Macro Attention Indices for Stock Return Predictability

Aaron Arauz Baumender
Michael Adrian Geiser Pasquel
Andreas Stavropoulos
Zhiyi Tang

December 2023

Abstract

We conduct forecasts for equity risk premia utilizing linear and neural network models trained on sets of macroeconomic factors and macroeconomic attention indices. The macroeconomic factors set comprises the 14 features recommended in previous works by Goyal and Welch (2008). The set of macro attention indices includes the eight features constructed by Fisher et al. (2022). Equity risk premia represent the annualized excess return of the one-month S&P 500 index over the prevailing risk-free rate, approximated by the yield on short-term Treasury Bills. Our analysis focuses on the period between 1985 and 2018, given the availability of the data. However, our results deviate from previous research, suggesting the need for further investigation into the datasets.

Keywords: Equity risk premia; Macroeconomic factors; Macro economic attention indices; Neural networks; Financial forecast

Outline

Introduction

- **Background**
  - Traditional focus on macroeconomic factors (MEF).
  - Behavioral finance introduces macro attention indices (MAI) reflecting market sensitivity to information.
  - Study recognizes interplay between MEF and MAI, and aims to contribute predictive models using linear and neural networks.
- **Objectives**
  - Assess S&P 500 (GSPC) Equity Risk Premia (ERP) predictive capacity of MEF and MEF using linear regression and neural networks.
- **Significance of the Study**
  - Goes beyond traditional forecasting methods.
  - Comprehensive analysis with linear and neural network models.
  - Aims to inform investors, policymakers, and researchers, as well as to enhance understanding of equity market dynamics.

Literature Review

- **Macroeconomic Factors**
  - Insights from Fama and French (1988) and Goyal and Welch (2003) reveal importance of dividends and book value in ERP forecasting.
  - Recent studies (Lo and Singh, 2003; Gu et al, 2019) use advanced techniques, revealing non linear dynamics.
- **Macro Attention Indices**
  - Studies by Andrei and Hasler (2006) and Nikkien et al. (2006) highlight the role in shaping investor sentiment.
  - Recent research (Ma et al., 2022) emphasizes improved predictive accuracy during market uncertainty.
- **Comparison of Factors and Indices**
  - No existing deep comparison of models models, which may offer a more robust framework.
  - Study uses linear regression models and neural networks for a comprehensive analysis.

Theoretical Framework

- **Market Dynamics Beyond Efficiency**
  - Challenges traditional Efficient Market Hypothesis.
  - Acknowledges anomalies and deviations from efficiency, especially during heightened investor attention.
  - Highlights the need for alternative frameworks beyond complete market efficiency.
- **Behavioral Finance and Investor Attention**
  - Integrates behavioral finance insights into decision-making.
  - Considers investor attention and herd behavior, leading to overreaction or underreaction.
  - Accounts for sentiment and attention in forecasting models, recognizing limitations of purely rational assumptions.
- **Neural Networks in Financial Forecasting**
  - Utilizes neural networks to capture complex relationships.
  - Addresses limitations of traditional linear models.
  - Enhances modeling of interactions between MEF and MAI impacting ERP.

- **Model Specification**
  - **MEF:** Log Dividend-Price ‖ Log Dividend Yield ‖ Log Earnings-Price ‖ Log Dividend-Payout ‖ Equity Premium Vol ‖ Book-to-Market Ratio ‖ Net Equity Expansion ‖ Treasury Bill Rate ‖ Long-Term Yield ‖ Long-Term Return ‖ Term Spread ‖ Default Yield Spread ‖ Default Return Spread ‖ Inflation
  - **MAI:** Credit Rating ‖ Gross Domestic Product ‖ House Market ‖ Inflation ‖ Monetary ‖ Oil ‖ Unemployment Rate ‖ US Dollar
  - **ERP:** GSPC Equity Risk Premia

Methodology

- **Data Management** Historical data from 1.1.1985 to 31.12.2018, daily, monthly, and quarterly frequencies. Collected from various repositories, organized chronologically for model training.
  - **Data Collection (Raw Data):** MEF and MAI data collected from specific GitHub repositories. GSPC data collected from Yahoo Finance.
  - **Data Cleaning (Interim Data):** Preprocessing steps applied to address missing values in MAI raw databases.
  - **Data Processing (Processed Data):** MEF and MAI data undergo processing to construct data for model training. Calculations include transformations and interpolations to derive key macroeconomic factors and attention indexes.

