How do media releases affect Netflix Stock

July 2024

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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 how the popularity of Netflix's content releases, measured through Google search trends, ratings, and social media activity, 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. Public interest, as measured by Google search volume, 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: Netflix, stock returns, media releases, Google Trends, linear regression, streaming industry

Chapter 1: Introduction

1.1 General Picture

The influence of public interest and media buzz on financial markets has garnered significant attention in recent years, especially with social media such as Reddit and Twitter. Media companies such as Netflix are uniquely positioned in this landscape where public reception to their content could have immediate and profound effects on their financial performance. This research explores the correlation between 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. Now, 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 both the type of emotion and its scale of popularity on Netflix stock's performance.

[1] "Netflix Subscribers History and Projection." Statista, 2023, www.statista.com/statistics/250934/quarterly-number-of-netflix-streaming-subscribers-worldwide.

1.2 Research Question

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 other streaming companies such as HBO and Amazon's Prime TV, the study also aims to understand the broader impact of TV releases by competitor firms on Netflix's stock prices.

1.3 Relevant Work

Several key studies provide a foundation for this research. Bollen, Mao, and Zeng (2011) demonstrated how public mood that was 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 its financial success.

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

[2] Bollen, Johan, et al. "Twitter Mood Predicts the Stock Market." Journal of Computational Science, vol. 2, no. 1, 2011, pp. 1-8.

examines whether these effects are immediate or lagged, to comprehensively understand how public interest impacts financial performance over time.

1.4 What this paper attempts to achieve

This study contributes to the broader field of financial economics by demonstrating the value of popularity and buzz metrics in predicting stock behavior of the producing company. The hypothesis of this research is that the popularity of a new Netflix Original significantly and immediately correlates with Netflix's stock price movements. Positive popularity metrics are expected to drive stock prices up, reflecting increased investor confidence due to anticipated subscriber growth, while negative metrics may result in stock price declines, indicating potential subscriber churn or dissatisfaction with Netflix’s offerings.

To achieve this, the study uses data from Google Trends, rating counts, and other popularity indicators, 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.

1.5 Paper Structure

This paper is structured to ensure a systematic exploration of the research question, beginning with Chapter 1: Introduction, followed by Chapter 2: Literature Review, Chapter 3: Methodology, and Chapter 4: Data Collection and Processing. It then presents the findings in Chapter 5:

Analysis and Discussion, concludes with Chapter 6: Conclusion, and evaluates the study's strengths and limitations in Chapter 7: Evaluation.

This structure ensures a systematic exploration of the research question, starting from the theoretical background, through thorough methodology and data analysis, to conclusion with results and finally evaluations of the study's strengths and limitations.

Chapter 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, that cover opinions, expectations, or beliefs of market participants toward the company that 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.[3] Similarly, a study by Tetlock, Saar-Tsechansky, and Macskassy (2008) confirmed that stock prices do react significantly to media sentiment based on news stories published in the Wall Street Journal and Dow Jones News Service.

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

[3] Tetlock, Paul C. "Giving Content to Investor Sentiment: The Role of Media in the Stock Market." The Journal of Finance, vol. 62, no. 3, 2007, pp. 1139-1168.

traders' messages.[4] They also found that the number of messages posted during a day can help predict the stock returns of the following day, suggesting the impact of the buzz irrelevant of sentiment. 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 the universality of this.[5] Similarly, Liu et al. (2020) examined how social media metrics, such as the number of tweets and search indices, impacted stock prices, concluding that there is a strong correlation between public interest and stock market performance.[6] And 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 the trends being investigated in this research.[7]

The use of 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] These findings are relevant to our research as they highlight the potential of popularity metrics in

[4] Antweiler, Werner, and Murray Z. Frank. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards." The Journal of Finance, vol. 59, no. 3, 2004, pp. 1259-1294.

[5] Bollen, Johan, et al. "Twitter Mood Predicts the Stock Market." Journal of Computational Science, vol. 2, no. 1, 2011, pp. 1-8.

[6] Liu, Siyi, et al. "ARIMA-Attention-Based Stock Dynamic Prediction via News and Social Media." Entropy, vol. 22, no. 10, 2020, p. 1170.

[7] Weng, Bin, et al. "Predicting Short-Term Stock Prices Using Ensemble Methods and Online Data Sources." Expert Systems with Applications, vol. 112, 2018, pp. 258-273.

[8] McNally, Sean, et al. "Predicting the Price of Bitcoin Using Machine Learning." 26th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP), IEEE, 2018, pp. 339-343.

predicting stock price movements. 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 also high. This suggests that when investors are actively seeking information, the sentiment expressed in the media plays a more significant role in shaping their expectations and trading decisions, which in turn affects market outcomes.

