BUSINESS CASE 3

FINTECH Academic year 2024/2025

POLITECNICO MILANO 1863

Investment replica

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INTRODUCTION & GOAL

We aim to reverse-engineer a target portfolio whose holdings and weights are unknown, extracting information about latent variables or functions and structural parameters from observed data. This **"black box"** approach allows us to replicate, analyze, and understand the portfolio's risk and return characteristics without direct access to its components.

We begin by constructing a synthetic portfolio with fractional weights using multiple techniques while minimizing the Information Ratio. Next, we translate these fractional allocations into real asset exposures based on an initial portfolio value, compute the associated costs, and introduce a **Total Expanse Ratio** (TER) that delivers our unique value proposition and competitive advantage.

DATASET DESCRIPTION

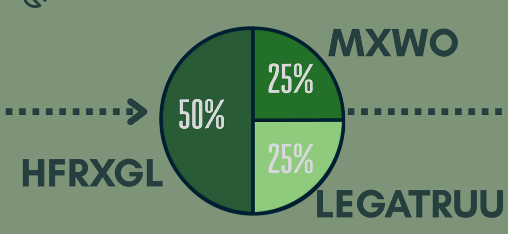
This dataset consists of financial data representing:

- **HFRX Index**: A popular index of Hedge Funds.
- **MSCI Index**: Global Equities, both MSCI World and MSCI ACWI.
- **Barclays Bloomberg Global Aggregate Bond Index**: Global Bonds (Developed & Emerging, Govt & Corporate).
- A broad range of **Futures contracts** on equity indices, benchmark bonds, currencies, and commodities.

Time Period: October 2007 – April 2021 with weekly frequency.
Source: Bloomberg.

ANALYSIS & METHODOLOGIES

1 **EDA & DATASET PREPARATION** → *Target Index Construction* → *Correlation Analysis & Rolling Correlation Analysis* → *Autocorrelation & Partial Autocorrelation Analysis* → *Stationarity & Cointegration Analysis* → *VECM Model*



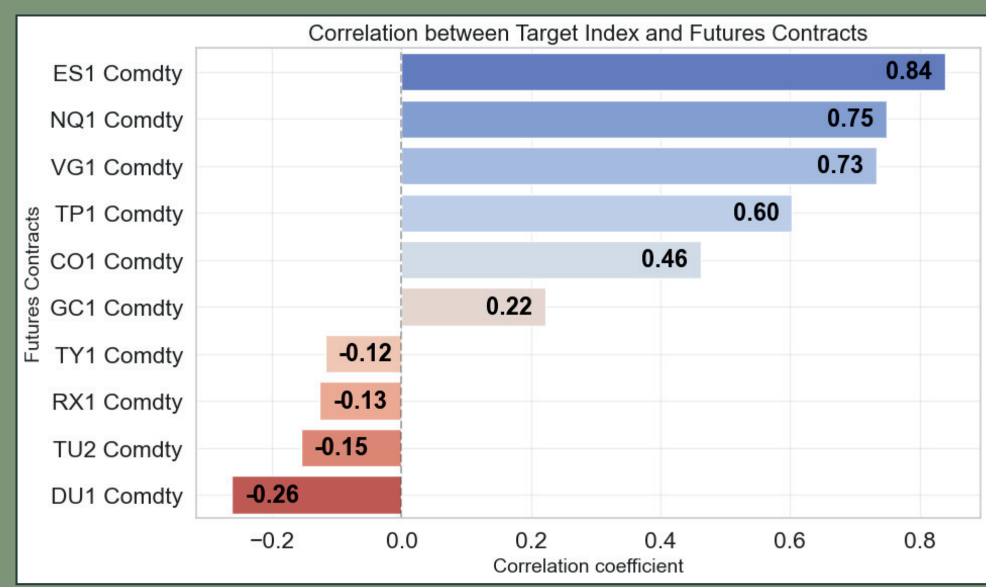
1 **Data Setup**: Constructed a DataFrame mapping Bloomberg tickers to asset names. Removed LLL1 futures due to incomplete time series and computed **log-returns** to ensure **stationarity**.

2 **EDA**: Plotted normalized prices' time series, return distributions, and computed key descriptive statistics.

3 **Correlation Analysis**: Measured correlations between the target index and Futures contracts, including rolling correlations to capture time-varying dynamics.

4 **Autocorrelation Analysis**: Assessed return normality, autocorrelation patterns, stationarity using ADF tests, and investigated cointegration relationships among asset prices.

