Overview: Financial markets are sophisticated and include macroeconomic drivers and investor sentiment. Most conventional asset pricing models revolve around simple models such as CAPM or Fama-French Factor models and often neglect current technical and economic indicators. The proposal below poses a question: Will asset price prediction and risk assessment be enhanced if a Bayesian statistical model incorporates technical trading signals in addition to macroeconomic indicators? The synthesis of numerous sources of information in a unified Bayesian framework should provide a more precise prediction of asset returns while providing a more precise quantification of uncertainty than standard methods. The proposed task is to formulate and assess such a model and thus to acquire a deeper understanding of asset pricing dynamics along with a novel, feasible solution for this complex problem. Background and Motivation: Technical analysis and macroeconomic analysis are handled separately in most of the existing financial models. Compute recent price movements, technical indicators size and rate like the Relative Strength Index, then calculate the short-term market position and mark when an asset is overbought or oversold. However, macroeconomic factors such as GDP growth, inflation, and interest rates exert a longer-term impact on the intrinsic value of assets. The literature and publication gap exists because not many asset pricing models blend these fundamental and technical perspectives. As seen during periods of market bubbles or busts, the movement of the market tends to be an intersection between investor philosophy and economic reality, and therefore, filling this gap is necessary. A formal solution to this problem is provided by Bayesian statistical modeling, which enhances model robustness by fusing continuous market data with prior knowledge. A benefit of modeling noisy, dynamic financial markets is that Bayesian methods can fit many inputs while shrinking noise parameters by using spike-and-slab priors and updating beliefs with our quantitative model from the technical indicators. The aim is to get both the underlying macroeconomic trends and the rapid shift in market sentiment by incorporating RSI and macroeconomic indicators within a Bayesian framework. Methodological Framework and Research Strategy: A Bayesian statistical modeling approach will be applied using publicly available financial data and cutting-edge computational methods to answer the research question. The Alpha Vantage API is the primary tool for conducting this research as it provides easy access to stocks, technical indicators, and macroeconomic time series [1]. The development of the project will be divided into three phases:

Phase 1: Preprocessing and Data Collection. Historical price information for a collection of financial instruments, including stock indices or portfolios of equity, will be gathered using the Alpha Vantage API. Daily and weekly Relative Strength Index (RSI) levels of the price series will be computed in a bid to assess momentum and rebalance the portfolio's expected returns [2]. To illustrate the economic condition, I will also simultaneously fetch important macroeconomic indicators (like GDP, interest rates, etc.) from Alpha Vantage or other public databases that align with FRED API terms of use [3]. After cleaning and date alignment, the data will be divided into training and validation periods. This phase creates a comprehensive dataset by merging macro and market characteristics.

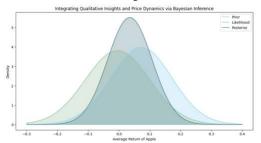
Phase 2: Development of a Bayesian Model. At this stage, I am going to develop a Bayesian asset pricing model that makes use of both RSI and macroeconomic indicators in predicting asset returns or price changes. A particular approach is to employ Bayesian regression or a state-space model where the next period return is the dependent variable while past RSI and macroeconomic signals are the independent predictors. I will provide informative prior distributions for model parameters. I will use a spike-and-slab prior to automatic factor selection when there are numerous predictors in order to ensure that only valuable variables are kept. Python toolkits such as 'PyMC' or 'Stan' will be utilized to carry out parameter inference using Markov Chain Monte Carlo (MCMC) methods. This is anticipated to yield predictive distributions for the returns of assets and posterior distributions for the model parameters. Throughout the development process, I will utilize the computational resources available to guarantee the implementation of the model with precision and speed.