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)

[9] Siering, Michael. "Investigating the Impact of Media Sentiment and Investor Attention on Financial Markets." Financial Markets and Portfolio Management, vol. 27, no. 4, 2013, pp. 445-468.

[10] Barber, Brad M., and Terrance Odean. "All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors." The Review of Financial Studies, vol. 21, no. 2, 2008, pp. 785-818.

[11] Busse, Jeffrey A., and T. Clifton Green. "Market Efficiency in Real Time." Journal of Financial Economics, vol. 65, no. 3, 2002, pp. 415-437.

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 the announcement of 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 an increased number of individual investors buying the stock, indicating a spillover effect from product advertisements to stock market interest.[13] So Netflix spending on advertisements to market the release of the new Original series could affect stock price more than the actual popularity of the show, which is only determined after its release.

2.4 Application of Linear Regression in Financial Market Analysis

Machine learning has been increasingly utilized in analyzing 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

[12] Da, Zhi, et al. "In Search of Attention." The Journal of Finance, vol. 66, no. 5, 2011, pp. 1461-1499.

[13] Chemmanur, Thomas J., and An Yan. "Product Market Advertising and New Equity Issues." Journal of Financial Economics, vol. 92, no. 1, 2009, pp. 40-65.

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 in understanding the impact of various factors on stock prices and predicting 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.

[14] Groß-Klußmann, Axel, and Nikolaus Hautsch. "When Machines Read the News: Using Automated Text Analytics to Quantify High Frequency News-Implied Market Reactions." Journal of Empirical Finance, vol. 18, no. 2, 2011, pp. 321-340.

[15] Heston, Steven L., and Nitish Ranjan Sinha. "News vs. Sentiment: Predicting Stock Returns from News Stories." Financial Analysts Journal, vol. 73, no. 3, 2017, pp. 67-83.

[16] Fama, Eugene F., and Kenneth R. French. "Common Risk Factors in the Returns on Stocks and Bonds." Journal of Financial Economics, vol. 33, no. 1, 1993, pp. 3-56.

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 provide a robust analysis of 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 as well.

[17] Engelberg, Joseph E., and Christopher A. Parsons. "The Causal Impact of Media in Financial Markets." The Journal of Finance, vol. 66, no. 1, 2011, pp. 67-97.

[18] Sprenger, Timm O., et al. "Tweets and Trades: The Information Content of Stock Microblogs." European Financial Management, vol. 20, no. 5, 2014, pp. 926-957.

Chapter 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. Additionally, further into the study the analysis also extends to competitors like Amazon Prime Video and Disney+.

Data sources

1. Netflix original Releases dates: A list containing all Netflix original series from the first, in 2012 to the last one in 2023 and their release dates was 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.[19]

   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.
2. 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]

[19] "Netflix Original Series Release Dates." Netflix Media Center, Netflix, 2023, media.netflix.com/en/originals.

[20] "Historical Data: Netflix, Inc. (NFLX)." Yahoo Finance, Yahoo, 2023, finance.yahoo.com/quote/NFLX/history.

Popularity Data

3. Google trends data: To quantify the dynamics of public interest in Netflix shows, daily Google trends search popularity data was compiled from 2012 to 2024.[21] For each show in this dataset, daily search interest data from January 1, 2012, to June 30, 2024 was collected. 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.
4. 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]
5. 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 take into account demographics that are more or less likely to watch a show and use the ratings website, which can limit its reliability for this calculation.

Data collection

Netflix Show data:

[21] "Google Trends." Google, 2023, trends.google.com/trends.

[22] "Google Ads Dashboard." Google, 2023, ads.google.com/home.

[23] "Audience Score." Rotten Tomatoes, 2023, www.rottentomatoes.com.

[24] "IMDb Ratings." IMDb, 2023, www.imdb.com.

A comprehensive list of Netflix original series was compiled. For each show, 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 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:

$$\left(price_t - price_{t-1}\right) / price_{t-1}$$

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:

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

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 shows for each day. Additionally, a binary 'Show Release' variable was created, indicating whether any show was released on a given day.

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)

Limitations:

Firstly, Google Trends data is relative and required 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, other factors affecting stock prices, such as overall market conditions, company financials, and broader industry trends, were not included in this specific analysis, 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 more specifically its LinearRegression class.

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 was calculated as the percentage change in the closing price from the previous day.