Methodology (continued)

- **Data Selection**
  - Utilizing the Interactive Shiny App facilitates visualization of the impact of various features and temporal ranges.
  - Flexibility to:
    - select any subset of the 14 MEF variables,
    - select any subset of the 8 MAI variables,
    - select any time window ranging from 1.1.1985 to 31.12.2018,
    - select different temporal frequencies of the data (daily, monthly, quarterly).
  - The MEF model results are denoted by blue lines, the MAI model results by green lines, and the veritable values by the red line.
  - In the next slides we provide a few cases.

Methodology (continued)

- Quarterly data between 1.1.1985 and 31.12.2018 of MEF Log Dividend-Price (solid blue), MEF Log Dividend Yield (dashed blue), MAI Credit Rating (dashed green), and MKT GSPC (solid red) are selected.

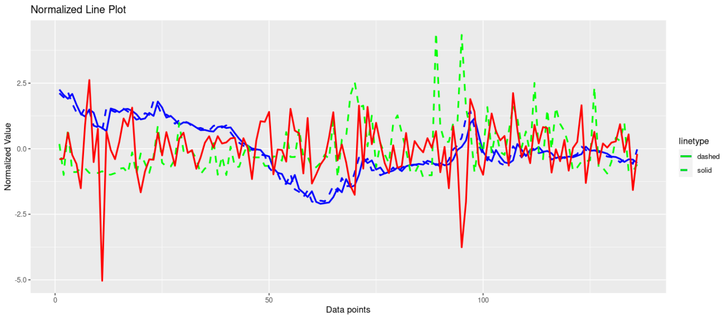

Figure 1: Shiny app variable selection outcome, Case 1.- Interactive Shiny App

Methodology (continued)

- Quarterly data between 1.1.1985 and 31.12.2018 of MEF Log Dividend-Price (solid blue), MEF Log Dividend Yield (dotted blue), MEF Log Earnings-Price (dashed blue), MAI Credit Rating (dotted green), MAI Gross Domestic Product (solid green), and MKT GSCP (solid red) are selected.

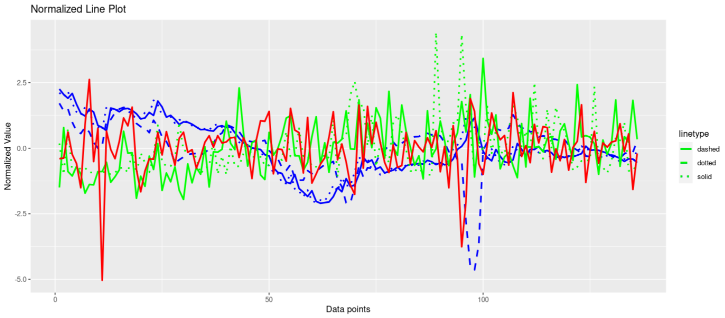

Figure 2: Shiny app variable selection outcome, Case 2.- Interactive Shiny App

Methodology (continued)

- Correlation heatmaps, MEF data between, 1.1.1985 and 31.12.2018.

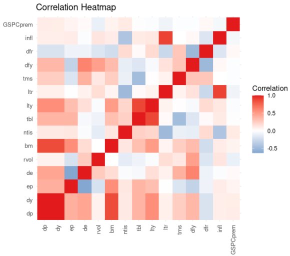

Figure 3: MEF daily.

