Modelling the Netflix Top Ten

Does Twitter Word of Mouth Influence the Netflix Top Ten?

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Preface

This thesis is the conclusion of my Master of science in Marketing Analytics at Tilburg University. It is the result of a five-month study on how electronic word of mouth can influence the popularity of movies and series on an online video streaming platform.

I would like to thank my supervisor professor Knox for his supervision, input, help and availability during this process. Furthermore I want to thank my fellow students who were part of the thesis group of professor Knox for being companions in this thesis process.

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I hope you enjoy reading this thesis.

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Abstract

The streaming video on demand industry is expanding rapidly, new streaming platforms are arriving, and the number of consumers is growing. The business model of streaming video on demand services is based on subscriptions, thus the biggest challenge is keeping the consumer entertained, engaged and keeping the churn rate as low as possible. To do that it is important that they showcase their broad video catalog, new content, and the content that is relevant to the consumers' personal taste. Besides a complex recommendation algorithm, Netflix launched the daily Netflix top ten in february 2020. An interesting move as research in the music streaming market pointed out that bestseller and popularity lists can increase the number of streams significantly. Finding out which factors influence these chart lists is thus valuable knowledge for the industry. Therefore, this study examines to what extent electronic word of mouth affects the life cycle of those video titles within Netflix's daily top ten chart.

288 video titles that were in the Netflix daily top ten chart in the period of January 2021 up until December 2021 were examined in this research. For each video title, Twitter data was gathered over a 60-day window: 30 days before release and 30 days after release. In total more than 1.8 million tweets were gathered for this project. Results of the multivariate linear regression analysis showed that Twitter volume pre-release negatively affects the lifecycle of a title in the Netflix daily top ten, but at the same time it affects debut rank positively. Post-release Twitter volume prolongs the lifecycle of a title in the Netflix top ten.

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Chapter 1 – Introduction

1.1 Business Problem background

Traditional broadcasting and media platforms such as newspapers, radio and television have witnessed a sharp decline in customers as more and more consumers started consuming and using digital media (Gandour, 2016). Something similar is happening to the way consumers consume visual media, as video streaming has become a more viable and popular method for households to consume visual media. This is displayed in the immense growth the video streaming market has shown over the last decade (Fortune Business Insights, 2021).

One of the first companies that started offering streaming services was Netflix back in 2007 (Lamare, 2008). However, since the market potential for the streaming video on demand (SVOD) industry is immense, the global market size is expected to reach 932.29 billion USD in 2028 according to Fortune Business Insight (2021), other companies have decided to start their own streaming platforms. The rise of other streaming services is also visible in the market share of Netflix. While the amount of Netflix subscribers was still increasing, the company lost about a third of its market share (Burch, 2021). The increased competition for Netflix is also visible in recent stock price developments. Whilst adding 8.3 million subscribers in the last quarter of 2021 and the expectation to add another 2.5 million subscribers in the first quarter of 2022, the stock price plummeted by almost 20 percent (Keck, 2022). The reason that the stock plummeted is because Netflix must grow at a certain rate to sustain its business model. The annual growth in subscribers is needed to pay off its debts, since the company has to borrow money to fund its own production studios. If the annual growth rate declines by too much, this financial construction is not feasible (Bloomberg, 2019).

The entry of new competitors on the SVOD market has also forced Netflix to change its business strategy. In the beginning of its online video streaming platform, the company was a distributor of productions produced by major film studios. However, those filmstudios started their own SVOD platforms and stopped selling the broadcast rights of their productions to Netflix (Shaw, 2021). This forced Netflix to become a producer of content to keep its customers entertained and make sure that their willingness to pay remains unchanged (Gomez-Uribe & Hunt, 2015). That means that customers need to keep spending time on Netflix and feel entertained. What they should not do is scroll endlessly through the catalog to find something new to watch. If users are spending too much time scrolling through the catalog, they might leave the website, look at the offering of a competitor and end their subscription (Breen, 2016).

Before deciding on which product to buy or consume, customers want to get to know the product. However, this is difficult in markets with a high number of available products, because the resources the consumer has are limited (Sorensen, 2017). This is problematic for Netflix and its competitors, as they all offer a broad catalog. To help consumers decide what to watch, Netflix makes use of a complex recommender system. The implementation of this recommender system is successful as it is involved in 80 percent of the choices made on the platform (Gomez-Uribe and Hunt, 2015). Another mechanism to help consumers find content is the daily Netflix top ten. Netflix added this list in February 2020 (Tassi, 2020). This list shows the ten most popular shows and movies on the site in a specific country. Adding this top ten list is an interesting move by the platform and one might raise the following question: Why add such a simple metric now while there is already a complex and established recommendation system?

An explanation for this can be found in the literature that studies bestseller lists. Bestseller lists can affect consumer choices in multiple ways (Carare, 2012; Sim et al., 2020). Consumers tend to follow the choices made by other consumers, because consumers prefer following the dominant trend in the marketplace. This is called the conformity effect (Sim et al., 2020). Another explanation is observational learning. Prior research found that consumers can opt to ignore their own private information and decide to follow the choices made by other consumers because they might have superior information. Thirdly, a consumer might not be aware of all the options available and makes a decision based on a popularity chart. This is called the saliency effect (Sim et al., 2020).

Consequently, bestseller lists can affect product performance. Being on the bestseller list increases future sales significantly (Carare, 2012). Recent research shows that if a song is added to the top 100 chart, the number of new listeners increase by 11-13% and total streaming increases by 2-3%, mostly due to the saliency effect (Sim et al., 2022). The saliency effect is interesting, as it might have similar effects for video streaming services. The idea is that zero marginal costs and subscription-based services with a big product catalog are responsible for creating the saliency effect. Since there is no cost associated with consuming new products, consumers might be insensitive to quality signals (Carare, 2012; Sim et al., 2022). So, the rank doesn’t matter, but being on the popularity list does. However, in the music streaming industry this effect might be greater than in the video streaming industry since movies and TV shows are generally more time consuming than listening to a new music song. Still, it is likely that shows and movies benefit from the exposure that comes with being on a bestseller or popularity list. Research on the economic benefit of the Netflix top ten is missing, but the current research from the music streaming industry is quite convincing, and it is a possibility that shows and movies experience improved view counts if they are displayed on the daily Netflix top ten list.

