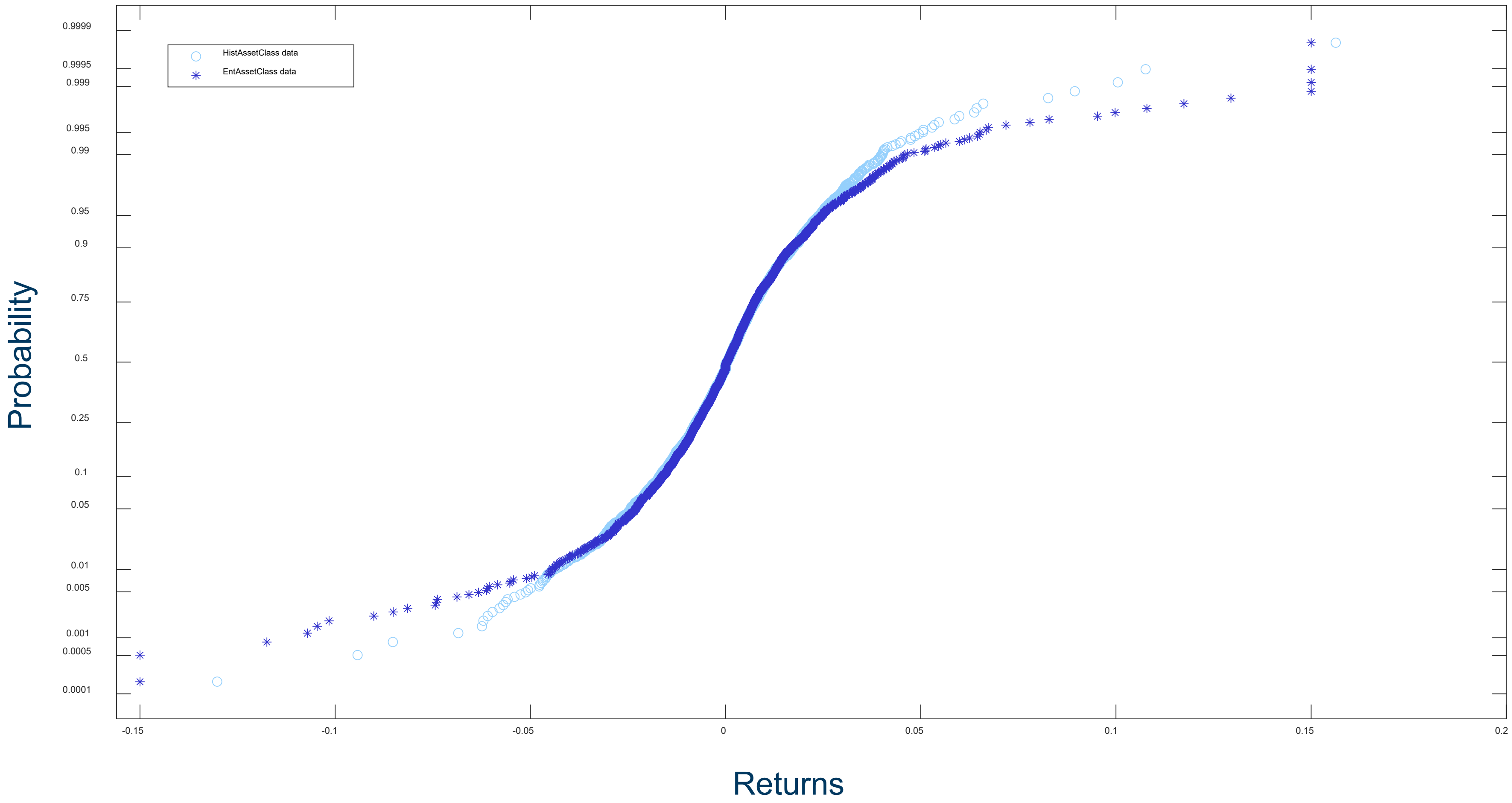
○ Portfolio Risk based on Extreme Value Theory





○ Portfolio Optimization: Conditional Value at Risk

- “Entropy Pooling Ranking” obtained expected cummulative distribution function for European Equities



○ Portfolio Optimization: Conditional Value at Risk

Mean CVaR Efficient Frontier

```
% Obtain simulated asset scenarios:

nScenario = nTrials;
AssetScenarios = THRetDaysScenariosPerAssetSampleArray;

% Construct a fully invested long only portfolio using |PortfolioCVaR|

p_Neutral_mcvar = PortfolioCVaR('Scenarios', AssetScenarios);

% Set Assets List

p_Neutral_mcvar = PortfolioCVaR(p_Neutral_mcvar,'AssetList',AssetsList);

% Set CVaR confidence level (95% in this case)

p_Neutral_mcvar = setProbabilityLevel(p_Neutral_mcvar, 0.95);

% Set assets bounds

p_Neutral_mcvar = PortfolioCVaR(p_Neutral_mcvar, 'LowerBudget', 1,
'UpperBudget', 1);
p_Neutral_mcvar = PortfolioCVaR(p_Neutral_mcvar, 'LowerBound',
LowerBoundLast, 'UpperBound', UpperBoundLast, 'BoundType', 'Simple');

% Set groups bounds

p_Neutral_mcvar = PortfolioCVaR(p_Neutral_mcvar, 'GroupMatrix', Groups,
'LowerGroup', LowerBoundGroups, 'UpperGroup', UpperBoundGroups);
```