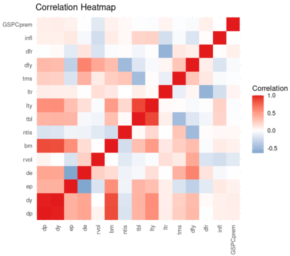

Figure 4: MEF monthly.

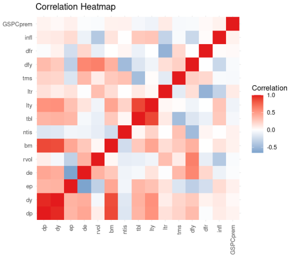

Figure 5: MEF quarterly.

- Correlation heatmaps, MEF data between, 1.1.2000 and 31.12.2018

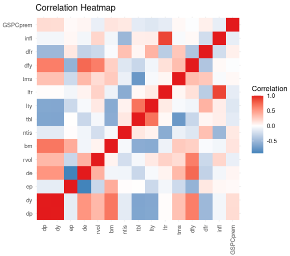

Figure 6: MEF daily.

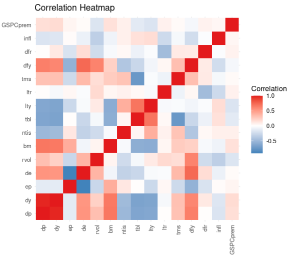

Figure 7: MEF monthly.

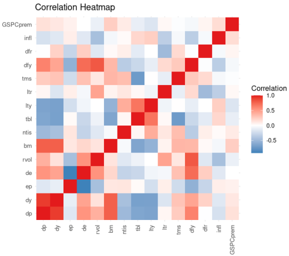

Figure 8: MEF quarterly.

Methodology (continued)

- **Model Training**
  - Two approaches: Ridge regression and neural network models.
  - Linear regression uses the standard equation with gradient descent and Ridge regularization.
  - Neural network employs traditional feedforward architecture.
  - Root Mean Squared Error (RMSE) used to assess performance.
- **Comparison and Interpretation**
  - Comparative analysis of results from both models.
  - Evaluation based on RMSE for different combinations of economic data (MAI and MEF) and target variable (1-month GSPC ERP).
  - Daily and monthly frequencies considered.

- **Data Overview**
  - We used six datasets with their characteristics summarized in the following table:

Dataset	# of Variables	Frequency	Time Period	# of Samples
MEF Daily	14	Daily	1985/01/02-2018/12/31	8523
MAI Daily	8	Daily	1985/01/02-2018/12/31	8523
MKT Daily	1	Daily	1985/01/02-2018/12/31	8523
MEF Monthly	14	Monthly	1985/01/31-2018/12/31	408
MAI Monthly	8	Monthly	1985/01/31-2018/12/31	408
MKT Monthly	1	Monthly	1985/01/31-2018/12/31	408

Table 1: Description of Datasets used for model training.

- **Model Implementation: Ridge Regression Model**
  - Implemented ridge regression using MEF and MAI data as independent variables.
  - Trained on four datasets: MEF monthly, MAI monthly, MEF daily, MAI daily, establishing a linear relationship with GSPC data (MKT monthly, MKT daily).
  - Specifications:
    - K-fold cross-validation (5 folds) to tune hyperparameter.
    - Grid of tested values: $[10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 1, 10, 10^{2}, 10^{3}, 10^{4}, 10^{5}]$.
    - Train-test split: 80
  - Training approach:
    - For monthly datasets (408 points), the model is trained 10 times with different splits, reporting average RMSE.
    - For daily datasets, the model is trained once, and RMSE is reported.

