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Original Article

How do Media Releases Affect Netflix's Stock

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Abstract *- This study investigates the relationship between media releases and Netflix's stock performance, extending the analysis to competitors in the streaming industry. Using data from 2012 to 2024, we examine the popularity of Netflix's content releases, measured through Google search trends, ratings, and social media activity, and correlates with its stock price movements. Our methodology employs a linear regression model, incorporating variables such as show release dates, Google search volumes, and S&P 500 returns. The results reveal a weak positive correlation between Netflix's show releases and its stock returns, but competitor show releases showed negligible correlation. The S&P 500 returns demonstrated the strongest relationship with Netflix's stock movements, underscoring the importance of broader market trends. As measured by Google search volume, public interest showed a minimal negative relationship with stock returns. These findings suggest that while content releases and public interest play a role in Netflix's stock performance, macroeconomic factors and overall market conditions are more influential. This research contributes to the understanding of media influence on financial markets and offers insights for investors and streaming platforms in evaluating the impact of content strategies on stock performance.*

Keywords *- Google trends, Media releases, Netflix, Stock returns, Streaming industry.*

1. Introduction

The influence of public interest and media buzz on financial markets has garnered significant attention recently, especially with social media such as Reddit and Twitter. Media companies like Netflix are uniquely positioned in this landscape where public reception of their content could have immediate and profound effects on their financial performance. This research explores the correlation between the popularity of show releases and the subsequent movements in the media platform's stock price.

Netflix, Inc. (NFLX) was a pioneer in the streaming industry. With its extensive library of original content, Netflix has cultivated a global subscriber base of almost 300 million. [1] Major content drops such as the latest seasons of popular series like Bridgerton and Stranger Things or new blockbuster movies generate substantial buzz across multiple platforms, including social media, review sites, and news outlets. This public interest can vary in sentiment from enthusiastic approval to critical disapproval, so it is vital to understand the impact of the type of emotion and its popularity scale on Netflix stock's performance. This research focuses on a specific question: How do the popularity and buzz related to Netflix's content releases correlate with its stock price movements, and do these effects extend to competitors in the streaming industry? This is significant because the relationship investigated could offer insights into potential drivers of stock price beyond traditional methods. By comparing these results with those of other streaming companies, such as HBO and Amazon Prime TV, the study aims to understand the broader impact of TV releases by competitor firms on Netflix's stock prices. Several key studies provide a foundation for this research. Bollen, Mao, and Zeng (2011) demonstrated how public mood, measured through social media, could predict stock market movements. [2] Another relevant study by Oyewola and Dada (2011) evaluated the effectiveness of different machine learning models and techniques for predicting a movie's net profit value based on IMDb reviews, highlighting the connection between media popularity and financial success. [3] However, limited research has focused on the streaming industry—a sector where consumer engagement is closely tied to content releases. While these studies broadly cover market indices or diverse sets of companies, this research focuses primarily on a single influential company within the media industry, Netflix, and how it is affected by its competitors. The study employs regression analysis to investigate this relationship between the popularity metrics (e.g., Google search volume, number of ratings) of Netflix releases and stock price movements. Additionally, it examines whether these effects are immediate or lagged to understand how public interest impacts financial performance over time comprehensively. Another critical gap lies in the lack of comprehensive studies analyzing competitor interactions within the streaming industry. For example, it remains unclear whether the release of a blockbuster show on a competing platform affects Netflix's stock performance. This study contributes to the broader field of financial economics by demonstrating the value of popularity and buzz metrics in predicting the stock behavior of the producing company. This research hypothesises that the popularity of a new Netflix Original significantly and immediately correlates with Netflix's stock price movements. Positive popularity metrics are expected to increase stock prices, reflecting increased investor confidence due to anticipated subscriber growth. In contrast, negative metrics may decline stock price, indicating potential subscriber churn or dissatisfaction with Netflix’s offerings. The study uses data from Google Trends, rating counts, and other popularity indicators to achieve this, correlating these with Netflix's stock price movements within the event window. Furthermore, the study extends the analysis to competitors' stock prices, examining if Netflix's content releases affect the financial performance of other major streaming services. This structure ensures a systematic exploration of the research question, starting from the theoretical background through thorough methodology and data analysis, concluding with results, and finally evaluating the study's strengths and limitations.

2. Literature Review

2.1. Media Sentiment and Financial Markets

Numerous studies have highlighted the impact of media sentiment on financial markets. Investors often base their trading decisions on new fundamental information, such as dividend announcements or management decisions. However, some also rely on media sentiment expectations, which cover market participants' opinions, expectations, or beliefs toward the company and ultimately influence stock prices. For instance, Tetlock (2007) analyzed a daily Wall Street Journal column and found that high media pessimism led to a decline in market prices. [4] Similarly, a study by Tetlock, Saar-Tsechansky, and Macskassy (2008) confirmed that stock prices react significantly to media sentiment based on news stories published in the Wall Street Journal and Dow Jones News Service. However, most studies focus primarily on traditional financial statistics and do not consider industry-specific dynamics, such as those in the entertainment and streaming sectors, where public interest in media content is essential to consumer engagement and stock movements. This study fills this gap by examining how the excitement around content launches affects Netflix's stock performance.

2.2. Impact of Popularity and ‘Buzz’ on Financial Markets

In addition to traditional media, the impact of popularity and buzz, especially expressed through social media and search trends, has been explored. Antweiler and Frank (2004) collected and analyzed text messages posted on finance message boards, concluding that trading volume increases when there is a disagreement in sentiment among the traders’ messages. [5] They also found that the number of messages posted during a day can help predict the stock returns of the following day, demonstrating that buzz, independent of sentiment, could predict stock movements. Bollen, Mao, and Zeng (2011) extended this analysis to microblogging services like Twitter, finding a significant correlation between the sentiment expressed and stock market performance for certain tickers, proving this universality. Similarly, Liu et al. (2020) examined how social media metrics, such as the number of tweets and search indices, impacted stock prices, concluding a strong correlation between public interest and stock market performance. [6] Moreover, Weng et al. (2018) demonstrated that social media data could predict stock price movements, with significant predictive power observed for short-term trends, such as those investigated in this research. [7] This study implies that immediate public reactions might operate as short-term drivers of market behavior, which is especially relevant for streaming companies whose content releases elicit rapid responses across social networks. In contrast to Bollen et al.'s general emphasis on sentiment, this study measures the direct financial impact of media popularity by focusing on particular metrics like search volume, ratings, and release schedules in the streaming industry. In contrast to previous research on general market sentiment, this study provides a detailed examination of how streaming services like Netflix react to public interest by combining these metrics. Using Google Trends data to measure public interest has also been proven useful. A study by McNally et al. (2016) used Google Trends alongside other technical indicators to predict Bitcoin prices, demonstrating significant accuracy. [8] This approach underlines the potential of search volume data as a proxy for public engagement, offering a novel way to study market dynamics for companies like Netflix. Furthermore, Siering (2013) investigated the interplay between media sentiment and investor attention on the Dow Jones Industrial Average (DJIA). [9] The study found that positive media sentiment has a larger impact on DIJA returns when investor attention is high. This suggests that when investors actively seek information, the sentiment expressed in the media plays a more significant role in shaping their expectations and trading decisions, affecting market outcomes. This study builds on Siering's findings by adding industry-specific context to investor attention metrics like search volume and critical reception. By concentrating on Netflix, the study deepens our knowledge of how public opinion and reception affect attention-driven sectors like streaming.

