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Consumer Confidence and Asset Returns

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Abstract: Investor sentiment is a key topic in financial research, with many studies exploring the potential of consumer sentiment to predict financial asset returns. However, a consensus on this relationship has yet to be reached. This paper extends previous research by utilizing the Long Short-Term Memory (LSTM) model, a powerful predictive tool, to examine the relationship between consumer confidence and stock, bond, and futures markets returns. Unlike prior studies that that focused primarily on linear relationships, particularly between investor sentiment and stock returns, this research considers the non-linear dynamics across multiple asset classes. The analysis uses monthly data from January 1978 to December 2021, including CCI from the University of Michigan official website, stock, bond and future market returns from main financial databases. The findings indicate that the CCI demonstrates significant predictive power for bond market returns (BMR), a noticeable ability to predict stock market returns (SMR) but limited forecasting capability for future market returns (FMR).

Keywords: consumer sentiments; Consumer Confidence Index; stock market returns; bond market returns; futures market returns

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1. Introduction

Investor sentiment is a key concept in behavioral finance and has become a central topic of research in recent years. Rooted in the understanding that psychological factors influence investor behavior, investor sentiment is often conceptualized as the general mood or attitude of investors toward financial markets. As traditional asset pricing models often assume rational behavior, the incorporation of sentiment into financial analysis has opened new avenues for exploring market inefficiencies and anomalies. Many studies have explored the extent to which consumer sentiment can predict returns on financial assets, yielding varying findings [1-3]. Although these studies offer valuable insights, the relationship between sentiment and asset returns remains far from conclusive, warranting further investigation.

Notably, Fisher & Statman highlighted the ability of consumer sentiment to forecast small market returns (SMR), particularly in segments of the market characterized by higher uncertainty, such as small-cap firms and innovative or emerging industries [4]. Their research emphasized the importance of the Consumer Confidence Index (CCI) as a crucial indicator in capturing investor expectations and forecasting market movements. Similarly, Chung et al. demonstrated that investor sentiment remains a statistically significant predictor of SMR across varying economic conditions [5]. Their findings suggest that sentiment maintains its predictive power both during expansionary and contractionary phases of the business cycle, implying that behavioral biases may persist irrespective of macroeconomic trends.

Furthermore, the study by Fang et al. contributed to this line of research by examining the interaction between investor sentiment and intermarket relationships, particularly between U.S. stock and bond markets [6]. Their results underscored the influence of sentiment on the long-term correlation between these asset classes, suggesting that shifts in sentiment can lead to structural changes in investor allocation strategies. Expanding upon this, Reis & Pinho provided further empirical evidence supporting the predictive utility of various sentiment measures in forecasting SMR, reinforcing the notion that sentiment may be an important, albeit complex, determinant of financial market dynamics [7].

However, despite these findings, the literature on investor sentiment and asset returns remains divided. Several researchers have raised skepticism regarding the robustness and consistency of sentiment-based forecasting models. For instance, Kling & Gao employed survey data to proxy investor sentiment and concluded that sentiment does not hold meaningful predictive power for broader stock market movements [8]. Their work called into question the reliability of sentiment indicators, particularly in light of the potential for noise and measurement error in survey-based metrics. Similarly, Wang et al. examined the crude oil futures market and found limited evidence of Granger causality between investor sentiment and market returns, especially during periods marked by extreme volatility or exogenous shocks [9]. These studies suggest that while sentiment may offer explanatory power in some contexts, its predictive capacity may be constrained or conditional on other economic or market variables.

These divergent findings highlight the complexity and context-dependent nature of the sentiment-return relationship. The lack of consensus in the literature underscores the need for further empirical exploration, particularly using methodologies capable of capturing non-linearities and temporal dependencies in financial time series data. In response to these limitations, this paper builds on existing research by applying advanced machine learning techniques — specifically, the Long Short-Term Memory (LSTM) model — to examine whether the CCI can predict market returns across various asset classes, including equities, fixed income, and commodity futures.

The empirical framework of this study leverages monthly data spanning from January 1978 to December 2021. Key variables include the Consumer Confidence Index, stock and bond market returns obtained from the Center for Research in Security Prices (CRSP) database, and commodity return data based on the Goldman Sachs Commodity Index (GSCI). While prior research has predominantly focused on the relationship between sentiment and stock market returns, this study offers a broader perspective by extending the analysis to the bond and futures markets. By doing so, the study accounts for potential differences in market behavior across asset classes and addresses the possibility that sentiment may have varying degrees of influence depending on the nature and structure of the market.

A notable innovation in this research is the application of the LSTM model, which is particularly well-suited for capturing the complex, dynamic patterns often present in financial data. LSTM, a type of recurrent neural network (RNN), is capable of learning long-term dependencies and modeling non-linear relationships between variables. This is particularly relevant in the context of investor sentiment, where the effects may unfold over extended periods and interact with various market conditions. Traditional econometric models may fail to adequately capture such intricacies, leading to underestimation or misinterpretation of sentiment effects.