Empirical Analysis (continued)

- **Model Implementation: Neural Network Model**
  - Implemented a feedforward architecture with the following specifications:
    - Two hidden layers (64 and 32 neurons).
    - Two dropout layers (30
    - Single neuron output.
    - Adam optimizer with a learning rate of 0.01.
    - Batch size: 32.
    - Number of epochs: 10.
  - Training approach:
    - For monthly data, the model is trained 10 times with different train-test splits, and the average RMSE is reported.
    - For daily data, the model is trained and predicted once.
  - Note: Meaningful results weren't expected from monthly datasets (408 points) due to limited data for efficient neural network training. However, this approach is used as a reference and for comparison with the regression model.

- **Results**
  - The average root mean square error (RMSE) of eight different models (two types of models on four datasets) is tested on ten different random train-test splits of each dataset.

Model	**Input Data**	**RMSE on Test Set**
Linear Model	MEF Daily	53.243
	MAI Daily	54.677
	MEF Monthly	54.307
	MAI Monthly	53.571
NN Model	MEF Daily	54.142
	MAI Daily	54.063
	MEF Monthly	52.717
	MAI Monthly	53.096

Table 2: Comparison of RMSE of different models

Empirical Analysis (continued)

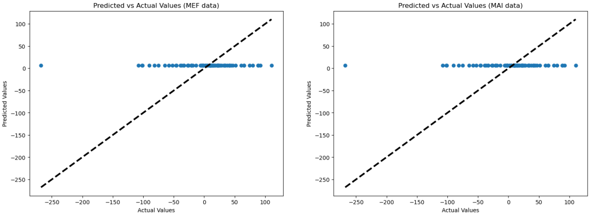

Figure 9: True vs Predicted values for monthly data (Regression)

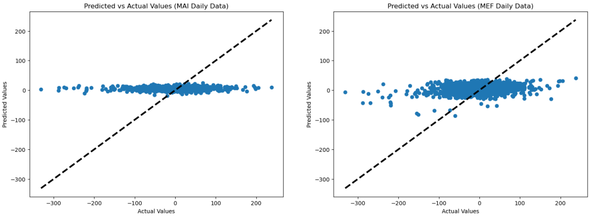

Figure 10: True vs Predicted values for daily data (Regression)

Empirical Analysis (continued)

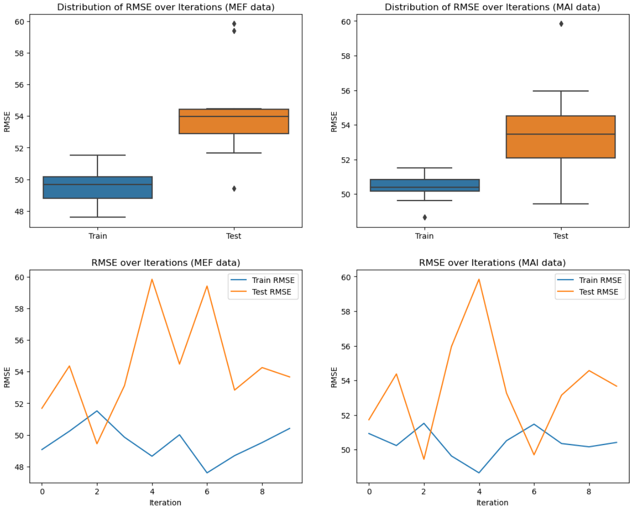

Figure 11: Distribution of RMSE over iterations, linear models on monthly data.

- Distribution and boxplots of RMSE over iterations, Neural Networks on monthly data

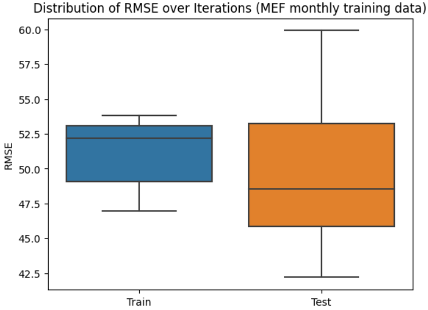

Figure 12: MEF monthly.