Independent Variable (X)

1. Lagged Netflix show release: A binary variable indicating whether a Netflix show was released on a given day.

2. Lagged Show release for competitors: A binary variable indicating whether a competitor platform's show was released on a given day.
3. Lagged total demand: Summed normalized Google search volumes, Google Ads search volume, number of ratings, and social media activity.
4. Lagged daily returns of the S&P 500: To account for broader market trends.

Regression model[25]

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 (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.

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 is different 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.

[25] Wooldridge, Jeffrey M. Introductory Econometrics: A Modern Approach. 5th ed., South-Western Cengage Learning, 2013.

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.[27]
- Heteroskedasticity: Assessed using Breusch-Pagan test to check if the variance of residuals is constant.[28]

3.3 Graphical Representation of Data

There was a total of 62 Netflix Original shows that are going to be taken in for this investigation.

[26] Durbin, J., and G. S. Watson. "Testing for Serial Correlation in Least Squares Regression: I." Biometrika, vol. 37, no. 3/4, 1950, pp. 409-428.

[27] O'Brien, Robert M. "A Caution Regarding Rules of Thumb for Variance Inflation Factors." Quality & Quantity, vol. 41, no. 5, 2007, pp. 673-690.

[28] Breusch, T. S., and A. R. Pagan. "A Simple Test for Heteroscedasticity and Random Coefficient Variation." Econometrica, vol. 47, no. 5, 1979, pp. 1287-1294.

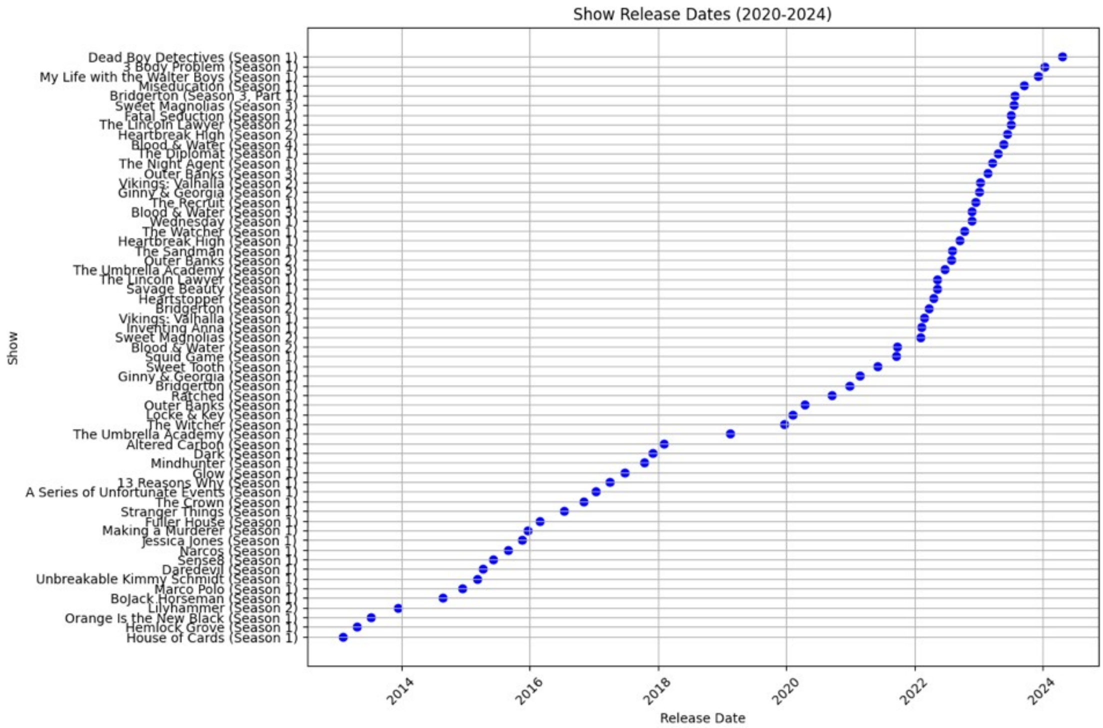

Figure 1 Netflix Releases

These can be plotted on a timeseries of Netflix stock closing prices like:

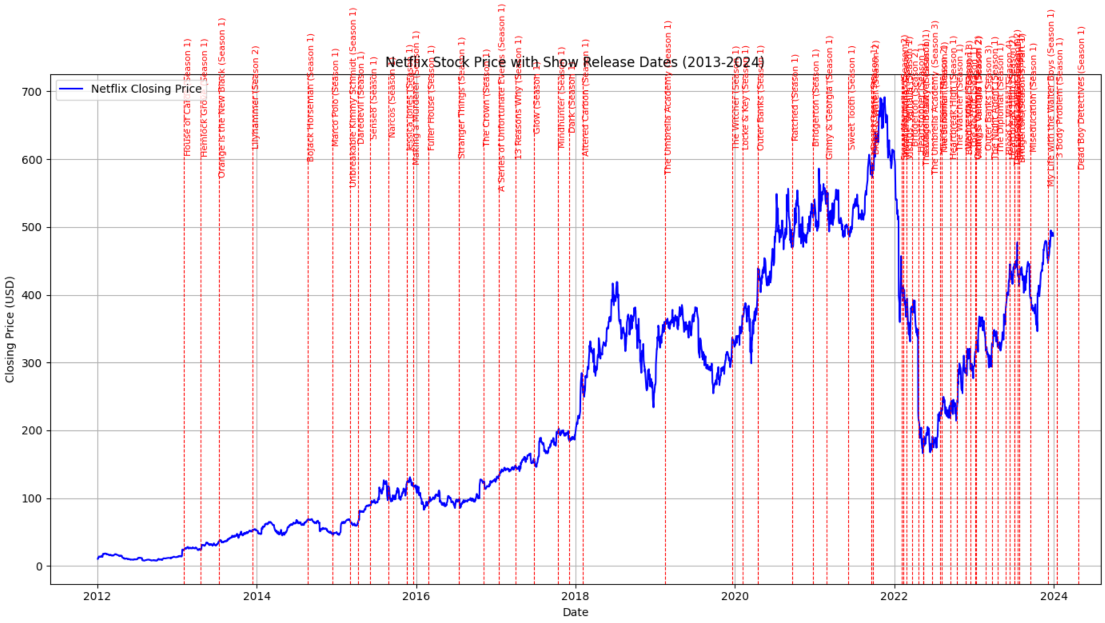

Figure 2 Netflix Closing Price with Show Release Dates

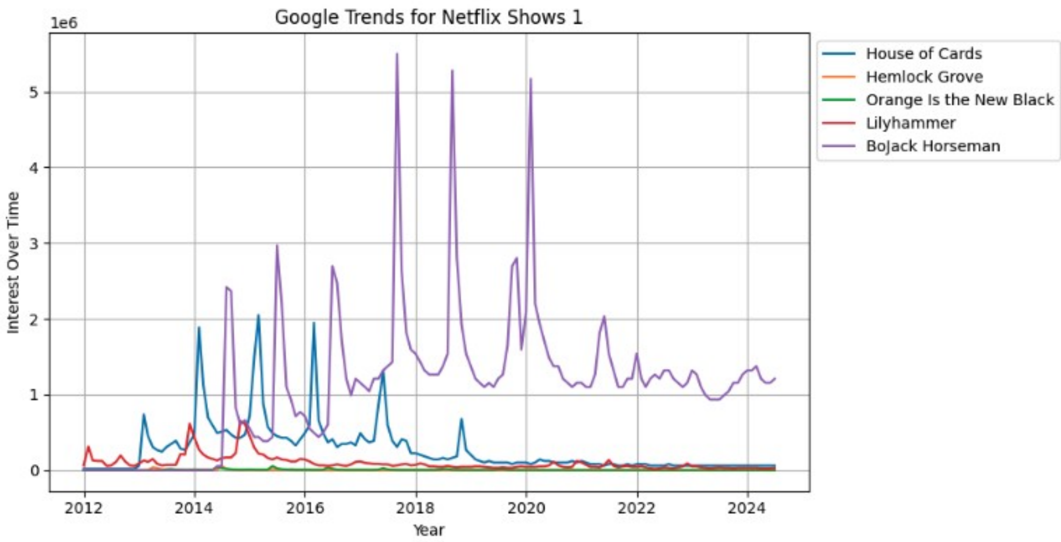

Figure 3 Processed Google Trends Data

This timeseries plot displays the daily number of searches for 5 Netflix shows' names from 2012 to 2024, in absolute number of searches.

As a variable for the model, the searches for all of the terms of the Netflix shows catalog were added to get a singular figure for amount of attention for any Netflix stock on a particular day.