2.3. Investor Attention and Financial Markets

Investor attention has been identified as a critical factor influencing financial market anomalies such as underreaction and overreaction to financial news. Barber and Odean (2008) found that individual investors are particularly drawn to "attention-grabbing" stocks, which are frequently discussed in the media and show large trading volumes and returns. [10] This highlights the role of media in attracting investor attention and its subsequent impact on trading behavior. Studies have also shown that stock recommendations published in the media can significantly influence investor attention. Busse and Green (2002) demonstrated that trading volumes increase after a stock is discussed on television. [11] Furthermore, Da, Engelberg, and Gao (2011) introduced a direct measurement of investor attention using Google's Search Volume Index (SVI). [12] They found that this measure is correlated with indirect proxies for investor attention and provides a timely reflection of investor interest, especially among retail investors. This is relevant for this investigation because simply announcing a new Netflix Original's release can inflate interest and stock price regardless of its actual quality and public popularity. Additionally, Chemmanur and Yan (2009) found that a firm's advertising expenses lead to increased individual investors buying the stock, indicating a spillover effect from product advertisements to stock market interest. [13] So, Netflix's spending on advertisements to market the release of the new 'Original' series could affect the stock price more than the actual popularity of the show, which is determined only after its release.

2.4. Application of Linear Regression in Financial Market Analysis

Machine learning has been increasingly utilized to analyze the popularity of media content and its financial implications. Studies have demonstrated the effectiveness of various machine learning techniques in predicting stock price movements based on popularity metrics. For example, Groß-Klußmann and Hautsch (2011) used automated text analytics to quantify the impact of high-frequency news on market reactions, showing significant predictive power of machine learning models in financial contexts. [14] Another study by Heston and Sinha (2016) compared the effectiveness of news sentiment analysis using machine learning algorithms to predict stock returns. [15] They found that custom-built financial models incorporating machine learning techniques outperformed traditional sentiment analysis tools, providing better predictions of stock price movements.

Linear regression is a widely used statistical method in financial market analysis to model the relationship between a dependent variable (e.g., stock returns) and one or more independent variables (e.g., sentiment scores, investor attention measures). This technique helps understand the impact of various factors on stock prices and predict future market behavior. Fama and French (1993) applied linear regression to develop their well-known three-factor model, which explains stock returns through market risk, size, and value factors. [16] This foundational work demonstrated the effectiveness of linear regression in capturing the relationship between stock returns and multiple predictors. In the context of sentiment analysis, Engelberg and Parsons (2011) used linear regression to study the effect of media coverage on stock returns, finding that increased media coverage leads to higher trading volumes and price volatility. [17] Similarly, Sprenger et al. (2014) applied linear regression to analyze the impact of Twitter sentiment on stock returns, concluding that sentiment derived from social media can significantly influence market performance. [18]

By leveraging machine learning, this research aims to comprehensively analyse the relationship between Netflix's content popularity, measured through various metrics, and its stock price movements. This approach offers a comprehensive understanding of how public interest and media buzz interact to affect financial performance, extending the analysis to competitors in the streaming industry.

3. Methodology

3.1. Data

This study examines the relationship between Netflix's original content releases, public interest in these shows, and the company's stock performance. Data was collected comprehensively on Netflix's original series releases, Google search trends for these shows, and Netflix's stock performance. Further into the study, the analysis extends to competitors like Amazon Prime Video and Disney+. [19]

3.1.1. Data Sources

Netflix original Release dates: A list containing all Netflix original series from the first in 2012 to the last one in 2023 and their release dates were compiled. This information was sourced from the company's official press releases and media reports. Each show's release date was recorded to create a binary variable indicating whether a new show was released on a given day. The same method was used to collect original releases from the competitors Amazon Prime Video, Disney+, Hulu, Paramount+, HBO Max (now just Max), Apple TV+, and Peacock. Stock market data: Daily closing prices for Netflix (NFLX) and the S&P 500 index from January 1, 2012, to June 30, 2024. This data was sourced from Yahoo Finance, a financial database API. [20] The dataset covers only historical data from January 1, 2012, to October 2023; no projections were used.

Popularity data: Google trends data: Daily Google trends search popularity data was compiled from 2012 to 2024 to quantify the dynamics of public interest in Netflix shows. [21] Daily search interest data from January 1, 2012, to June 30, 2024, was collected for each show in this dataset. However, Google Trends provides relative search volume on a scale of 0 to 100, where 100 represents peak popularity for the term in that time period. Google Ads Search Volume data: Average search volume data for Netflix show names were obtained from the Google Ads dashboard. This is absolute search volume, which provides a more direct measure of the number of searches compared to Google Trends. [22]

Ratings data: The number of user ratings for Netflix shows on popular review platforms such as IMDb and Rotten Tomatoes was collected. [23, 24] Actual viewership data is not published by any platform, but the number of ratings a show garners could be approximately correlated. Though, this does not consider demographics that are more or less likely to watch a show and use the ratings website, which can limit its reliability for this calculation.

3.1.2. Data Collection

Netflix Show data: A comprehensive list of Netflix original series was compiled. Each show's release dates were recorded in a time series where each day was marked as 1 if a show was released and 0 otherwise. Netflix typically releases its new content at midnight Pacific Time (PT), and this practice aligns with the trading hours of United States stock exchanges, providing sufficient time for the market to react to the just released content before the trading day ends.

Popularity data: Using the 'pytrends' library, Google Trends data was queried for each show. Daily search interest data was collected for each show over the specified time period. To address limitations in Google Trends' date range, data was first fetched in a 12-year view, then individually fetched in 6-month chunks from 2012 to 2023. The data was then scaled by multiplying the daily values for each month with the monthly value from the 12-year view.