**Phase 3: Evaluation and Validation.** The hypothesis will be severely tested, and the model's performance will be thoroughly examined by employing out-of-sample datasets and performing a sensitivity analysis. As an example, the Bayesian model-based forecasts will be compared with those based on a conventional non-Bayesian approach (e.g., a standard CAPM benchmark or an ordinary least

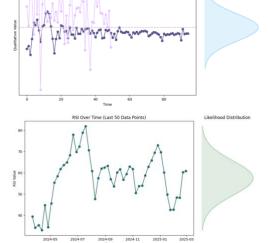
squares regression using identical inputs). Prediction error reduction, calibration of predictive intervals, and economically meaningful known parameters will be the most important evaluation criteria. I will also conduct case studies of previous market history, i.e., recessions or volatile periods, to ascertain whether the model changes its beliefs given changing conditions and use L1/L2 regularization to ensure model robustness [4]. Evidence that the inclusion of RSI and macro factors in a Bayesian model improves asset price predictions or risk assessments over models excluding these factors would be a successful outcome.

**Preliminary Findings:** An initial prototype Bayesian model for Apple Inc. was developed using technical indicators and past prices obtained using the Alpha Vantage API. There were three essential aspects that were explored:

- (1) **Prior Distribution:** The predicted return was arrived at by combining sentiment scores of news articles about Apple with macroeconomic factors like yearly growth in GDP.
- (2) Likelihood Distribution: Simple returns were calculated from historical price data and then scaled using RSI data.
- (3) **Posterior Distribution:** The Bayesian update generates a posterior distribution by normalizing the product of the prior and likelihood. The figures illustrate the model's capacity to



adapt to real market conditions. These early findings



demonstrate the Bayesian framework's viability and ability to combine many data sources into a coherent model. The promising results on Apple data provide a solid basis for expanded use and more improvement.

Intellectual Merit: The project can contribute to improving our knowledge in quantitative finance through the innovative integration of heterogeneous data sources for asset pricing. It aims to develop a novel Bayesian model framework that connects macroeconomic variables and technical market indicators—a relatively unexploited area. The approach is explained to be the new state-of-the-art by integrating methods from econometrics, machine learning, and finance. It has the potential to transform the discipline by addressing a long-standing issue: making reliable predictions in volatile markets. The expected outcomes would enhance our scientific grasp of market dynamics, elucidating the interplay between macroenvironmental conditions and transient momentum signals in asset returns. From a methodological perspective, the factor selection procedure and dynamic updating through Bayesian priors may make possible novel applications in numerous areas with numerous predictors.

**Broader Impacts:** This is a consequence of its ability to enhance risk management and financial decision-making, which would be beneficial to society. More sophisticated asset price models can lead to more stable, efficient markets to foster individual wealth accumulation and economic growth. Improved forecasting and risk assessment mechanisms can de-link financial crisis effects on society by enabling regulators and investors to detect emerging risk (or bubble in assets) sooner. Above all this, this endeavour has additional possible gains in the context of open science and academic learning. The generated code will be open-source, allowing other researchers, students, and practitioners to utilize and build upon the Bayesian modeling methods.

**Reference:** [1] Alpha Vantage. (n.d.). *API documentation*. <a href="https://www.alphavantage.co/documentation/#">https://www.alphavantage.co/documentation/#</a>
[2] Alpha Vantage Market Data Primers. (n.d.). *Relative Strength Index (RSI)*.

<a href="https://www.alphavantage.co/relative\_strength\_index\_rsi/">https://www.alphavantage.co/relative\_strength\_index\_rsi/</a>
[3] Federal Reserve Bank of St. Louis. (n.d.).

\*\*FRED® API terms of use. <a href="https://fred.stlouisfed.org/docs/api/terms\_of\_use.html">https://fred.stlouisfed.org/docs/api/terms\_of\_use.html</a>
[4] Pykes, K. (2023, August 4). \*\*Fighting overfitting with L1 or L2 regularization: Which one is better? Neptune Blog. <a href="https://neptune.ai/blog/fighting-overfitting-with-11-or-12-regularization">https://neptune.ai/blog/fighting-overfitting-with-11-or-12-regularization">https://neptune.ai/blog/fighting-overfitting-with-11-or-12-regularization</a>