For Netflix, it could be of economic interest as the top ten might lead to increased total streaming time just as it did for Spotify (Sim et al., 2022). This makes the Netflix top ten an interesting research subject for the company itself, the SVOD industry, the producers of shows, and those that invest in this market. The economic benefits of the Netflix top ten might be an interesting study field, but is difficult to conduct currently due to the lack of available data. However, one area that can be examined are the potential factors that influence the Netflix top ten. Based on prior research in different segments that found that hit lists can boost demand and total streaming time, finding the factors that prolong placement on a hit list is valuable knowledge (Sim et al, 2022).

One potential factor that might influence placement in the Netflix top ten is the popularity of a series or movie on social media. Twitter is a relevant social media platform for product reviews and opinion seeking (Jansen, Zhang, Sobel, & Chowdury, 2009; Smith, Fischer, & Yongjian, 2012). Literature concluded that Twitter word of mouth (WoM) can affect movie sales and that positive WoM contributes to more movie sales (Rui, Liu, & Whinston, 2013). Experts have blamed negative microblogging WoM to be the reason why multimillion movies have failed, while other productions thrived unexpectedly (Singh, 2009; Hennig-Thurau, Wiertz, & Feldhaus, 2015). Deer, Chintagunta and Crawford (2019) concluded that Twitter is the most important online channel for large franchise movies to generate buzz which influences the box office earnings in the opening weekend. They also found that maintaining Twitter buzz in the post-release phase is critical for sustained movie success. It would be interesting to know if Twitter WoM does also affect the demand for shows and movies on Netflix and other streaming services. And if Twitter WoM can be used to prolong the lifetime of a show or movie in the Netflix top ten.

What also matters besides the quantity of Twitter WoM, is the perception of quality consumers have. This can be measured by looking at the sentiment displayed in tweets, which can function as a measure for these perceptions. Sentiment is of interest as it can lead to social learning, which happens when the perceptions of consumers are shared with their peers on, for example, Twitter (Deer et al., 2019). Twitter offers a great platform for this kind of learning as active users of the platform are likely to share their opinion after seeing a movie and potential consumers, who also have a Twitter account, can use these tweets to learn about a productions' quality to reduce their risk (Jarvey, 2014; Deer et al, 2019). This is helpful for a sector that sells experience goods as most consumers are risk averse and want to reduce their product uncertainty. Research indicates that consumers look for online reviews to reduce their risk and to get pre-purchase information (Goldsmith and Horowitz, 2006). Looking at the sentiment expressed in tweets can give consumers an idea of the quality of a video production and which one they want to watch. Deer et al. (2019) concluded that for smaller movies the sentiment expressed in tweets increased the demand significantly.

1.2 Problem Statement

Based on the problem indication discussed in the previous section, this study will focus on the following problem statement:

"To what extent does Twitter WoM influence which series and movies are in the Netflix top ten; can Twitter WoM increase the period a production spends in this Netflix top ten?"

1.3 Research Questions

The central problem statement translates in the following theoretical and empirical questions that are proposed to give an answer to the problem statement:

<u>Theoretical research questions:</u>

- How does the SVOD industry differ from the movie industry?
- What is the effect of bestseller lists?
- Why did Netflix add the daily top ten list?
- What is the effect of online WoM in other industries according to the available literature?
- What is the effect of Twitter volume pre- and post-release on sales according to the literature?
- What is the effect of Twitter sentiment pre- and post-release on sales according to the literature?

<u>Empirical research questions:</u>

- What is the effect of Twitter WoM volume on the lifecycle duration of a production in the Netflix top ten?
- What is the effect of Twitter sentiment in tweets on the lifecycle duration of a production in the Netflix top ten?

1.4 Research Method

To answer the problem statements and the research question of this thesis, a literature review and empirical research will be used. The literature review will provide insight on the online video streaming industry, the influence of bestseller lists, the effect of worth of mouth on social media, Twitter in general and the effect tweet volume and sentiment has in related industries according to the available literature. This literature will be used to explain why Twitter WoM might affect the Netflix top ten, why pre- and post-release tweet volume matters and what the expected effect of tweet sentiment is. The data for the empirical part of this thesis will be retrieved from several sources. The data about the Netflix top ten will come from the numbers.com. The twitter data will come from Twitter's API V2 and lastly some control variables will be conducted from IMDb.com. Once the data has been gathered it will be analyzed with a linear regression model.

1.5 Relevance

1.5.1 Academic Relevance

From an academic point of view, this research adds to the literature by looking at explanatory factors of Twitter WoM for streaming services in general. It also extends the literature on Twitter WoM in market-based subscriptions, which hasn't been researched in detail yet. This research tests if findings found in past research on movies and box office performance are also applicable in a video streaming scene (Hennig-Thurau and Wiertz, 2015; Gelper, Peres, and Eliashberg, 2018; Deer et al., 2019).

The recent literature also seems divided about the effect of sentiment on product sales. Research found that the sentiment doesn't affect sales if the product is popular (Shibab and Putri, 2019). Henning-Thurau et al. (2015) mention a relationship between a faster drop in earnings over the weekend a movie is released and negative tweets. With movies it also seems that positive reviews can increase the box office revenue (Reinstein and Snyder, 2005). This feeds into the assumption that a positive sentiment can increase demand. Deer et al, (2019) concludes that positive WoM is especially important for the demand in smaller movies in the subsequent weeks after release. This research adds to this literature by studying the effects of sentiment on more popular experience goods in a contractual setting.