The primary contribution of this study lies in its investigation into the predictive power of the Consumer Confidence Index across multiple asset classes using state-of-the-art machine learning methodologies. By adopting a broader asset scope and leveraging the predictive capabilities of LSTM networks, this paper offers new insights into the nuanced relationship between sentiment and financial returns. The findings of this study may have significant implications for both academic research and practical investment strategies. In particular, the results could inform the development of sentiment-based trading algorithms, portfolio optimization tools, and risk management frameworks.

Moreover, understanding the predictive role of investor sentiment may assist in anticipating market shifts and managing macroeconomic challenges such as inflation and financial instability. For policymakers and financial analysts, insights derived from sentiment analysis may enhance the interpretation of market signals and improve the timing of interventions. Overall, this study aims to bridge the gap between behavioral finance theory and modern data-driven approaches, offering a more comprehensive understanding of how sentiment influences market behavior in an increasingly complex and interconnected financial landscape.

2. Research Method

This study uses the Consumer Confidence Index (CCI) as the primary indicator of investor sentiment due to its widespread use in prior literature and its established role in capturing consumer perceptions of current and future economic conditions. The CCI data were obtained directly from the official University of Michigan website, ensuring the credibility and reliability of the source. This index is based on surveys that reflect the opinions of households regarding business conditions, personal finances, and expectations about inflation and unemployment, making it a comprehensive proxy for aggregate investor mood.

In addition to sentiment data, this study incorporates key financial market indicators to evaluate the relationship between sentiment and asset returns across various classes. Specifically, stock market data, including 1-month Treasury bill (T-bill) returns, were retrieved from the Kenneth R. French data library, a well-known and reputable source for academic research in finance. The inclusion of T-bill returns provides a risk-free rate benchmark, which is critical for evaluating excess returns and for comparative analysis. Commodity market data, in the form of the S&P Goldman Sachs Commodity Index (GSCI), were sourced from Investing.com. This index serves as a representative proxy for commodity futures and allows the study to expand its scope beyond equities and fixed income markets. All datasets used in this research cover monthly observations from January 1978 to December 2021, offering a long-term historical perspective across different economic cycles and market regimes.

Prior to conducting the modeling analysis, the dataset underwent extensive preprocessing to ensure robustness and reliability. First, incomplete or missing samples were excluded from the analysis. Data cleaning is essential to prevent distortions or biases in model training, especially for machine learning algorithms that are sensitive to anomalies and irregularities. After the data cleaning process, the final dataset included complete and consistent monthly observations across all relevant variables for the full study period.

To further enhance the accuracy and generalizability of the model's predictions, the data were normalized. Normalization adjusts the scale of the input features, bringing them into a consistent range, which is particularly important when combining financial time series with different magnitudes and units. This step helps improve model convergence and stability during training, especially in deep learning models like LSTM that are prone to issues such as vanishing gradients.

Given the possibility of non-linear interactions and time-dependent patterns in the relationship between sentiment and market returns, the study employs the Long Short-Term Memory (LSTM) model. LSTM is a type of recurrent neural network (RNN) that is well-suited for sequential data analysis. Its architecture is specifically designed to capture long-range temporal dependencies by using memory cells and gating mechanisms, which allow it to retain and update information across time steps.

To train the LSTM model, the data were split into training and testing subsets. Specifically, 80% of the data were allocated for training, allowing the model to learn from historical patterns, while the remaining 20% were reserved for testing. This partitioning ensures an objective evaluation of the model's performance on unseen data, thereby providing a realistic assessment of its predictive capabilities.

In the implementation of the LSTM model, a time step of two was chosen. This means that the model uses two consecutive periods of past data as input features for predicting future outcomes. This design is intended to capture short- to medium-term temporal dependencies, which may be crucial for understanding how lagged consumer sentiment and historical market returns influence subsequent asset performance. By incorporating multiple time lags, the model is better equipped to detect subtle patterns and dynamic shifts that might not be captured through linear methods or single-lag models.

3. Results

The performance of the predictive model is assessed using the Mean Absolute Error (MAE), which measures the average magnitude of errors in predictions without considering their direction. Specifically, MAE quantifies the average absolute difference between the predicted values and the actual observed values. A lower MAE indicates a smaller discrepancy between predicted and actual values, reflecting higher predictive accuracy. The results indicate that the CCI exhibits significant predictive power for BMR, with a marked ability to predict SMR. However, the model's forecasting ability for FMR is more limited (see Table 1 and Figure 1-3).

Table 1. MAE Value.