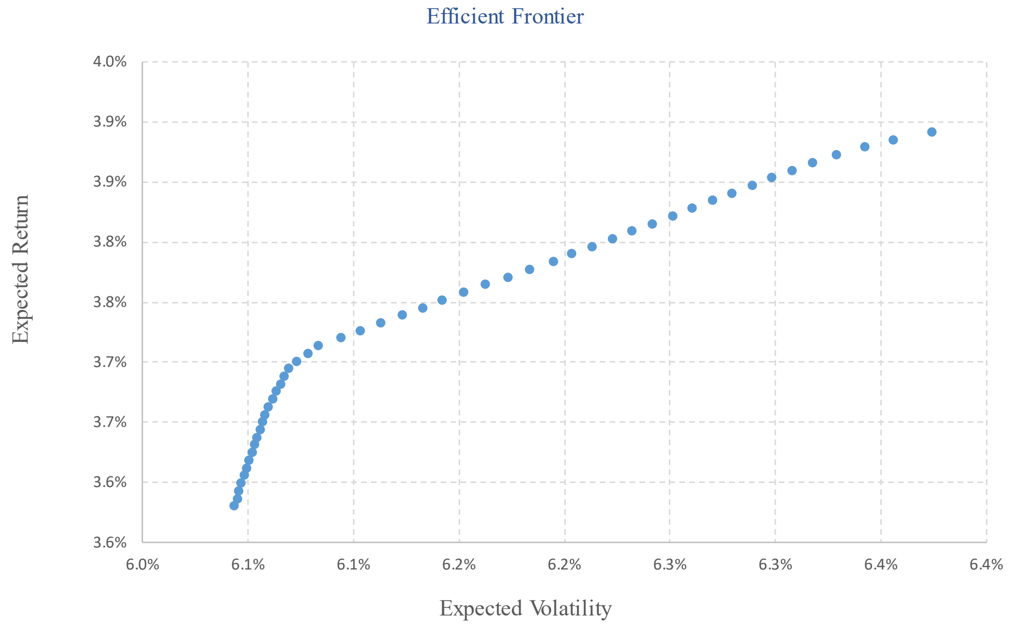
```
% Calculate portfolio weights, efficient frontier and plot efficient
% frontier.
% We use 50 portfolios along the efficient frontier.

p_Neutral_mcvar_weights = p_Neutral_mcvar.estimateFrontier(50);
figure;

plotFrontier(p_Neutral_mcvar,p_Neutral_mcvar_weights);

p_Neutral_mcvar_Retn = estimatePortReturn(p_Neutral_mcvar,
p_Neutral_mcvar_weights);

p_Neutral_mcvar_Risk = estimatePortRisk(p_Neutral_mcvar,
p_Neutral_mcvar_weights);

Scale = 260;

HistCovRets = cov(InvestAssetsReturns{:,:})*Scale;

p_Neutral_mcvar_Std =
sqrt(p_Neutral_mcvar_weights'*HistCovRets*p_Neutral_mcvar_weights);

p_Neutral_mcvar_Std = p_Neutral_mcvar_Std(:,1);

p_Neutral_mcvar_VaR = estimatePortVaR(p_Neutral_mcvar,
p_Neutral_mcvar_weights);
```

RAMS

Client Customized Final Portfolio

○ Portfolio Optimization: Conditional Value at Risk

		Portfolio	vs Benchmark
EQUITIES		36.3%	0.3%
	MSCI USA Net Total Return Local Index	14.2%	0.16%
	MSCI Europe Net Total Return Local Index	13.4%	-0.61%
	MSCI Japan Net Total Return Local Index	3.0%	-0.49%
	MSCI Emerging Net Total Return Local Index	5.7%	1.23%
GOVERNMENT		17.1%	-3.4%
	Bloomberg Barclays US Treasury Total Return Unhedged USD	7.2%	-0.35%
	Bloomberg Barclays EuroAgg Treasury Total Return Index Value Unhedged EUR	10.0%	-3.01%
CREDIT		34.8%	0.8%
	Bloomberg Barclays US Corporate Total Return Value Unhedged USD	11.1%	0.56%
	Bloomberg Barclays Euro Aggregate Corporate Total Return Index Value Unhedged EU	11.3%	-0.20%
	Bloomberg Barclays US Corporate High Yield Total Return Index Value Unhedged USD	4.3%	-0.21%
	Bloomberg Barclays Pan-European High Yield (Euro) TR Index Value Unhedged EUR	4.2%	-0.26%
	Bloomberg Barclays EM Hard Currency Aggregate+ Local Currency	3.9%	0.89%
	Bloomberg Barclays EM Hard Currency Aggregate TR Index Value Unhedged USD	2.3%	0.76%
	Bloomberg Barclays EM Local Currency Core Net Ret Total Return Unhedged USD	1.6%	0.14%
ALTERNATIVE		10.5%	2.5%
	Hedge Fund Research HFRX Equal Weighted Strategies Index	3.2%	0.22%
	Hedge Fund Research HFRX EH Equity Market Neutral Index	7.2%	2.19%
	Bloomberg Commodity Index Total Return	0.1%	0.08%
CASH		1.3%	-0.2%



Thank You. Any questions?

RECOGNITION
ASSET
MANAGEMENT
SOLUTIONS