1.5.1 Managerial Relevance

The video streaming market is vastly different from the movie industry. While there are similarities between the two, the way revenue is created is completely different. Movies have a short life cycle and most of the box office revenue is earned early in the life cycle (Deer et al., 2019). Because of the importance of the first week's sales, managers need a good prediction of how the movie is going to perform and build a pre-release strategy around that prediction (Divakran et al, 2017). For streaming services like Netflix, the revenue model is based on subscriptions. The goal is not to sell as many tickets as possible, but to increase the number of subscribers to the service. This involves reaching new subscribers, but also preventing churn. For this, Netflix needs to produce quality content that makes them stand out amongst the companies' competitors and this content needs to be popular amongst subscribers, so that they remain a subscriber to the platform.

However, this is not an easy job to do. Producing content is difficult, risky and expensive. Quality is not easy to determine, as the demand is uncertain, which in turn makes it hard to predict the quality of the production (Divakran et al., 2017). More knowledge about the popularity of products, the characteristics, ratings and life cycle in charts like the top ten can help managers make better decisions. Staying in the top ten longer is important, as it can increase the discovery of series and can lead to an increase in total view time (Sim et al, 2022). This research will give managers more insights on factors that influence the life cycle of videos in the Netflix top ten and how big the influence of social media is. The findings of this research can help in improving decision making about which programs to produce and how to promote these.

1.6 Structure of the Thesis

This thesis has five chapters of which the first was the introduction. Chapter two contains the theoretical dimensions of this research and explains the expected relationships between variables in order to draw the research hypotheses. In chapter three the research methodology will be explained. The results and analyses will be explained in chapter four. Lastly, in chapter 5, the results will be discussed along with theoretical and practical implications. Chapter 5 will conclude this research by discussing its limitations and recommendations for future research.

Chapter 2 – Theoretical Framework

In this chapter the theoretical framework for this project will be created. First, information is provided about the streaming industry, bestseller lists, word of mouth and Twitter. After that, based on prior research findings, hypotheses will be provided and explained using the available literature. The aim of this chapter is to develop the hypotheses that will be empirically tested in this thesis, based on the findings of prior research.

2.1 The USA Video Streaming Industry for Netflix

Most big SVOD platforms are available all over the whole world. However, the biggest market is still the United States. The amount of video streaming subscription contracts exceeds the population of the USA (Holleran, 2021). It is also the biggest sales market for Netflix with 62 million subscribers in 2021 (Cook, 2021). The average Netflix subscriber uses the service approximately 3.2 hours per day in 2020. The company is responsible for 15 percent of the global internet traffic (Business Strategy Hub, 2019). In the US, the Netflix library contains more than 5800 titles, so users from the USA pay around $0.00266 for each movie or series (Moody, 2022).

The video streaming services generate income through subscription payments. Most of the time the customers pay a monthly fee to the company to make use of its services. To end the subscription the consumer must notify the company. There are no extra marginal costs for seeing a movie on Netflix besides the monthly subscription fee, this could influence the effects that observable characteristics have on the popularity of a show.

This is not the only difference with the movie industry. In the movie industry the life cycles are short. Every week a couple new movies come out and a similar quantity leaves the market. In the video streaming market this is different. The movies and series Netflix produces (Netflix Exclusives) are likely to stay in the catalog the entire time. In the streaming market, there is also no such thing as wide releases; there are no differences between larger or smaller productions. All the products just end up on the website on the release day. There is also no box office revenue for the productions on Netflix.

The only metric that is currently publicly available is the Netflix top ten, which can be used to measure the popularity of a show. Netflix does not publish a view count, which makes research towards this subject difficult. The streaming service company focuses on attracting new subscribers, retaining subscribers and upselling (Business Strategy Hub, 2019). The effect of Twitter WoM on subscription-based services is not clear. In the demand for movies, Twitter and Twitter sentiment does matter (Deer et al., 2019).

2.2 Bestseller lists

Bestseller lists or top-ranking charts are nothing new in the book, movie and music industry. For example, the most influential bestseller lists for books, the New York Best Sellers Lists, has been published regularly since 1942 (Wiegand, 2003).

Bestseller lists are being used by manufacturers and retailers for strategic reasons. Providing consumers with this information gives them an impression of choices made by other consumers. These choices are likely to influence decision making of consumers who have not yet finished forming their own preferences (Kalra & Mathur, 2000). Available literature shows that when the perception of perceived risk is high or when there is a lot of uncertainty around a product, potential consumers' evaluations are influenced by the opinions of others (Dowling & Staelin, 1994). Observational learning has been identified as a reason why people choose to ignore their own private information and decide to follow the herd (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992; Shi, Chiang, & Rhee, 2006).

Early empirical research on the effects of bestseller lists concluded that book sales increase average with 13-14 percent if they appear on the New York Bestseller list (Sorensen, 2017). For first time authors this effect was even bigger as their average sales increased with 57 percent after having appeared on the New York Bestseller list (Sorensen, 2007). This increase in sales can be explained because the books benefit from the informational effect. This informational effect was also visible in an experimental setting conducted in a restaurant (Cai, Chen, & Fang, 2009). This experiment showed that the sales of the five dishes that were on the bestsellers list increased by 13-20 percent, while this was not the case for the dishes in the saliency group (Cai et al., 2009). Tucker and Zhang (2011) concluded that observational learning is different for narrow-appeal products versus broad-appeal products. Narrow-appeal products benefited more from being on the bestsellers list since consumers recognize that these products had to clear.a higher hurdle to become popular (Sorensen, 2017).

Recent research indicates that for streaming services the effect of bestseller lists is different. As pointed out by Sim et al. (2022) subscribers are not troubled with the extra financial burden of purchase decisions which they did have in the setting prior research was conducted. Sim et al. (2022) found that bestseller lists influence the consumer choices significantly in streaming services that have a contractual business model. However, this is happening through a different mechanism than observational learning, possibly due to the non-existing marginal costs and the overload of choice in the music streaming market. Sim et al. (2022) concluded that the ranked position doesn't matter, only being on the list does. Based on that, the saliency effect is a more prominent effect compared to observational learning. Future research could potentially identify which effect is more prominent in the video streaming market, as the choice set is smaller compared to the music industry. However, what can be concluded from the available literature is that bestseller lists can increase sales or number of streams. This can explain why Netflix introduced the Netflix top ten in the first place.