Stock Market Data: Daily closing prices for Netflix stock and the S&P 500 were collected. Daily returns for both Netflix and the S&P 500 were calculated using the formula:

$$(price_t - price_{t-1}) / price_{t-1}$$

3.1.3. Data Processing

Search volumes were normalized by multiplying the Google Trends index (0-100) with a known peak volume for each show obtained from supplementary sources such as ratings and search volume. A formula for estimating the viewership data for Netflix sources was developed as follows:

$$Viewership\ Score = (IMDb\ Ratings \times 0.66) + (Rotten\ Tomatoes\ Audience\ Ratings \times 0.34)$$

Due to IMDb having over 200 million unique monthly users compared to 97 million for Rotten Tomatoes, the former had a larger weight. All datasets were aligned to ensure consistent daily entries from 2012 to 2024. Missing values, if any, were handled by forward-filling. A 'Total Demand' variable was created, summing the normalized search volumes across all daily shows.

A binary 'Show Release' variable was created, indicating whether any show was released on a given day. Public interest is quantified using Google Trends data (scaled to a range of 0–100) and Google Ads search volume. Ratings data from IMDb and Rotten Tomatoes were included to measure qualitative public engagement. Rating information from Rotten Tomatoes and IMDb was incorporated to gauge qualitative public engagement. Combining social media activity (such as Twitter mentions) created a composite popularity metric.

3.1.4. Final Dataset

The final dataset consisted of daily observations from 2012 to 2024, with each entry containing Date, Netflix stock daily return, S&P 500 daily return, Binary indicator for show release, Total demand (sum of normalized Google search volumes, Google Ads search volume, number of ratings, and social media activity for all shows)

3.1.5. Limitations

Firstly, Google Trends data is relative and requires additional normalization, which may introduce some estimation errors. Secondly, the study assumes that Google search volume is a reliable proxy for public interest in Netflix shows, which may not capture all aspects of viewer engagement, affecting accuracy. Additionally, this specific analysis did not include other factors affecting stock prices, such as overall market conditions, company financials, and broader industry trends, which could influence the findings.

3.2. Model

For this investigation, a linear regression model is sufficiently detailed. It is implemented using the Python library, Scikit-Learn, and its Linear Regression class.

3.2.1. Model Structure

The regression analysis aims to identify the extent to which the popularity metrics (Google Trends, Google Ads search volume, number of ratings, and social media activity) can explain variations in Netflix's stock price. The analysis includes immediate and lagged effects to capture any delayed impacts.

Dependent Variable (Y): Netflix's daily stock returns were calculated as the percentage change in the closing price from the previous day.

Independent Variable (X): The independent variables include a binary variable indicating whether a Netflix show was released on a given day, a binary variable indicating whether a competitor platform's show was released on a given day, a composite metric combining normalized Google search volumes, Google Ads search volume, the number of ratings, and social media activity, and the lagged daily returns of the S&P 500 to account for broader market trends.

Control variables include competitor release schedules (e.g., Prime Video and Disney+ release dates) and critical reviews (aggregated Rotten Tomatoes critic scores). These variables guarantee that, besides internal content strategies, the analysis considers external factors influencing the dependent variable.

3.2.2. Regression Model [25]

The linear regression model was implemented using Scikit-Learn's LinearRegression class. The model includes independent variables like Google Trends data, competitor release indicators, market-wide factors (like S&P 500 returns), and dependent variables like Netflix stock returns. A limitation of using Linear regression is that complex or non-linear interactions may not be captured by linear regression since it assumes linear relationships. Additionally, excluding other influencing factors (such as geopolitical events) could result in omitted variable bias. Also, residual heteroscedasticity may distort coefficient estimates if it exists.

The regression model can be expressed as an equation for a line:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 D_{t-1} + \beta_3 P_{t-1} + \beta_4 S_{t-1} + \epsilon_t$$

where:
R_t is the daily return of Netflix stock at time t.
R_{t-1} is the lagged return of Netflix stock (the previous day's return).
D_{t-1} is the lagged total demand (composite popularity metric).
P_{t-1} is the lagged daily returns of the S&P 500.
S_{t-1} is the lagged show release indicator.
ϵ_t is the error term.

3.2.3. Statistical Tests and Significance

Coefficient Estimates (β): Measure the strength and direction of the relationship between independent and dependent variables.

P-values: Test the hypothesis that each coefficient differs from zero (significance level set at 0.05).

R-squared (R^2) Indicates the proportion of variance in the dependent variable explained by the independent variables.

3.2.4. Model Diagnostics

Autocorrelation: Checked using Durbin-Watson statistics to ensure no serial correlation in residuals [26]

Multicollinearity: Evaluated using Variance Inflation Factor (VIF) to ensure independent variables are not highly correlated.

Heteroskedasticity: Assessed using the Breusch-Pagan test to check if the variance of residuals is constant.

3.3. Graphical Representation of Data

A total of 62 Netflix Original shows will be included in this investigation. These can be plotted on a timeseries of Netflix stock closing prices like:

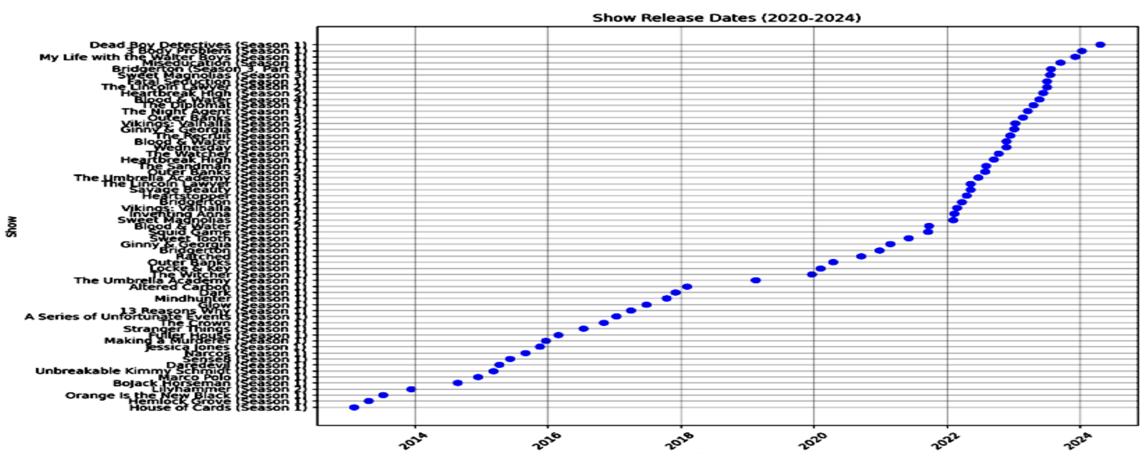

Fig. 1 Show release dates

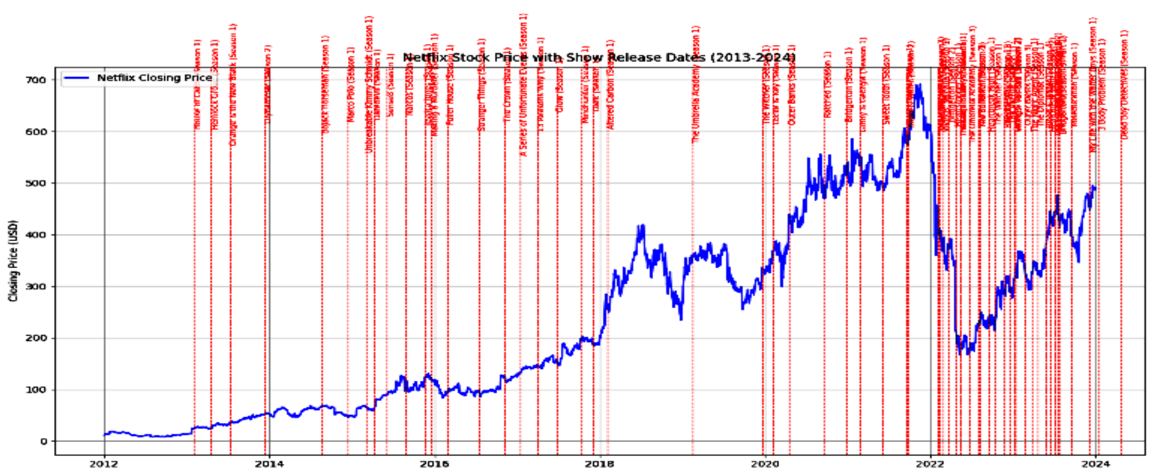

Fig. 2 Netflix closing price with show release dates

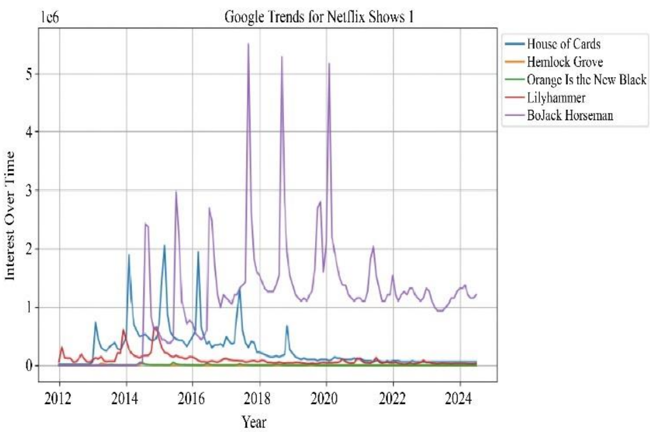

Fig. 1 Processed google trends data

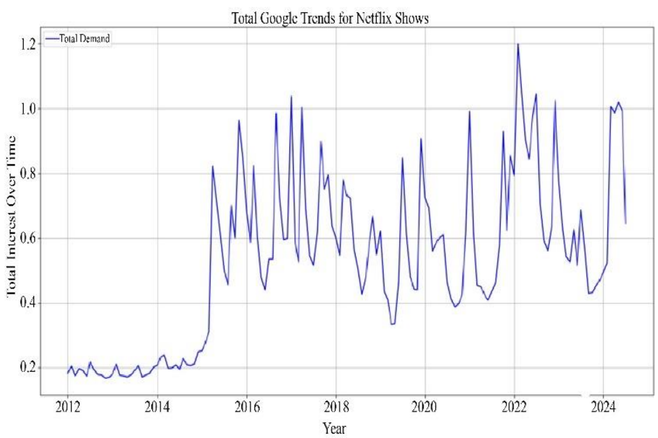

Fig. 2 Total Google Trends for Netflix Shows Graph

Table 1. Impact of competitor platform releases on Netflix stock returns

Competitor Platform	Coefficient	S.E.	t-value	p-value
Prime Video	0.0006	0.004	0.142	0.887
Disney Plus	0.001	0.005	0.202	0.84
Hulu	-0.0004	0.004	-0.103	0.918
Paramount Plus	0.0025	0.006	0.444	0.657
HBO Max	-0.0021	0.005	-0.413	0.68
Apple TV Plus	0.0008	0.005	0.220	0.826
Peacock	0.004	0.005	0.895	0.371

This timeseries plot displays the daily number of searches for 5 Netflix shows' names from 2012 to 2024 in an absolute number of searches. As a variable for the model, the searches for all the terms of the Netflix shows catalog were added to get a singular figure for the amount of attention for any Netflix stock on a particular day.

4. Results and Discussion

4.1. Model Overview

The Ordinary Least Squares (OLS) regression model was used to analyze the impact of various factors on Netflix's daily stock returns. The model demonstrates a moderate explanatory power with an R-squared value of 0.164, indicating that approximately 16.4% of the variance in Netflix's daily stock returns can be explained by the variables included in the model, and most of this is due to the S&P stock movements.

4.2. Significance of Variables

4.2.1. Netflix Show Releases

The regression analysis shows a positive coefficient of 0.0057 with a standard error of 0.004 for Netflix show releases. This indicates a slight increase in Netflix's stock returns on days when new shows are released.

However, this effect is not statistically significant, as reflected by the p-value of 0.132. This suggests that, while there may be a minor uptick in stock returns associated with content releases, the impact is not strong enough to be considered a definitive driver of stock performance.

4.2.2. Competitor Show Releases

The impact of releases by competitors on Netflix's stock returns shows varying effects, as shown in Table 1. These results suggest that releases by competing platforms do not statistically impact Netflix's stock returns, as their p-values are greater than 0.15.

This indicates that while Netflix's content releases may have a slight impact on its stock performance, the releases by competitors like Prime Video, Disney Plus, and others do not significantly influence Netflix's stock returns.

4.2.3. Market Influence

The S&P 500 daily return shows a strong positive relationship, with a coefficient of 1.1688 and a standard error of 0.047 with Netflix's stock returns, indicating that Netflix's stock is significantly influenced by overall market trends, reflected by the p-value of 0.000. This suggests that macroeconomic factors are crucial to Netflix's stock performance.

4.2.4. Media Attention

Coefficient: -3.934e-11, Standard Error: 1.99e-11, t-value: -1.974, p-value: 0.048

The Total Demand variable, representing Google search interest, shows a small negative relationship with Netflix's stock returns. While statistically significant, the economic significance of this effect appears minimal due to the minimal coefficient.

