Literature Review

Research on media sentiment by (Fang & Peress, 2009) Suggested that social media sentiment can significantly influence stock market returns and consumer perceptions of the current state of the economy. This is supported by (Affuso & Lahtinen, 2019) That found that negative tweets have a significant impact on daily stock returns. (Fang & Peress, 2009) also showed that individual stock with less coverage on social media had higher returns than its high coverage counterparts. Considering the more traditional news media, (Morin et al., 2004) found that there are three key channels that influence consumers, conveying economic data and expert opinions, signaling economic conditions through reporting and tonality, and the more frequent the news about the economy or stock is the more likely a consumer will update their expectations about the aforementioned. (Morin et al., 2004) concluded that consumers tend to update their economic expectations more often during times of high news coverage, which are typically during and immediately following recessions. Consumer outlook may, however, deviate from the underlying economic realities when media coverage fails to accurately depict the state of the economy.

An interesting study by (Ren et al., 2021) shows that the influence of media sentiment both traditional news media and social media can shape a media sentiment in the short run and reinforce this sentiment over time, creating a "feedback loop" that amplifies the current media narrative. During the Covid-19 pandemic (Umar et al., 2021) found that heightened media coverage amplifies returns and volatility, especially from the healthcare and energy sector. The abovementioned research articles highlights the potential of media sentiment to provoke investor for better or for worse. This behavioral finance theory phenomenon emphasizes the role of psychological factors in investor sentiment and decision making. (Kapoor & Prosad, 2017) review aims to help better explain behavioral finance to bridge the gap left by traditional financial theories. (Steve Y. Yang & Sheugn Yin Kevin Mo, 2016) discovered enduring relationships between market fluctuations and media sentiment, with sentiment-based investing methods producing better risk-adjusted returns.

The abovementioned research underscores how media sentiment can shape public perceptions about the current economic environment, investor behavior, and asset price volatility. This also provides a great argument that media sentiment requires more in depth research to better understand how media sentiment can impact our everyday lives.

To better understand how markets react to media sentiment we must try and better understand how investor behavior interacts with financial markets. (Lillo et al., 2012) stated that different economic groups react at varying levels based on media and news. Specifically, households and governments are highly responsive to both exogenous (news volume and sentiment) and endogenous (returns and volatility) factors. The processing of news and media sentiment by investors is influenced by their cognitive filters, behavioral biases, and attention mechanisms (Kamal et al., 2022). This can lead to an under- or over-reaction that deviate from efficient market hypothesis. (Baker et al., 2014) mentions that investors can be subject to anchoring and representative biases, where investors are still hold less equities within their portfolio's as a result of the 2008 global financial crisis.

The GARCH model has been a foundational econometric approach in modeling financial volatility by its inert ability to capture and explain autocorrelation and clustering effects, yet they have shortcomings with regards to exogenous shocks (Ederington & Guan, 2005). GARCH models and its derivatives are effective and accurate tools for volatility forecasting in financial markets, particularly for heteroscedastic time series data (Kargar, 2021). (Kargar, 2021) showed that the GARCH and GJR-GARCH showed promising results in predicting financial market volatility. What makes the GARCH model preferable to the ARIMA model is following the findings of (Sparks & Yurova, 2006), where GARCH models outperformed ARIMA in one-step ahead forecasts. While ARIMA models may provide comparable point estimates, their downside is that the ARIMA model struggles to produce normally distributed residuals. The non-constant volatility estimations by the GARCH models is what contributes to their preferable performance in financial time series modeling, making them more suitable.

(Alomari et al., 2021) showed that when sentiment data is incorporated into a GARCH forecasting model it can improve their performance, indicating that sentiments have strong effects on volatility, with a specification that social media impacts correlations more significantly. (Berry et al., 2019; Sadik et al., 2019) both created a news augmented GARCH model (NA-GARCH). The comparison between NA-GARCH and GARCH showed the NA-GARCH outperformed the GARCH model in predicating volatility for multiple shocks. What makes the news augmented GARCH model very applicable is the ability to measure volatility given economic shock. (Guidolin & Pedio, 2020) found that augmented GARCH models with media sentiment and tonality scores had better performance than traditional GARCH models when forecasting FTSE 100 return volatility during the economic shock of Brexit. The abovementioned studies shows that having a media sentiment augmentation within the GARCH model can enhance volatility accuracy, highlighting its importance in financial modeling.

But the complexity of the NA-GARCH model its weighted patterns perform better within in-sample but can struggle with out-of-sample forecasting, this problem can be attributed to additional estimation errors (Ederington & Guan, 2005). A significant limitation in the abovementioned study by (Berry et al., 2019) is the relatively small sample size of 9 stocks from the NASDAQ 100 stocks chosen. This small sample size can affect generalizability and robustness of the findings. The small sample size can also lead to potential biases and cannot accurately depict the population effect.

But why is the size so important? (Kasch et al., 2014) argues that the presence of the S&P 500 index effect is permanent and that observed changes in market value and return co-movement are due to existing patterns over time rather than the inclusionary effect of the index. (Graham et al., 2003) also help support our macroeconomic and media sentiment ideas by finding that macroeconomic news has an impact on stock market dynamics significantly, this contribution to our financial market understanding convinces me that using the indices of the S&P500, Nasdaq 100, and the Dow Jones are the best ways to measure the sentiment of media.

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