	FMR	SMR	BMR
MAE	52.15	3.53	0.02

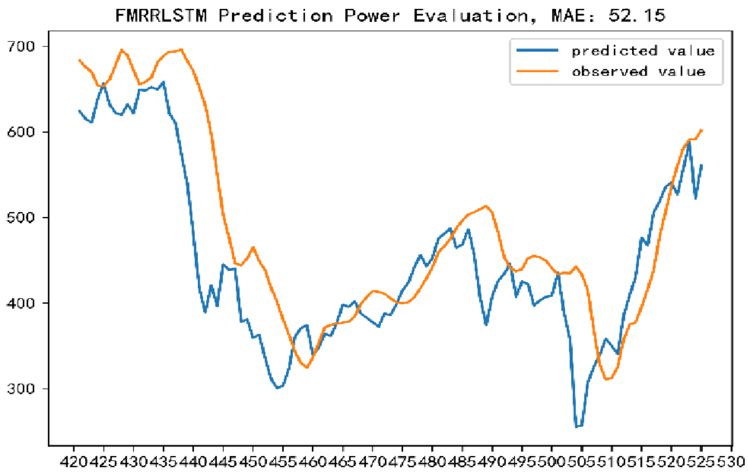

Figure 1. FMR Value.

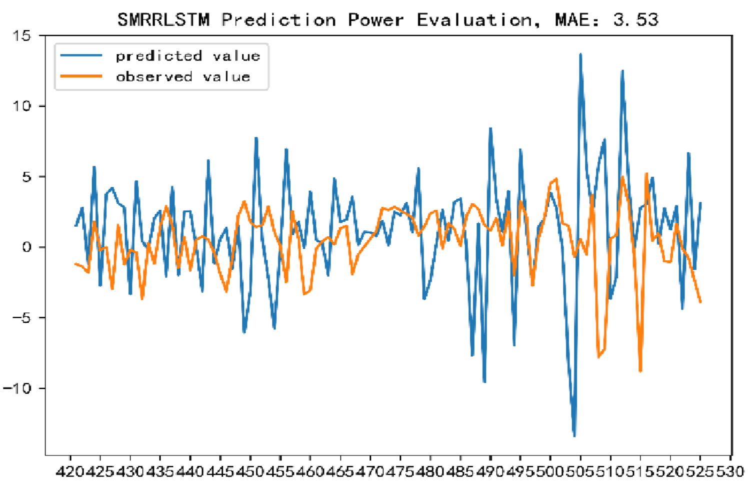

Figure 2. SMR Value.

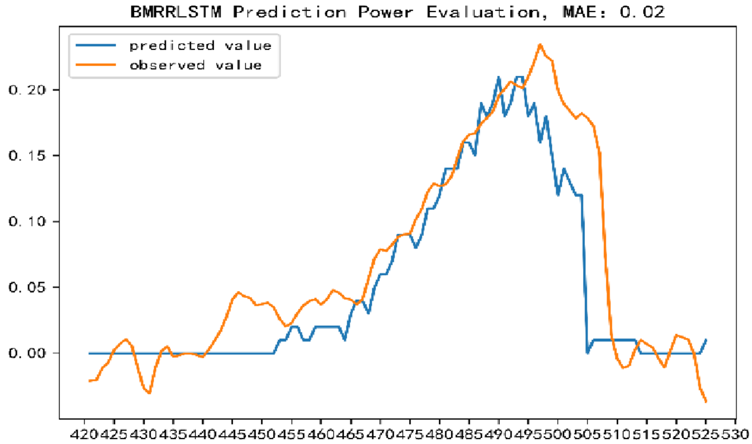

Figure 3. BMR Value.

4. Conclusion

This study explores the impact of investor sentiment on financial markets, reviewing relevant literature on the influence of sentiment on asset returns. Specifically, we investigate whether consumer confidence, as measured by the CCI, can predict the returns of three key financial assets: stocks, bonds, and futures. Our analysis reveals that the CCI demonstrates significant predictive power for BMR and exhibits strong predictive ability for SMR. However, the predictive capability for FMR is more limited. Future research could consider the application of principal component analysis, which combines multiple individual indicators to provide a more comprehensive representation of investor sentiment. Additionally, the advancements in big data and text mining techniques open the possibility of constructing more sophisticated sentiment indicators by leveraging computer scraping technologies to capture a broader range of investor sentiment data. A limitation of this study is the use of monthly data, which may not fully capture the high-frequency fluctuations of financial asset prices. Given that financial markets are dynamic, future studies could incorporate higher-frequency data, such as weekly or daily data, to provide a more granular view of sentiment's impact on asset returns. Furthermore, the LSTM model in this study employs a fixed time step of 2, which may be relatively simplistic. The model's performance could be further explored by varying the number of epochs and batch sizes, as different configurations have been shown to influence results in related studies. Future research may experiment with these parameters to identify the optimal configuration for predicting financial market returns. Moreover, this study uses the same LSTM model to analyze stock, bond, and futures markets, without fully accounting for the specific characteristics of each market. Future studies could explore the use of different models tailored to the unique features of these markets, comparing their performance and selecting the best-performing model for further analysis.

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