2.3 Twitter

Twitter was launched in 2006 and is a platform on which users can write microblogs with a maximum of 280 characters per blog. The number of characters was limited to 140 till 2017 (Rosen, 2017). With a revenue of 3.7 billion dollars in 2020 and 300 million active users it is the biggest microblogging platform online (Iqbal, 2022). The site is in the top ten most visited websites in the USA (BroadbandSearch, 2022).

Users mainly use the platform to write a small blog (microblog) about something they are doing, keeping up with the news, sharing their opinion or sharing information (Rosenstiel et al., 2015). This small blog is called a 'tweet'. Another important act active users of the platform can perform is 'retweeting'. This allows users to share something from someone else with their own followers and expand the visibility of the original tweet. Users can decide to follow each other, which can be seen as some sort of subscription to other's their tweets. A large part of twitter users (44 percent) has never posted a tweet and just uses the platform for information gathering (Koh, 2014). This is visible in the amount of search queries per day as Twitter handles more than 1.6 billion search queries per day (Siegler, 2011).

One thing Twitter excels in is creating a platform to share opinions. This is nothing different for TV shows. Many Twitter users have an extra screen when watching a show to engage in conversations about the productions they are watching (Macmillan, 2015). This makes Twitter one of the best platforms for conversation about television shows (Macmillan, 2015; Twitter, 2017). The movie industry is also one of the most brought up topics on Twitter (Suslak, 2014). This makes sense since the core audience of Twitter and movies are the same (Deer et al, 2019). Recent studies show that people with a Twitter account watch more movies compared to non-users and are more likely to watch a new movie in the first 10 days since its release (Jarvey, 2014; Robehmed, 2015). A survey among Twitter users showed that their recent movie visits were influenced by tweets of others (Deer et al., 2019). Twitter is not only important to the entertainment industry; past literature found that Twitter's topic-based sentiment can improve the prediction accuracy in stock market prediction models (Si et al, 2013). This showcases the potential value Twitter WoM has in different industries. It is likely that something of a similar trend is the case for productions on streaming services. The next section of this chapter will outline the conceptual framework of how tweet volume and the sentiment in them can possibly influence consumer demand in a contractual setting.

2.4 Tweet Volume

When a new experience good is brought to the market, there is an occurrence of information asymmetry since there is a shortage of quality-related information from other consumers (Kirmani & Rao, 2000). Experience goods are goods that are difficult to qualify in advance. The buyer can only qualify the goods during and after consumption. This risk is something potential buyers want to reduce, as people are in general risk averse. This can be seen when studying consumers' attitude toward brands and explains why people that are risk averse stick to a brand they already know (Mishra, Kesharwani, & Das, 2016).

Social media word of mouth can reduce potential risk. This word of mouth makes it possible for early consumers to quickly spread their experience with a new product. This might affect other consumers' product adoption as it reduces the perceived risk (Hennig-Thurau & Wiertz, 2015). This might also be applicable to shows and movies. Following the research from Deer et al. (2019) Twitter volume is used to measure social media word of mouth.

2.4.1 Twitter volume pre-release

Advertisements before the release of a new movie or before new episodes of a show air are nothing new. However, the rapid development of social media combined with the widespread use of mobile devices is changing the advertisement landscape. Early research about the effect of online reviews on product sales concluded that online box office sales are influenced significantly by the volume of online posting due to the awareness effect of online posts (Duan, Gu, & Whinston, 2008). Online discussion communicates the existence of a new product and after seeing this, potential consumers might put it in their choice set (Duan et al., 2008). Research aimed towards online word of mouth communication for TV shows concluded that a show can benefit significantly from a dispersion effect at the beginning of the show's lifecycle (Godes & Mayzlin, 2004). They concluded that cross-newsgroup dispersion creates more awareness than within newsgroup dispersion, also indicating that awareness has a significant effect on the TV show's performance. In a more recent paper the authors found that pre-consumption Twitter WoM has a larger effect on movie sales than post-consumption Twitter WoM, because of the awareness effect (Rui et al., 2013). Deer et al. (2019) explains that a Twitter post can raise awareness directly and indirectly. First, directly through seeing a movie trailer or other information that is posted or retweeted by someone they follow. Secondly, indirectly through reinforcing previous advertising a consumer has seen, but forgot about (Deer et al., 2019). Previous research concluded that consumers forgot about advertising messages they see, but that can be reinforced by more exposure (Campbell and Keller, 2003). Seeing something about a TV show or movie in their Twitter feed can thus remind an individual about the message that a production is going to be released soon or is already online, this can increase the probability that someone will look up the production on Netflix.

According to available literature there is another manner through which the volume of tweets can influence demand and that is the phenomenon product ‘buzz’. Product buzz is defined in the literature as the aggregation of observable expressions of anticipation about a forthcoming new product and cannot be equated with word of mouth (Deer et al., 2019; Housten et al., 2018; Divakaran et al., 2017). Especially for experience goods with a strong social consumption component and short lifecycle, buzz is thought to be an important determinant, especially for the initial sales (Housten et al., 2018; Divakaran et al., 2017). The effect on demand for movies is thought to be influenced by buzz because consumers enjoy seeing movies that their peers have seen and are talking about (Deer et al., 2019). This might be strengthened in the video streaming market since the marginal costs are zero, which means there is no risk for the consumer to check what this ‘buzz’ is all about (Sim et al., 2022). According to past research this ‘buzz’ manifests itself in the volume of tweets. The tweets about the product are placed by customers who see themselves as opinion leaders, share their interest, enthusiasm and share their expectations (Chu & Kim, 2011; Toubia & Stephen, 2013; Sun, Youn, Wu, & Kuntaraporn, 2006; Deer et al., 2019). Since the product is not available yet, the sentiment is likely to be neutral (Deer te al., 2019)

Because of the awareness effect and product ‘buzz’ which are both established by tweet volume and the low-risk consumers face in the video streaming market the following hypothesis is drawn up:

H1: Pre-release tweet volume has a positive impact on how long a title stays in the Netflix Daily top 10 list.