This variable was tested in two ways, the first being multiplied by Google Search Volume, and the second being a formula of IMDb and Rotten tomatoes ratings. The latter was ultimately not used as it showed a larger p-value than Google search volume. The table below summarizes the results from the regression analysis using Google Search Volume and the combined IMDb and Rotten Tomatoes ratings formula for the Total Demand variable.

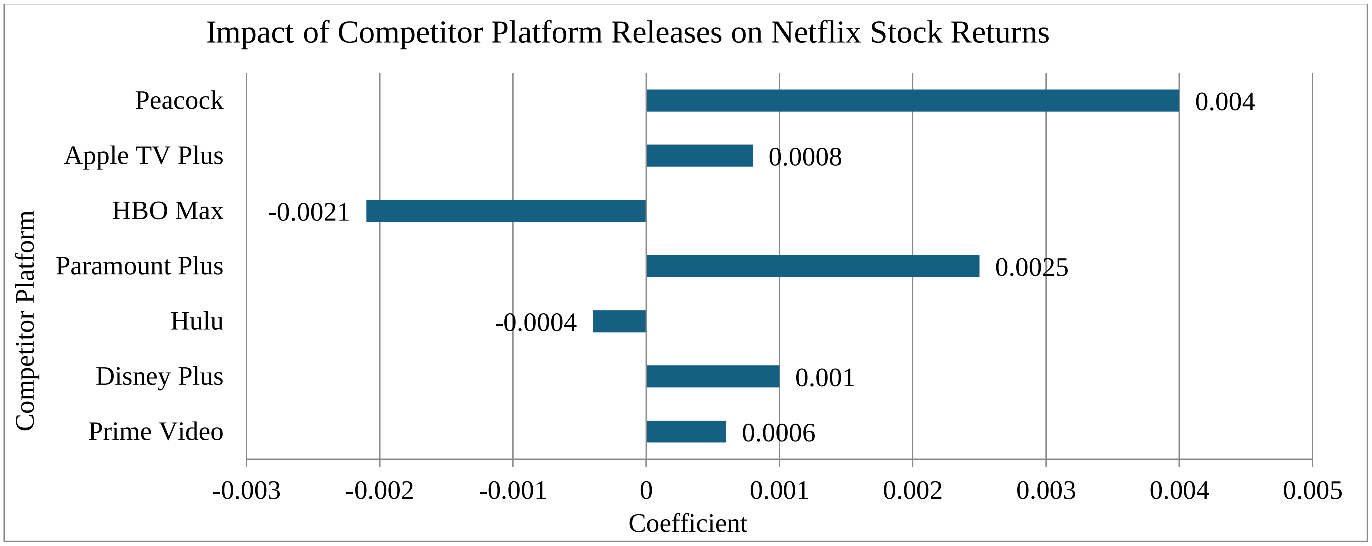

Fig. 5 Impact of competitor platform releases on Netflix stock returns

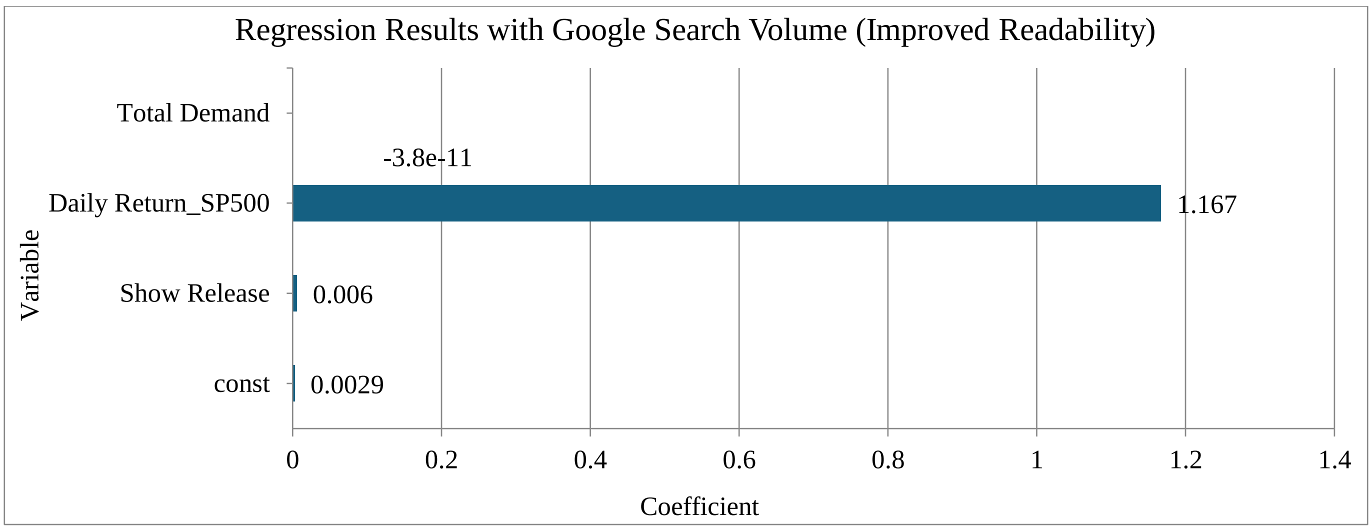

Fig. 6 Regression results with google search volume

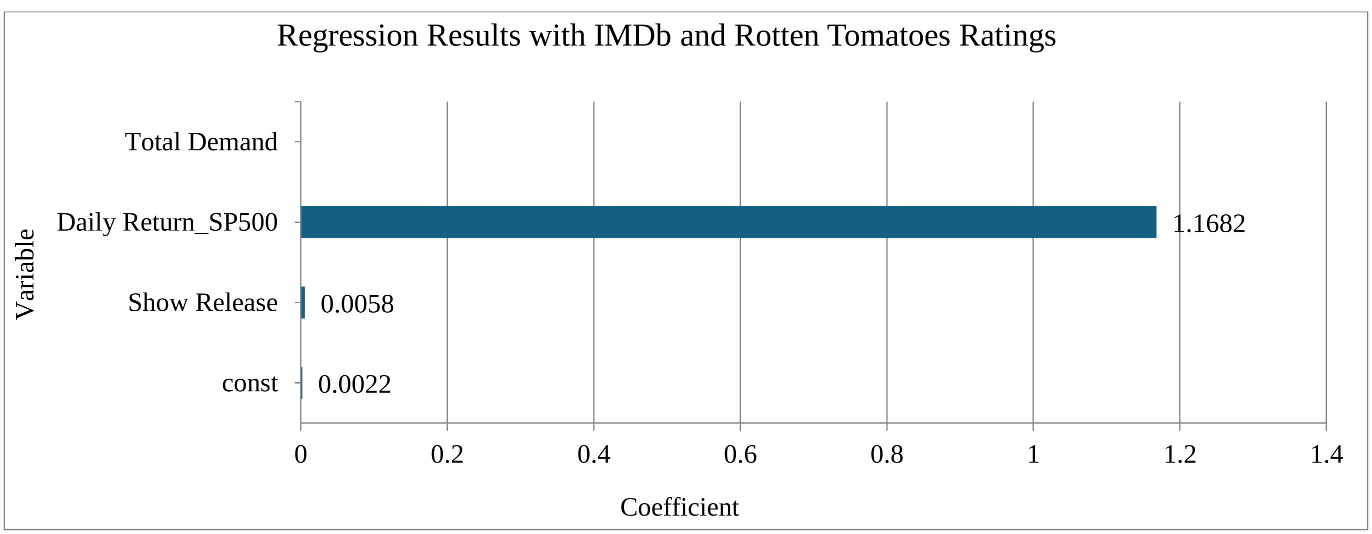

Fig. 7 Regression results with IMDb and rotten tomatoes ratings formula

Table 2. Regression results with google search volume

Variable	Coefficient	S.E.	t-value	p-value	95% CI
const	0.0029	0.001	2.691	0.007	[0.001, 0.005]
Show Release	0.0060	0.004	1.617	0.106	[-0.001, 0.013]
Daily Return_SP500	1.1670	0.047	24.645	0.000	[1.074, 1.260]
Total Demand	-3.819e-11	1.98e-11	-1.931	0.054	[-7.7e-11, 5.79e-13]

Table 3. Regression results with IMDb and rotten tomatoes ratings formula

Variable	Coefficient	S.E.	t-value	p-value	95% CI
const	0.0022	0.001	1.540	0.124	[-0.001, 0.005]
Show Release	0.0058	0.004	1.562	0.118	[-0.001, 0.013]
Daily Return_SP500	1.1682	0.047	24.690	0.000	[1.075, 1.261]
Total Demand	-4.144e-12	4.82e-12	-0.859	0.390	[-1.36e-11, 5.31e-12]

The model was also run with different interactions between Show Release and other variables to understand how robust the results obtained were.

- Only Show Release and S&P500: r-squared of 0.162
- Show Release, S&P500, and Total Demand: r-squared of 0.163
- Lagged Show Release, S&P500, and Total Demand: r-squared of 0.002
- Show Release, S&P500, Total Demand and Competitor Releases: r-squared of 0.164
- Lagged Show Release, S&P500, Total Demand and Competitor Releases: r-squared of 0.004

The marginal increase in R-squared values from the base model (0.162) to the comprehensive model (0.164) suggests that adding variables such as Total Demand and competitor show releases minimally contributes to the model's explanatory power.

Furthermore, the models incorporating lagged effects (3 and 5) show substantially lower R-squared values, indicating that the immediate impact of show releases is more relevant than lagged effects.

