Multi-Factor Timing

with Deep Learning

Alpha Strategies

March 13, 2024

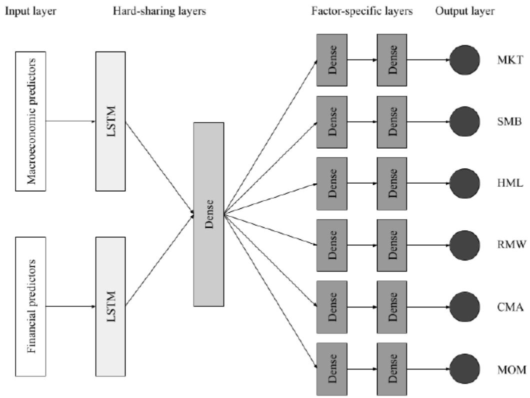
LOOMIS | SAYLES

Introduction

- This paper proposes a deep learning approach called Multi-Factor Timing (MFT) that jointly models fundamental and macro indicators to predict future factor returns.
- Prior works have focused on either group of indicators. This is the first to efficiently integrate both data sources with a sophisticated deep learning architecture.

Model Architecture

- Two-branch network architecture with separate branches:
- Fundamental inputs: valuation ratios, returns, profitability
- Macro inputs: default spreads, inflation, production
- Branches concatenated for final return prediction



Paper Results

- Outperforms other methods with over 6% ann. excess returns

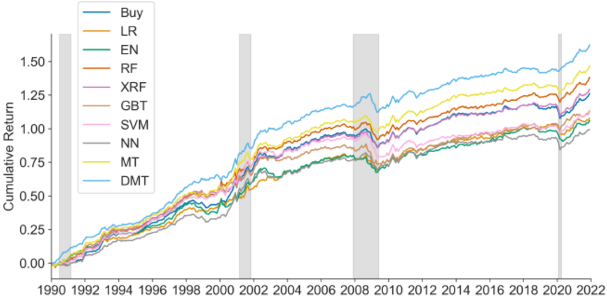


Figure 2: Out-of-sample cumulative returns Jan 1990 - Dec 2021.

Our Replication

- The training cutoff around Oct 2019, and it did capture the COVID meltdown pretty well. But it didn't do much for the 2022 drop. Then it attempts on May 2023 but quickly abandoned the short.

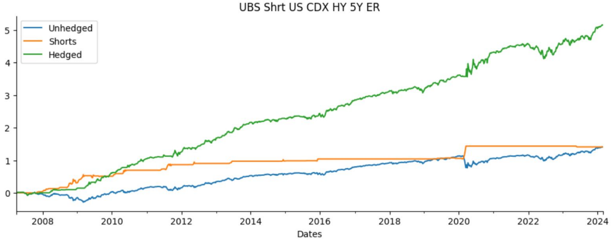


Figure 3: Cumulative returns Apr 2007 - Feb 2024

Next Steps

- Identify use cases in our investment processes: MAC, SIS, others?
- Input layers: Branching by asset class instead of Fundamental/Macro?
- Output layers: Replace Fama-French factors with premia, indices, hedges?
- Architecture engineering: Modifying inner layers design?

LOOMIS | SAYLES

Appendix

- Introduction and Methodology
  - Factor risk premia understanding is crucial in financial economics and factor investing.
  - Traditional models with limited predictors have yielded inconsistent outcomes, leading to debates about factor timing.
  - This paper introduces deep neural networks with economically motivated restrictions to address factor timing challenges.
  - A dynamic multi-task deep learning model is developed to forecast six well-known factors using 123 macroeconomic and 149 financial predictors from January 1965 to December 2021.

Appendix

- Key Findings and Conclusion
  - Incorporating economic structure and time series dynamics significantly improves the predictive accuracy of factor timing models.
  - Deep learning models with economic structure produce significant economic gains in a multi-factor portfolio.
  - Integrating multi-task learning with time series dynamics yields consistent economic gains across all factors.
  - Important variables for factor timing include tail risk, price trends, leverage, and profitability categories.
  - Nonlinear interactions among these influential variables are important for effective factor timing.
  - The improved factor timing from our dynamic multi-factor deep learning approach paves the way for a more reliable investigation of the economic mechanisms driving factor risk premia.

Appendix

- Data Used Overview
  - The model parameters are estimated on a training sample of 20 years (1965 - 1984).
  - Hyperparameter optimization is performed, validating the model's fit in the next five years (1985 - 1989).
  - The predictive power is assessed in the one-year testing sample (1990).
  - This procedure is replicated, extending the number of years in the training sample by one year in each iteration, for a total of 32 out-of-sample years (1990 - 2021).