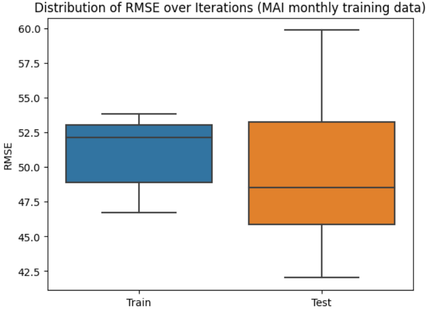

Figure 13: MAI monthly.

Empirical Analysis (continued)

- True vs Predicted values for daily data (Neural Network)

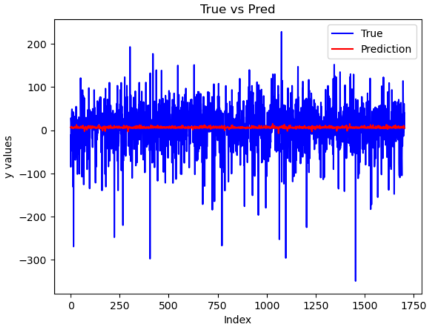

Figure 14: MEF daily.

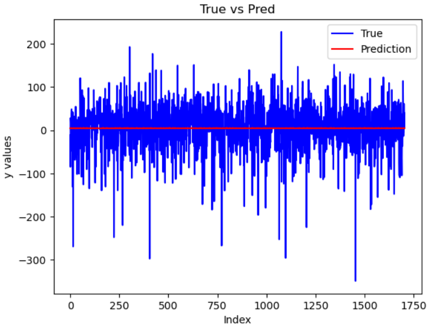

Figure 15: MAI daily.

- **Model Selection**
  - The inefficiency of both models (Ridge Regression, Neural Network) is evident in Table 2, highlighting their inability to predict the excess annualized returns of S&P500.
  - These results do not suggest a mere bad fit; rather, all models exhibit a lack of effective training and prediction within a narrow range.
  - Given these findings, selecting a superior-performing model becomes challenging.

Discussion

- **Summary**
  - Study aimed to forecast ERP using regression and neural network models, incorporating MEF and MAI datasets, targeting S&P500 excess return.
  - Despite utilizing data from 1985 to 2018, sourced from GitHub repositories and Yahoo Finance, predictive models showed significant deviations from established research.
- **Interpretation of Results**
  - Lack of predictive efficacy in MAI data contradicts literature.
  - Limited usefulness of traditionally used MEF data in predicting stock returns (issues with data preprocessing, model complexity, or capturing relationships over a wide time frame).
  - Reasons for poor model performance include weak relationships between features and the target variable, inadequate data preprocessing, inappropriate hyperparameter tuning, insufficient model complexity (especially for neural networks), and non-stationarity of statistical properties in stock returns.

Discussion (continued)

- **Summary**
  - Experiment with combinations of MAI and MEF features as inputs to predictive models.
  - Explore advanced preprocessing techniques, outlier detection methods, and strategies for handling missing data to enhance the quality of model inputs.
  - Conduct a comprehensive hyperparameter search to optimize model performance.
  - Explore more sophisticated modeling approaches beyond regression and neural networks.
  - Consider focusing on shorter time ranges instead of the entire dataset or implement advanced time series analysis techniques to address non-stationarity.

References

- Fama and French (1988): *Dividend Yields and Expected Stock Returns*
- Goyal and Welch (2003): *Predicting the Equity Premium with Dividend Ratios*
- Lo and Singh (2003): *Deep-learning models for forecasting financial risk premia and their interpretations*
- Gu, Kelly, and Xiu (2019): *Empirical Asset Pricing via Machine Learning*
- Andrei and Hasler (2012): *Investors' Attention and Stock Market Volatility*
- Nikkinen, Omran, Sahlström, and Äijö (2006): *Global stock market reactions to scheduled U.S. macroeconomic news announcements*
- Ma, Lu, Liu, and Huang (2022): *Macroeconomic attention and stock market return predictability*