4.3. Correlation Analysis

The correlation analysis reveals weak relationships between most variables and Netflix's daily returns. One star shows a very weak correlation, and two stars show a weak correlation:

Table 4. Correlation analysis of Netflix and competitor platforms with stock returns

Platform	Correlation
Netflix Show Release	0.0188**
Prime Video	0.0067*
Disney Plus	0.0058*
Hulu	-0.0054*
Paramount Plus	0.0154 **
HBO Max	-0.0018
Apple TV Plus	-0.0039
Peacock	0.0095 *

Table 5. Correlation of lagged competitor and netflix show releases with stock returns

Platform	Correlation
Lagged Netflix	0.0171 **
Lagged Prime Video	0.0039
Lagged Disney Plus	-0.0145 **
Lagged Hulu	-0.0029
Lagged Paramount Plus	-0.0004
Lagged HBO Max	-0.0140 **
Lagged Apple TV Plus	-0.0015
Lagged Peacock	-0.0100 **

4.3.1. The lagged variables test also reinforced these results

The correlations between Netflix's daily returns and the lagged release dates of shows on competing platforms are generally very weak or negligible. This indicates that the immediate effect of content releases from competitors like Prime Video, Disney Plus, Hulu, Paramount Plus, HBO Max, Apple TV Plus, and Peacock on Netflix's stock returns is minimal. The strongest correlation was observed with Netflix's show releases, but this was very weak (0.0171).

These findings suggest that the streaming market is not heavily influenced by the immediate release of content from competing platforms in terms of Netflix's stock performance. Instead, broader market trends and other factors might play a more significant role in driving stock price movements.

4.4. Time Lag Analysis

Netflix's lagged effect (0.0171**), which shows delayed investor reactions influenced by social media sentiment and reviews, is still small but significant. Disney Plus (-0.0145**) and HBO Max (-0.0140**), two rival platforms, show negative lagged correlations, suggesting that competitive pressures are delayed.

Peacock and Prime Video have very slight delayed effects. In general, immediate effects—especially for competitors—are less strong than lagged ones. Disney Plus, for instance, exhibits a stronger delayed negative influence (-0.0145**) but a less pronounced immediate effect (0.0058*).

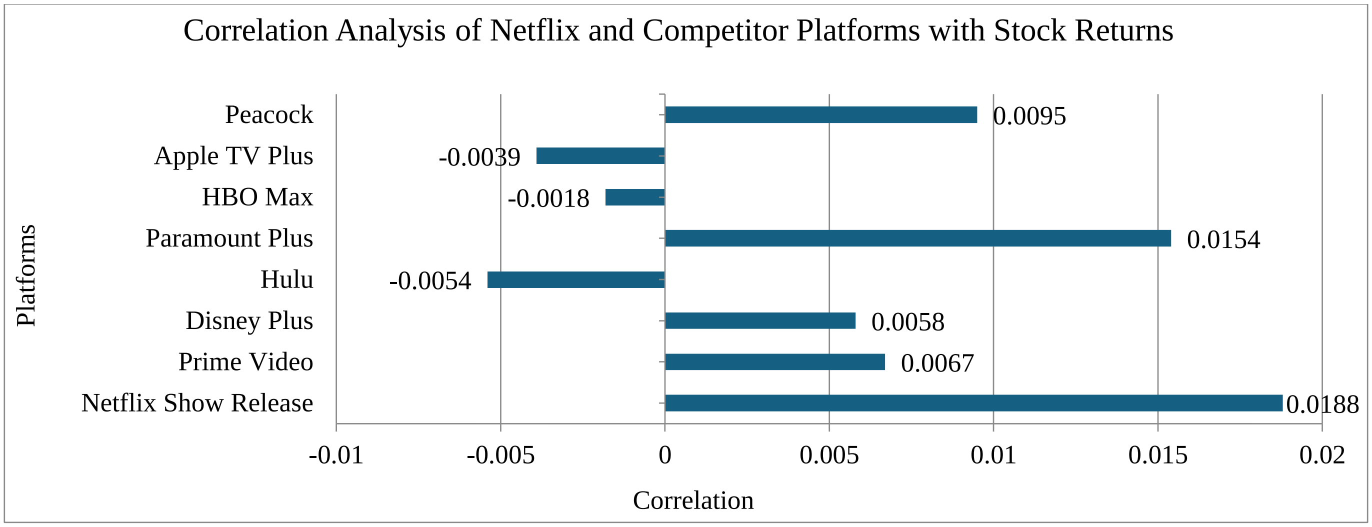

Fig. 8 Correlation analysis of Netflix and competitor platforms with stock returns