It should be noted that Twitter is not the only source of buzz and customer awareness for series on Netflix. There are other online platforms where consumers can discuss shows on

Netflix or even offline possibilities. Additional control variables are added to account for this effect, this will be discussed in chapter 3.

2.4.2 Tweet volume post-release

Once a video production is in the top ten of Netflix, it is important that it stays there as long as possible to benefit from a potential saliency effect. Being on the most viewed watchlist is likely to increase the number of new viewers and the amount of total streaming (Sim et al, 2022). In the mobile app market, demand is increased if the mobile app is on the bestsellers list (Carare, 2012).

Like Deer et al. (2019) the framework in this research allows for tweet volume to influence demand over a longer period than just the pre-release phase. In the movie industry, tweet volume after release is likely to increase awareness that the movie is available in the theater and that can stimulate demand in the subsequent week and might trigger curiosity from consumers that have not yet seen the movie. The product 'buzz' can also affect the demand since consumers might become curious about a TV show or movie after reading all the anticipatory emotions expressed on Twitter after seeing the movie (Deer et al., 2019). Combined with the marginal costs at zero, this might influence the consumer to check out the production for themselves and see what the discussion is all about. Also, not every consumer can watch the show or movie directly when it is published.

In the movie industry, tweet volume after release is likely to increase awareness that can stimulate demand in the subsequent week and might trigger curiosity from consumers that have not yet seen the movie (Deer et al, 2019). Possibly, the effect is stronger in the streaming market as there are, like music streaming, no extra marginal costs associated with more consumption. In their research on the movie industry, Deer et al. (2019) found that the effect of post-release Twitter volume is larger than the effect of pre-release Twitter volume. Therefore, it is expected that the effect of post-release Twitter volume is larger than the effect of pre-release Twitter volume in the video streaming industry as well, based on the similarities between the industries. From this the following hypotheses are drawn up:

H2: Post-release Twitter volume has a positive impact on how long a title stays in the Netflix Daily top 10 list.

H3: The effect of post-release Twitter volume is greater than that of pre-release Twitter volume.

2.5 Tweet Sentiment

Measuring consumer perception of a video production is not possible by only looking at the volume of tweets. The sentiment in the tweets can provide a measure of the perceptions. According to Deer et al. (2019), sentiment impacts movie sales as it allows knowledge to diffuse through the population, creating a channel for social learning. This occurs when information or indications of a movie's quality are revealed to potential consumers through interaction with their peers. Twitter is a perfect platform for social learning in this situation as active users of the platform post their short reviews or opinions after viewing a movie (Jarvey, 2014; Robehmed, 2015). Consumers that are considering viewing a movie can use this information to decide if they want to go see this movie. In other words, they use this information to change their purchase decisions (Goldsmith and Horowitz, 2006; Deer et al., 2019). The number of short reviews or Twitter posts accumulate quickly after release, which can differ from pre-release expectations because there are more opinions in general.

The perception of others can be important, as it can lead to a persuasive effect on other consumers. The persuasive effect is an effect of WoM that can alter people's preferences towards a product and can thus influence an individual's purchase decision (Rui et al., 2013). Past research on the effect of this persuasive effect is divided. Duan et al. (2008) concluded that the ratings of online user reviews didn't affect movie box office revenues, indicating that online user reviews have little persuasive effects. Which is in line with earlier findings (Eliashberg and Shugan, 1997). The reviews reflect quality, but it doesn't affect product sales. Other research concluded that valence does not affect product sales, but only positive tweets were used in this paper (Wong, Sen and Chaing, 2012). Which can be problematic, because consumers can start questioning the credibility of the reviews if all the reviews are positive (Lee, Jung and Park, 2017). According to the same paper, this can be resolved with many positive reviews that are not from consumers that are dependent on each other. More recent research states that if the product is very popular, negative reviews of credible sources do not affect the purchase intention of consumers but does affect their attitude towards a product. (Shibab and Putri, 2019). For unpopular products, the negative reviews did affect the product sales. This is in line with earlier research, which concluded that critic rating does not have a significant effect on opening box office revenue (Divakaran, Plamer, Søndergaard, & Matkovskyy, 2017).

Other research concluded that there is a positive relationship between demand and post-release sentiment (Deer et al., 2019). Rui, Liu and Whinston (2013) found that valence affects movie sales throughout the entire lifecycle and do not report that there is a difference between the effects of negative tweets or the effects of positive tweets. This is not in line with other research that concluded that negative WoM is more influential on demand for movies than positive WoM (Chakravarty, Lui and Mazumdar, 2010). Hennig-Thurau, Thorsten and Feldhaus (2015) concluded that early Twitter WoM has an impact on early adoption behavior, especially when negative reviews are included. They also state that a negativity bias can be found when it comes to Twitter WoM. The theory on diagnostics of information and the prospect theory can explain this negativity bias. According to the diagnosticity of information, negative informations runs opposite to consumers' expectations which result in a higher diagnostic value for consumers, this is stimulated since negative WoM is more sparse than positive WoM (Chen, Wang and Xie, 2011; Hennig-Thurau, Thorsten and Feldhaus, 2015). On Twitter this number of negative tweets are also a minority when compared to positive tweets about movies (Rui, Liu and Whinston, 2013). According to prospect theory, people assign more value to negative information than positive information (Kahneman and Tversky, 1979; Kanouse, 1984). Meaning that a consumer is more conscious about making sure that they don't suffer from an unwise product choice than they are about benefiting from a wise choice (Luo and Homburg, 2007).