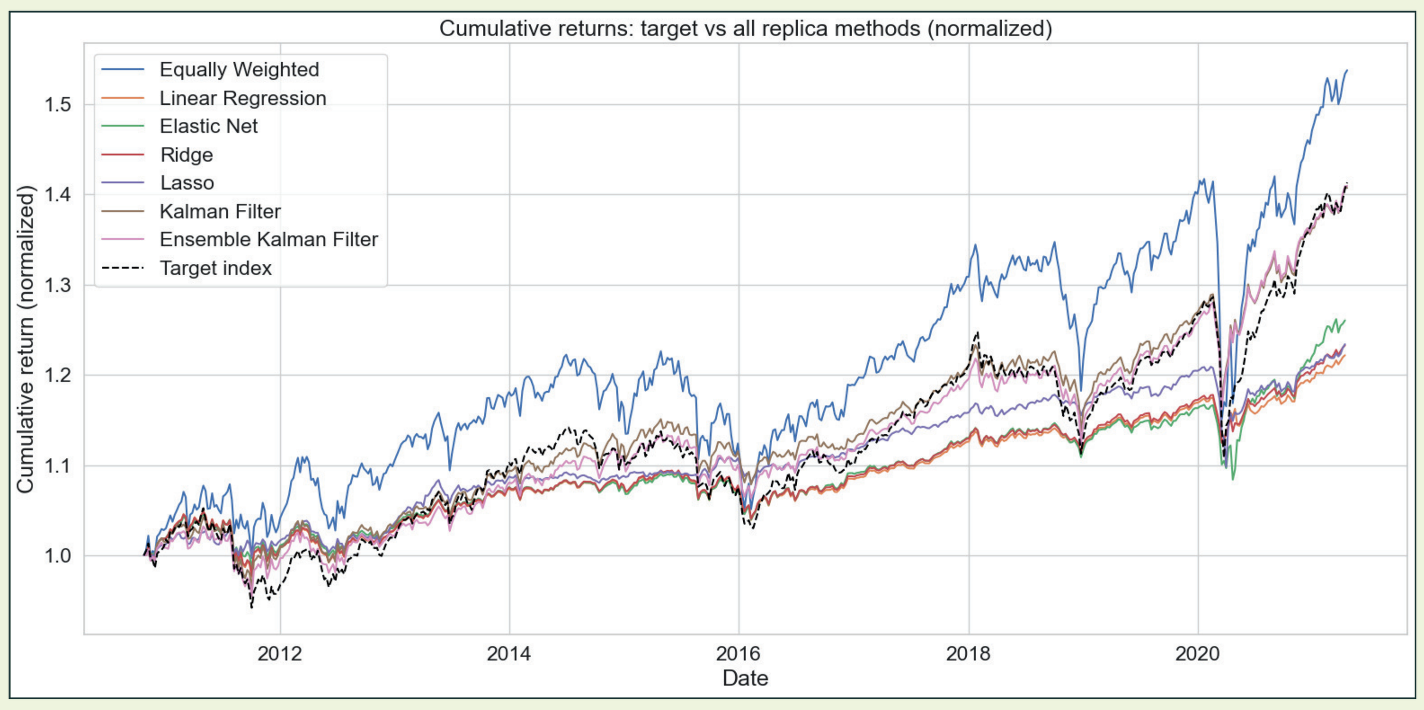
5 **Cointegration & Stationarity Analysis**: Implemented VECM model and developed a replication strategy.



2 **REPLICATION AND MODELLING** → **BASELINE MODELS**: *Equally Weighted Portfolio*, *Simple Linear Regression* → **PENALIZED REGRESSION MODELS**: *Elastic Net*, *Ridge Regressiont*, *Lasso Regression* → **STATE SPACE MODELS**: *Kalman Filter*, *Ensemble Kalman Filter*

6 **Replication Model Implementation**: Defined multiple replication strategies, including an equally weighted portfolio and regression-based methods (OLS, Elastic Net, Ridge, and Lasso), using rolling-window approaches with hyperparameter tuning (via **Optuna**) and ensuring VaR requirements.

7 **Dynamic Modeling with Kalman Filters**: Implemented both a standard **Kalman Filter** and an **Ensemble Kalman Filter** to dynamically update replication weights in real time based on new market data, incorporating **transaction costs** and risk scaling.