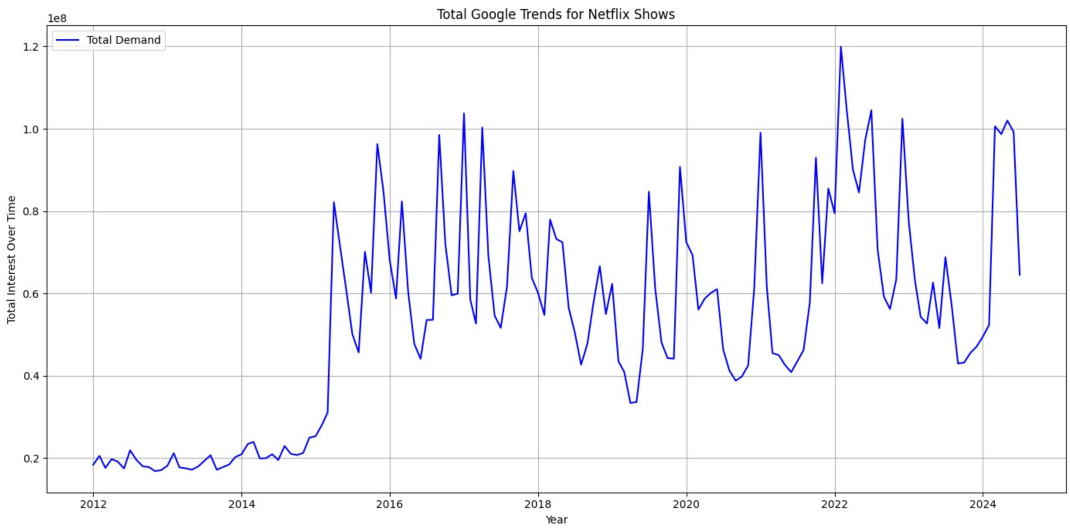

Figure 4 Total Google Trends for Netflix Shows Graph

Chapter 4: Analysis 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

Netflix Show Releases

The regression analysis shows a positive coefficient or 0.0057 with standard error 0.004 for Netflix show releases, indicating 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.

Competitor Show Releases

The impact of releases by competitors on Netflix's stock returns shows varying effects:

COMPETITOR PLATFORM	COEFFICIENT	STANDARD ERROR	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	0.22	0.826
PEACOCK	0.004	0.005	0.895	0.371

These results suggest that releases by competing platforms do not have a statistically significant impact on Netflix's stock returns as their p-values are all 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.

Market Influence

The S&P 500 daily return shows a strong positive relationship, with a coefficient of 1.1688 with 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 play a crucial role in Netflix's stock performance.

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 very small coefficient.

This variable was tested in two ways, the first being multiplied with 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.

Regression Results with Google Search Volume

Variable	***Coefficient***	***Std. Error***	***t-value***	***p-value***	***95% Conf. Interval***
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]

Regression Results with IMDb and Rotten Tomatoes Ratings Formula

Variable	***Coefficient***	***Std. Error***	***t-valu***	***p-valu***	***95% Conf. Interval***

			e	***e***	
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.

1. Only Show Release and S&P500: r-squared of 0.162
2. Show Release, S&P500, and Total Demand: r-squared of 0.163
3. Lagged Show Release, S&P500, and Total Demand: r-squared of 0.002
4. Show Release, S&P500, Total Demand and Competitor Releases: r-squared of 0.164
5. 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 the addition of variables such as Total Demand and competitor show releases contributes minimally to the model's explanatory power. Furthermore, the models incorporating lagged effects (3 and 5) show substantially lower R-squared values, indicating 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:

- 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 *

These results were also reinforced by the lagged variables test:

- Lagged Netflix Show Release: 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 **

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 observed is with Netflix's own show releases, but even this is 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 Discussion

The results suggest that while Netflix's own show releases have a slight positive impact on 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 indicate that the streaming market is not as zero-sum as might be expected, with each platform potentially serving distinct audience segments.

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 play a more crucial role 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 there may be lagged effects not captured in this model.

Chapter 5: Conclusion

5.1 Summary of Findings

This research aimed to explore 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. Through a detailed analysis of Netflix's daily stock returns, show release data, and public interest metrics (such as Google search volume), several key findings emerged:

1. **Impact of Netflix's Own Show Releases**: The analysis revealed a weak positive correlation between Netflix's own show releases and its daily stock returns.
2. **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.
3. **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 Netflix's stock is significantly influenced by overall market trends. This underscores the importance of macroeconomic factors in determining Netflix's stock performance.
4. **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 very small 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

1. **Data Normalization**: Google Trends data is relative and required additional normalization, which may introduce some estimation errors.
2. **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.
3. **Scalar impact of competitors:** The study assumes that all competitor releases will have impact on 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.

4. **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. 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.

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, popularity of Netflix shows at any moment time, 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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Chapter 6: Appendix

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

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 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}")
```