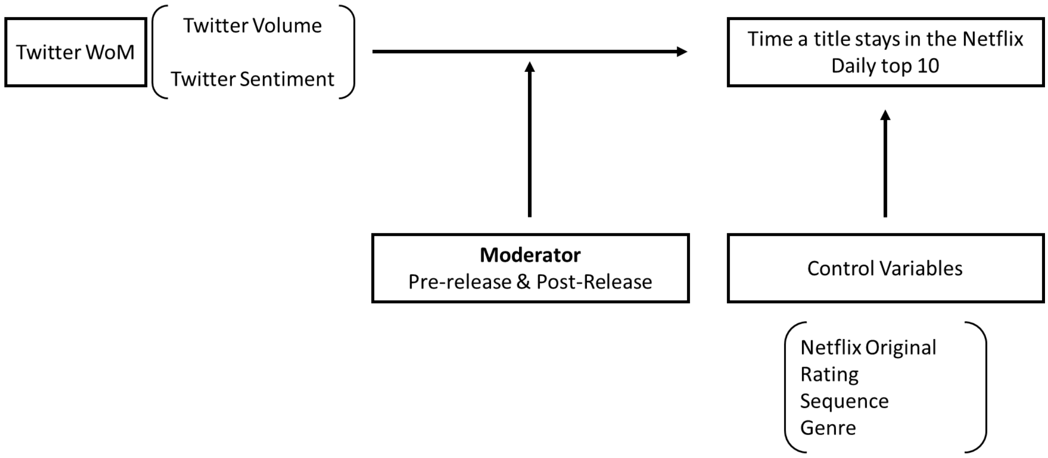
According to the findings listed above, negative Twitter WoM should influence people's purchase decisions more than positive Twitter WoM. Hennig-Thurau et al. (2015) tested this theory and concluded indeed that this is true. Consumer's value negative tweets more because they stand out from all the positive information about a movie, they come across as more honest and can help consumers decide if a media production is worth their time and money. In the video streaming market consumers only have to decide if a product is worth their time, as the marginal costs are at zero (Sim et al., 2022). Which means that there is almost no risk for the consumer and the negativity bias effect might be weaker as it is in the movie industry. Because of that the following hypothesis is drawn up:

H4: There is a positive relation between pre-release sentiment and the time a show or movie spends in the Netflix top ten.
H5: There is a positive relation between post-release sentiment and the time a show or movie spends in the Netflix top ten.

It can be expected that the effect of pre-release sentiment is smaller than that of post-release sentiment, as there is not a lot of knowledge about the quality of a production pre-release (Deer et al., 2019). The quality can only be determined completely after release. In their research on the movie industry, Deer et al. (2019) found that the effect of post-release tweet sentiment was larger than that of pre-release tweet sentiment. Based on that finding the following hypothesis is drawn up:

H6: The effect of post-release Twitter sentiment is larger than the effect of pre-release Twitter sentiment

2.6 Conceptual Framework



Chapter 3 – Methodology

The goal of this thesis is to provide insights on how Twitter WoM influences the popularity of series or movies on SVOD platforms. To analyze this the leading SVOD platform, Netflix, was examined (Fortune Business Insights, 2022). One problematic key feature in this research is that Netflix or other video streaming services barely discloses viewership data. However, since the release of the daily Netflix top ten list some data that contains some information about the popularity of a video production on the platform is now publicly available. This chapter will describe the data collection, the data cleaning, data transformation and the statistical model that is going to be used.

3.1 Data Collection

3.1.1 Netflix Top Ten

The data for the Netflix top ten was obtained via web scraping the website the-Numbers[1]. This website is an online platform which contains information about movies, box office revenue, DVD sales and it contains a daily updated chart for the Netflix top ten. With the use of a web scraper build in Python the top ten data can be gathered. For this, data is gathered from the daily Netflix top ten in the United States and covers the year 2021. The data contains the following features: Rank, Yesterday's rank (YD), Last week's rank (LW), Title, Type, Netflix Exclusive, Netflix release date, Days in top 10 and Viewership score. However, only rank, Title, Type and Netflix release date are kept for further analysis. Table 1 contains a more detailed overview of all the variables. The total dataset consists of 3650 rows of raw movie data. The Python script can be found in Appendix 1 and the raw data files can be found in Appendix 2a.

3.1.2 Twitter data

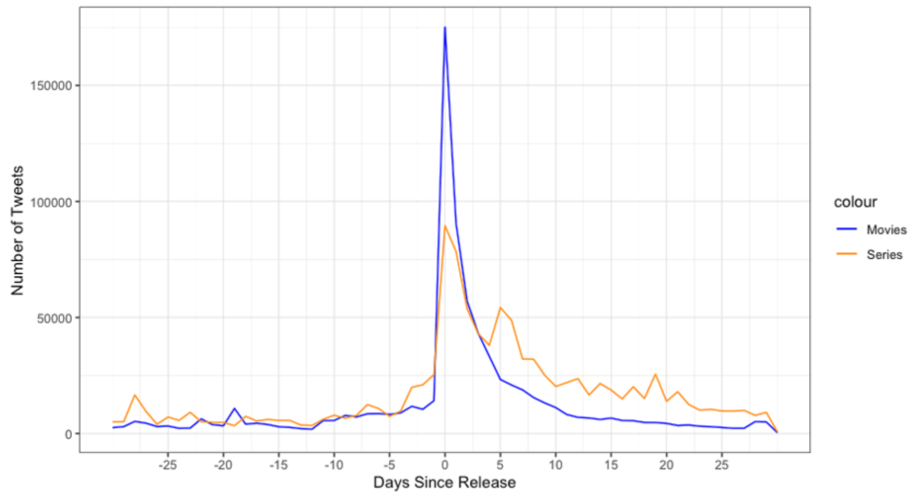
The Twitter variables data was obtained through the Twitter API V2 and the programming language Python. This API archives the complete history of tweets since the beginning of Twitter in 2006. To collect the relevant tweets for this research project specific searches were constructed for all the movies and tv series that were in the Netflix top ten in 2021, totaling 308 unique video titles. The searches are constructed to include the Title name (primary title on IMDb), Original Title and relevant abbreviations. The coding for usage of the Twitter API V2 can be found in Appendix 1.