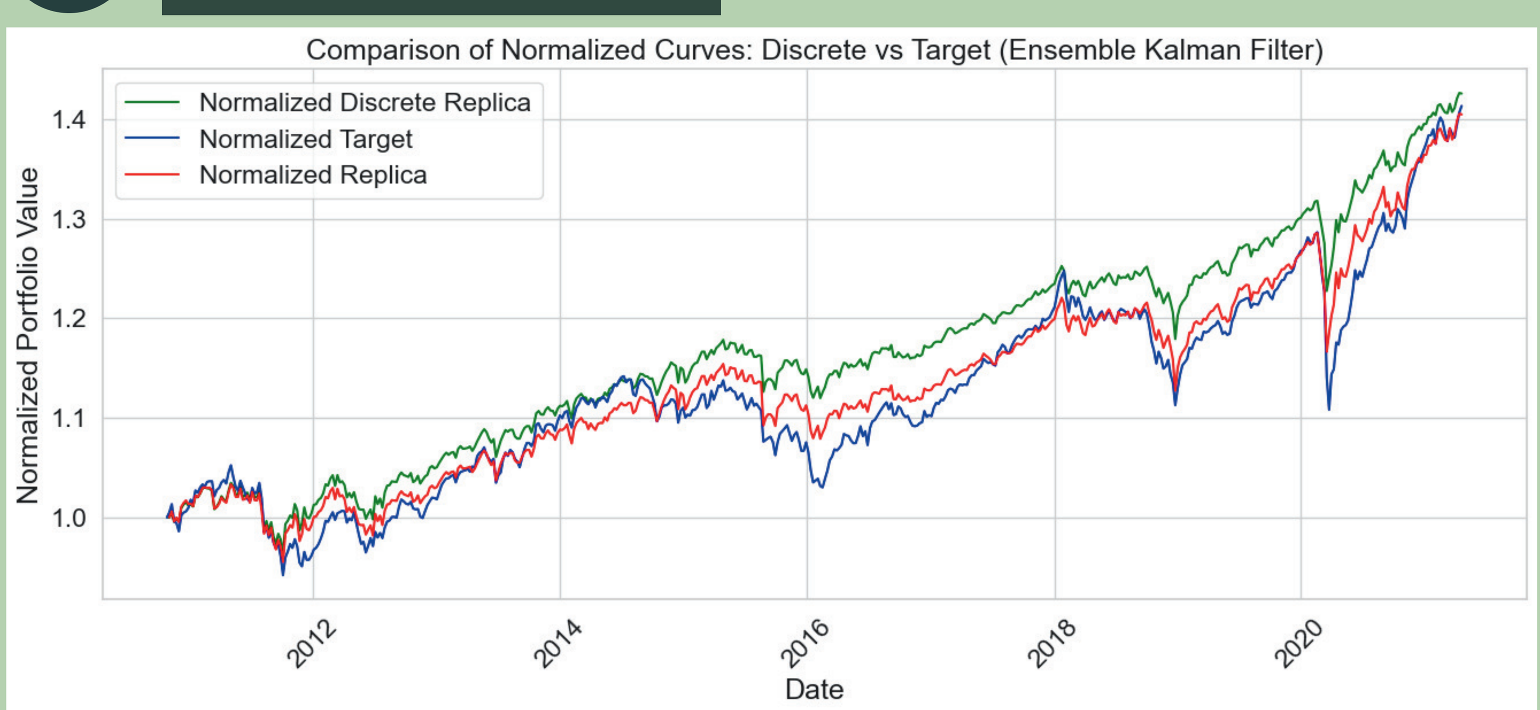


3 **PERFORMANCE EVALUATION** → **METRICS**: *Annualized Return*, *Annualized Volatility*, *Sharpe Ratio*, *Max Drawdown*, *Tracking Error*, *Information Ratio*, *Correlation*, *Average Gross Exposure*, *Average VaR*

8 **Performance Evaluation and Discrete Simulation**: Evaluated each model based on annualized return, volatility, Sharpe ratio, drawdown, tracking error and information ratio.
We then simulated a **real-world** discrete **implementation** by converting continuous weights to integer futures positions and calculates the transaction costs and equity curve of the replicating portfolio.

Model	Ann Ret	Ann Vol	SR	Max DD	Track Err	IR	Corr
Target Portfolio	**3.45%**	**5.60%**	**0,62**	**13.86%**	**N/A**	**N/A**	**N/A**
Equally Weighted	4.52%	8.82%	0,51	18.79%	5.55%	0,19	0,7933
Linear Regression	1.99%	3.27%	0,61	6.93%	3.67%	-0,39	0,7797
Elastic Net	2.30%	3.66%	0,63	7.11%	3.91%	-0,29	0,7185
Ridge	2.07%	3.28%	0,63	6.77%	3.67%	-0,37	0,7794
Lasso	2.09%	3.18%	0,66	9.18%	4.33%	-0,31	0,6386
Kalman Filter	**3.39%**	**5.05%**	**0,67**	**9.19%**	**2.96%**	**-0,02**	**0,8502**
Ensemble Kalman Filter	**3.41%**	**5.06%**	**0,67**	**9.20%**	**2.98%**	**-0,01**	**0,8488**

4 **BUSINESS ORIENTED APPLICATION**



Ensemble Kalman Filter Robustness:
We chose the Ensemble Kalman Filter for its **robustness**: varying the rolling window size or rebalancing frequency does not affect performance, maintaining optimal tracking error and information ratio.

Realistic Implementation Through Discretized Weights:
Continuous model weights are **discretized** into integer numbers of futures contracts, making the replication strategy operationally realistic and executable under **real trading** conditions.

Asset Under Management (AUM) & Trading Costs:
Our simulation uses a realistic initial AUM of **1.000.000$**, incorporating trading commissions of **5 bps per futures** contract, resulting in an annualized average **trading cost** of **0.0004%** of **AUM**.

Proposed Competitive Pricing (Total Expense Ratio - TER):
Given our efficient synthetic replication approach with futures, we propose a competitive TER of **0.04%**, significantly lower than comparable traditional financial products.

5 **POSSIBLE FUTURE DEVELOPMENTS**

- Investigate **Autoregressive** (AR) or **ARMAX** forecasting models to capture and leverage time-series dynamics and improve short-term prediction accuracy.
- **Real-time testing** investigating real world performance