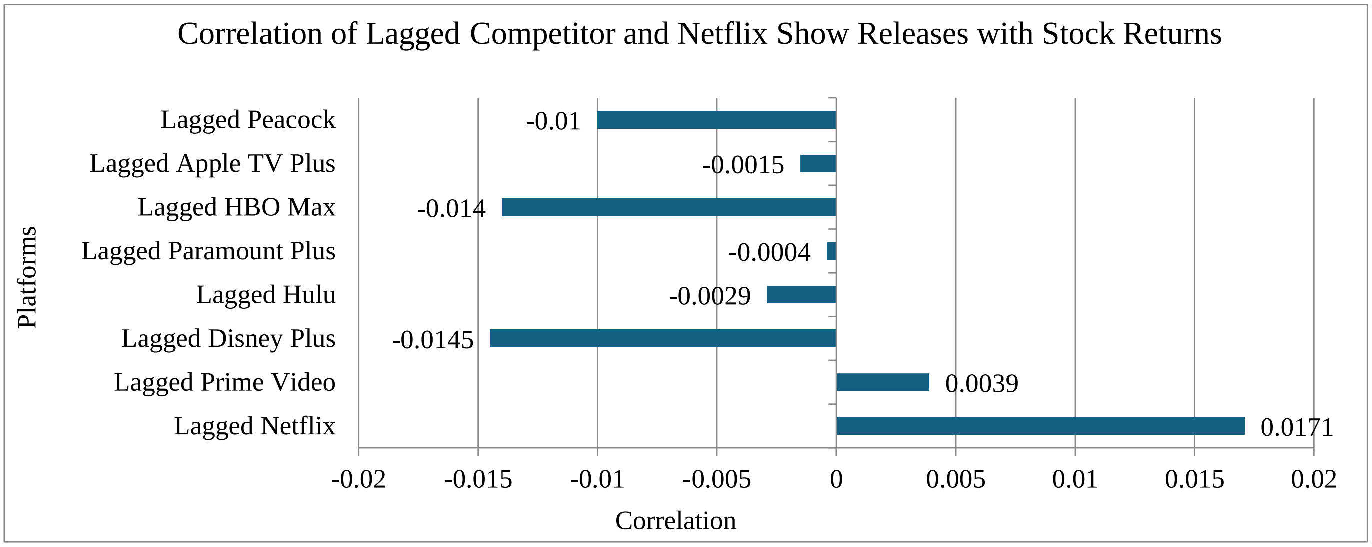

Fig. 9 Correlation of Lagged competitor and Netflix show releases with stock returns

4.5. Discussion

The results suggest that while Netflix's show releases slightly positively impact its stock returns, this effect is not strongly significant. Surprisingly, releases by competing platforms show no significant impact on Netflix's stock performance. This could suggest that there may be different audience segments on different platforms. For instance, there may be less direct competition between Prime Video and HBO Max because they serve different demographics. As an alternative, investors may perceive the market as growing rather than zero-sum, which would lessen the impact of competition on stock performance. The strong relationship with S&P 500 returns underscores the importance of overall market conditions in determining Netflix's stock performance. This suggests that macroeconomic factors may be more crucial in Netflix's stock movements than individual content releases or competitor actions. The weak negative relationship between Total Demand (Google search interest) and stock returns is counterintuitive and warrants further investigation. It might suggest that high public interest does not necessarily translate to positive stock performance or that this model may not capture lagged effects. The performance of Netflix's stock is significantly influenced by broader market factors such as inflation rates, geopolitical tensions, and Federal Reserve interest rate policies.

5. Conclusion

5.1. Summary of Findings

This research explored the correlation between the popularity and buzz surrounding Netflix's content releases and the subsequent movements in the company's stock price, extending the analysis to competitors in the streaming industry. The following key findings emerged through a detailed analysis of Netflix's daily stock returns, show release data, and public interest metrics (such as Google search volume).

Impact of Netflix's Show Releases: The analysis revealed a weak positive correlation between Netflix's show releases and its daily stock returns.

Impact of Competitor Show Releases: The releases of shows by competing platforms (such as Prime Video, Disney Plus, Hulu, Paramount Plus, HBO Max, Apple TV Plus, and Peacock) showed negligible correlations with Netflix's stock returns. This suggests that immediate content releases from competitors do not significantly influence Netflix's stock performance.

Market Influence: The S&P 500 daily return showed a strong positive relationship with Netflix's stock returns with a p-value of 0.000, indicating that overall market trends significantly influence Netflix's stock. This underscores the importance of macroeconomic factors in determining Netflix's stock performance.

Media Attention: The Total Demand variable, representing Google search interest, showed a small negative relationship with Netflix's stock returns. The Total Demand variable showed a small negative relationship with Netflix's stock returns (coefficient: -3.934e-11, standard error: 1.99e-11, p-value: 0.048). While this result is statistically significant at the 5% level, the economic significance is questionable due to the minimal coefficient.

5.2. Implications for Investors and Streaming Platforms

Investors should consider the broader market trends and macroeconomic factors as more significant determinants of Netflix's stock performance rather than immediate content releases. While public interest metrics can provide some insights, their impact appears minimal compared to overall market conditions.

For streaming platforms, the minimal impact of competitor releases on Netflix's stock performance suggests that the market is not highly competitive in terms of immediate content releases. Platforms may benefit from focusing on their unique audience segments and long-term content strategies rather than short-term competitive actions.

However, the counterintuitive moderately strong negative relationship between public interest and stock returns warrants further investigation. Future research could explore the role of investor sentiment through social media sentiment analysis and other such factors.

5.3. Limitations of the Study

Data Normalization: Google Trends data is relative and requires additional normalization, which may introduce some estimation errors.

Proxy for Public Interest: The study assumes that Google search volume is a reliable proxy for public interest in Netflix shows, which may not capture all aspects of viewer engagement.

Scalar impact of competitors: The study assumes that all competitor releases will impact Netflix stock in the same direction. However, good and bad releases by competitors will have different effects on Netflix stock, if any and this was not accounted for.