[1] The Numbers Netflix Top 10: https://www.the-numbers.com/netflix-top-10

For each movie or series, data was gathered over a 60-day window: 30 days before release and 30 days after release. For each given movie or series, the pre-release volume is the sum of all tweets and retweets over a 30-day pre-release period till the midday of the release day. The post-release tweet volume for each movie is the sum of all tweets and retweets from the midday of the release day till 30 days after release. Figure 1 shows the tweet distribution in this time period Retweets are important due to two reasons. First, consumers can become aware of the video release through observing a retweet rather than the original tweet itself (Deer et al, 2019). Second, instead of posting a new tweet themselves, Twitter users can share content that represents their feelings through retweets (Deer et al, 2019).

For this research, a couple restrictions were implemented for gathering tweets. First, the searches were restricted to tweets written in English and the tweets had to be posted in the 60-day window. Secondly, no geological restrictions were used in the tweet gathering as it is quite easy for Twitter users to view Tweets posted by others from different countries (Deer et al., 2019). Third, the US East Coast time zone was used for this research and a day is defined as the 24-hour period from 12.00 pm to 11.59 am. In total around 1.8 million tweets were retrieved. All the Twitter data can be found in Appendix 2b

Figure 1: Tweet volume distribution



<u>3.1.3 Additional / Control Variables</u>

To extend the data retrieved from TheNumbers website, additional variables were added as control variables. The data for these variables comes from the internet movie database (IMDb), a website that is considered as one of the most popular sources of information for consumers about video productions (Fisher, 2021). A short description and overview of the variables can be found in Table 1.

Genre is not new for predicting the success of a movie and has been used over and over in research aimed towards predicting a movie's success (Lee, Park, Kim, & Choi, 2018), (Deer et al, 2019), (Sharda & Delen, 2006). The downside of the genre variable is the fast array of potential genres a production can have. For simplicity the most popular genres on Netflix in the USA were used for this research project (Moore, 2021). The following classification for genres was used: Action, Adventure, Comedy, Documentary, Drama, Fantasy, Reality, Romance, Horror, Thriller.

The second additional control variable is if the production has a sequel or not. Sequels are made because they are seen as less risky and seem to reduce uncertainty as well (Ellashberg, Leenders, & Elberse, 2006). Sequels can build on people's perception of previous versions which can reduce the perceived risk for consumers and reduce costs of marketing for producers (Sood & Dreze, 2006; Jang, Baek & Kim, 2021). In the movie market sequels are used to create brand loyalty as sequels can be seen as brand extensions (Kim & Kim, 2017). Brand loyalty is often used to reduce the search costs for consumers and can thus increase the revenue for producers (Dekimpe, Steenkamp, & Abeele, 1997). Sequels might thus lower the search costs for consumers and perform better than non-sequels. Dhar, Sun and Weinberg (2012) found that sequels often do better than non-sequels, generating more popularity in the first week. Other research found that sequels performed better in the streaming video on demand industry and people tend to download sequels more often than non-sequels (Jang, Baek & Kim, 2021; Kim and Kim, 2020). Because of these findings sequels were included as an additional control variable as they might influence the duration and ranking in the Netflix top ten.

The two movie characteristics were complemented with the average rating of a production and the total number of votes it had received on the IMDb platform. This was added since customers can obtain information from other platforms or sources than Twitter. To control for this, the numbers from IMDb were added to the dataset. On IMDb it is possible for viewers to leave a rating on a video, they can rate the video title with a number between 1 and 10. To compute a score, the platform takes the average of all the reviews it has received of one show. Online ratings are important information for consumers in their decision-making process (Ho, Wu, & Tan, 2017; Li, Zeng, Xu, & Yao, 2020) and are reviewed as a great source of information, as it comes from other moviegoers who see the reviews as the “wisdom of the crowd’ and find it useful to reduce uncertainty (Ho, Wu, and Tan, 2017; Schneider et al., 2021; Lee, Hosanagar, and Tan, 2015). Because of these effects the IMDb data was added to the dataset.

Source	Data Variable	Variable Description
The Numbers	Rank	Today’s rank of a title in the Netflix top ten
	Title	The title of the production
	Type	The type of content: movie or TV show
	Netflix Exclusive	Whether a title is a Netflix Exclusive, yes or no
	Netflix Release Date	The date a title was released on Netflix
IMDb	IMDb Rating	The average consumer rating (on a scale from 1 to 10) assigned to a video title on the online platform IMDb
	IMDb Number of Votes	Number of votes a title has received on the online platform IMDb
	Genre	The genre of a title
	Sequal	Does the movie or TV show have a sequel, yes or no
Twitter	Pre-release volume	Sum of the volume of tweets 30 days before release
	Pre-release sentiment	Sentiment of the pre-release tweets aggregated
	Post-release volume	Sum of the volume of tweets 30 days after release
	Post-release sentiment	Sentiment of the post-release tweets aggregated

Table 1. Overview of all the data retrieved

3.2 Data Transformation and Cleaning

After all the data is collected and stored in csv files, data cleaning and transformation is necessary. The data cleaning is done in the program R, this program will also be used to conduct the analyses. The data transformation consists of checking and where needed adding missing values, filtering out video productions that were already in the top ten in 2020, control for duplicates, add data variables by using calculations, combine the three datasets together and to transform the dataset into a tidy dataset which can be used for the statistical analysis.

3.2.1 The Numbers data

As a first step, dates were added to all the 3650 entries retrieved from the-numbers.com, because this was not in the raw dataset. The date variable is needed to create more variables and is necessary for the analysis. After that a dummy variable for the type of the production is created. The entries with the type 'Stand-Up Comedy' were deleted as there were only 18 entries with that type. This means that only movies or series are in the dataset. Next the dataset was aggregated on title-level. Each title got the following variables assigned: Rank, First_Appearance, Last Appearance, Highest Rank, Days in Top ten, NetflixExcl., and Type. NetflixExcl. is also a dummy variable with the score 1 if the production is a Netflix Exclusive. From the raw data file, the variables LW and YD were removed as they won't be needed for the analysis. The values First_Appearance and Last_Appearance are created by using the Date variable that was added to the dataset by using the Min (minimum) and Max (maximum) functions in R. The variable "Days in Top Ten" was created by looking at the difference between "Last_Appearance" and "First_Appearance". Using the "Days in Top 10" variable from the raw data set was not possible as the values were incorrect. For example, the variable Days in Top 10 has at the first appearance of the series "All American" a value of 66. Because of this the variable was recreated.