Omitted Variables: Other factors affecting stock prices, such as overall market conditions, company financials, and broader industry trends, were not included in this specific analysis.

5.4. Future Research Directions

Based on the findings and limitations of this research, several avenues for future research can be identified. The long-term effects of content releases on stock performance using time series analysis techniques could be very insightful, as shown by research by Parrot Analytics. Furthermore, extending the study to examine how content releases affect Netflix’s performance in different international markets could be highly insightful.

A longitudinal study of Netflix's stock performance over multiple years could provide insights into cyclical trends, such as the impact of recurring franchise releases (e.g., "Stranger Things") on long-term investor behavior. Seasonal effects, such as holiday content spikes, would further improve understanding.

Future research could also investigate whether similar dynamics apply in gaming or live sports streaming industries. Furthermore, analyzing regional variations in content reception and stock performance may reveal differences in consumer behavior across international markets.

5.5. Synthesis

In summary, this research provides valuable insights into the relationship between the popularity of Netflix's content releases and its stock performance, extending the analysis to competitors in the streaming industry.

While the direct impact of content releases on stock returns is minimal, broader market trends and macroeconomic factors play a more significant role.

However, the popularity of Netflix shows at any moment, as described by the Total Demand variable, is highly significant in this analysis. These findings highlight the complex nature of factors influencing stock performance in the dynamic streaming industry.

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Appendix 1

Data sets and libraries used
The main Python libraries utilized in this project are:
pandas: for data manipulation and analysis
numpy: For numerical operations
yfinance: For fetching stock market data
scikit-learn: For implementing machine learning models
statsmodels: For statistical modeling and econometrics
pytrends: For accessing Google Trends data
matplotlib: For data visualization

The main data sets used in this project are:
Netflix original series release dates (2012-2024)
Google Trends data for Netflix shows (2012-2024)
Netflix (NFLX) stock price data (2012-2024)
S&P 500 index data (2012-2024)
Google Ads search volume data for Netflix shows
IMDb and Rotten Tomatoes ratings data for Netflix shows
Release dates for competitor streaming platforms:
Prime Video
Disney+
Hulu
Paramount+
HBO Max
Apple TV+
Peacock

Appendix 2: Code Used

Data Collection and preprocessing

```
# Netflix show data collection
show_data = {
    'House of Cards (Season 1)': '2013-02-01',
    'Hemlock Grove (Season 1)': '2013-04-19',
    # ... (rest of the show data)
}

# Google Trends data collection
import pandas as pd
from pytrends. request import TrendReq

pytrends = TrendReq(hl='en-US', tz=9)
terms = [
    "House of Cards", "Hemlock Grove", "Orange Is the New Black",
    # ... (rest of the terms)
]
timeframe = '2012-01-01 2024-12-31'

# Function to get trends data
def get_trends_data(term):
    # ... (rest of the function)

# Stock market data collection
import yfinance as yf

netflix_stock = yf.download('NFLX', start='2012-01-01', end='2024-12-31')
```

```
sp500_stock = yf.download('^GSPC', start='2012-01-01', end='2024-12-31')
```

Data Normalization

```
# Normalize Google Trends data
known_volumes = {
    'House of Cards': 344877.1,
    'Hemlock Grove': 49.5,
    # ... (rest of the known volumes)
}

df = pd.read_csv('netflix_shows_trends_2012_2024.csv', parse_dates=['date'])
normalized_df = pd.DataFrame({'date': df['date']})

for show in df.columns[1:]:
    if show in known_volumes:
        normalized_df[show] = df[show] * known_volumes[show]
    else:
        print(f"Warning: No known volume for '{show}'. Skipping normalization.")
        normalized_df[show] = df[show]

normalized_df.to_csv('norm_show_trends.csv', index=False)
```

Model Implementation

```
import statsmodels.api as sm

# Prepare data for the model
data = pd.merge(netflix_stock[['Daily Return']], sp500_stock[['Daily Return']], left_index=True, right_index=True, suffixes=('_NFLX', '_SP500'))
norm_show_trends = pd.read_csv('norm_show_trends.csv', index_col=0, parse_dates=True)
norm_show_trends['Total Demand'] = norm_show_trends.sum(axis=1)
monthly_demand = norm_show_trends.resample('M').sum()['Total Demand']
daily_demand = monthly_demand.resample('D').ffill()
data = pd.merge(data, daily_demand, left_index=True, right_index=True, how='left')
data['Total Demand'].fillna(0, inplace=True)

# Create features
data['Netflix Show Release'] = 0
for the show, date in show_data.items():
    release_date = datetime.strptime(date, '%Y-%m-%d')
    if release_date in data.index:
        data.at[release_date, 'Netflix Show Release'] = 1

# Define features and target
X = data[['Netflix Show Release', 'Daily Return_SP500', 'Total Demand']]
y = data['Daily Return_NFLX']

# Add constant and fit the model
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()

# Print model summary and correlations
print(model.summary())
correlations = data[['Netflix Show Release', 'Daily Return_SP500', 'Total Demand', 'Daily Return_NFLX']].corr()
for col in ['Netflix Show Release', 'Daily Return_SP500', 'Total Demand']:
    correlation = correlations.loc[col, 'Daily Return_NFLX']
    print(f"Correlation between {col} and Netflix Daily Return: {correlation}")
```

Competitor Platform Analysis

```
# Load platform releases data
platform_releases = pd.read_csv('platform_releases.csv', index_col=0, parse_dates=True)

# Merge platform releases with the main data
data = data.merge(platform_releases, left_index=True, right_index=True, how='left')
data.fillna(0, inplace=True)

# Define features including competitor platforms
X = data[['Netflix Show Release', 'Prime Video', 'Disney Plus', 'Hulu', 'Paramount Plus', 'HBO Max', 'Apple TV Plus', 'Peacock',
'Daily Return_SP500', 'Total Demand']]
y = data['Daily Return_NFLX']

# Add constant and fit the model
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()

# Print model summary and correlations
print(model.summary())
correlations = data[['Netflix Show Release', 'Prime Video', 'Disney Plus', 'Hulu', 'Paramount Plus', 'HBO Max', 'Apple TV Plus',
'Peacock', 'Daily Return_SP500', 'Total Demand', 'Daily Return_NFLX']].corr()
for col in ['Netflix Show Release', 'Prime Video', 'Disney Plus', 'Hulu', 'Paramount Plus', 'HBO Max', 'Apple TV Plus',
'Peacock']:
    correlation = correlations.loc[col, 'Daily Return_NFLX']
    print(f"Correlation between {col} and Netflix Daily Return: {correlation}")
```