After that a sequel variable was created by going through the dataset and looking at the information from IMDb.com. If a movie or series has a sequel it is assigned a 1, if it's any nonsequel it is coded as 0. Next, the variable Debut_rank was added to the dataset by looking at the rank of the first observation of each production. Lastly, a couple observations were taken out due to censoring. This is necessary as this study focuses on the Netflix daily top ten list in 2021. Some observations that are on the list on 31 December 2021 continue to be on the list in 2022. So, their total time in the top ten is only partially measured which results in incorrect data. In total only 5 observations were affected by censoring, therefore it was decided to remove them from the dataset.

3.2.2 IMDb Data

For the control variables genre and review score data from IMDB was used. The datasets title.basics.tsv.gz and title.ratings.tsv.gz were downloaded and merged on the variable 'tconst' using the left_join function in R. This complete dataset was merged with the Netflix top ten dataset and was cleaned to get rid of duplicates after, because some shows use similar names. Lastly for this part rows with missing values are deleted, so the total dataset was reduced to 296 observations.

3.2.3 Twitter Data

In the statistical analysis Twitter data is split into pre-release Twitter volume, pre-release tweet sentiment, post-release Twitter volume and post-release tweet sentiment. The pre-release volume for a given movie or series i as:

$$prevol_i = \sum_{r=-30}^{-1} tweets_{ir}$$

With the $tweets_{ir}$ including all original and retweets about a movie *i* on a given day r relative to the release date. The post-release twitter volume contains all the tweets from the date of release till until the 30th day after release summed up:

$$postvol_i = \sum_{r=0}^{30} tweets_{ir}$$

A day *t* is defined as the 24-hour period from 12.00 pm till 11.59 am. The post-release tweets were gathered till 30 days after release.

For all the tweets that were gathered with the API the sentiment needed to be classified. To classify the sentiment in the tweets the VADER lexicon was used. The VADER lexicon can classify tweets as positive, neutral, and negative (Gilbert & Hutto, 2014) and is specifically designed to analyze the sentiment of text on microblogs and social media. The lexicon incorporates internet slang, capitalization, emoticons, and punctuation into the scoring process and has a correlation of 0.88 (Gilbert & Hutto, 2014). These features are not incorporated in other lexicons as LIWC.

The VADER lexicon assigns a sentiment score to each tweet in the range [-1, 1] after analyzing the words, and structure of the text. This score is used in this research to classify each tweet into one of three categories: positive, negative or neutral using the following rule:

$$\text{sentiment} = \begin{cases} \text{Negative if VADER score} < -0.05 \\ \text{Neutral if VADER score Î}[-0.05, 0.05] \\ \text{Positive if VADER score} > 0.05 \end{cases}$$

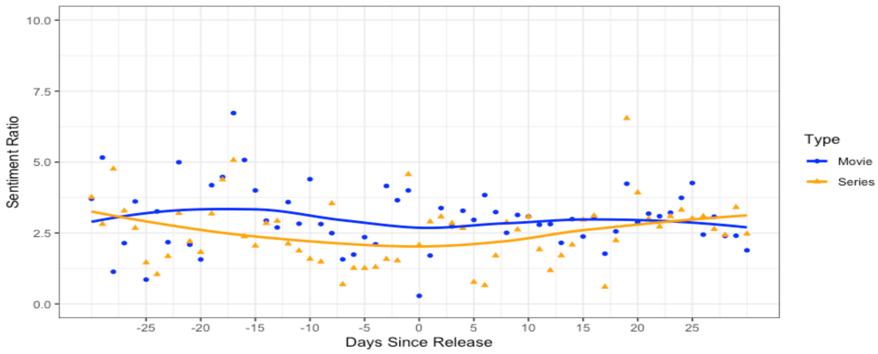
If the tweet has a VADER score of <-0.05 it is placed in the negative category, if the score sits between [-0.05, 0.05] it is placed in the neutral category and if the tweet has a VADER score of >0.05 it is placed in the positive category. This method of classifying is based on previous research and the recommendations from the Lexicon's developers (Deer et al., 2019; Gilbert & Hutto, 2014).

The category counts were then aggregated and used to compute a positive-negative ratio for each movie or series i for both pre-release and post-release period:

$$sentiment_i = \frac{\Sigma \text{ \#Number of Positive Tweets}}{\Sigma \text{ \#Number of Negative tweets}}$$

This ratio was computed by dividing the number of positive tweets by the number of negative tweets. This is a popular way in research to measure sentiment in classified text (Nguyen et al, 2012; Si et al., 2013; Deer et al., 2019). The problem with this type of sentiment classification is that movies and series with a low number of tweets obtained a sentiment score of infinity or zero. It is not possible to log transform those variables thus the variables were removed from the dataset that is used for the model that includes the variables pre-release sentiment and post-release sentiment. After removing those variables, the dataset contains 255 observations. This potential selection bias will be further discussed in the result section and in the discussion. This dataset can be found following the link in Appendix 3.

Figure 2: Sentiment Ratio Distribution



3.3 Statistical Model

The objective of this thesis is to find out if Twitter WoM is a driver of chart success in the SVOD industry. Twitter WoM is measured by tweet volume and tweet sentiment. The Twitter data was divided in pre- and post-release categories. Twitter data is ideal for analyzing Twitter WoM as its short text messages are great for voicing an opinion or sharing information. Past research has shown that Twitter data can be used to predict stock market movements or box office revenue (Si et al., 2013; Deer et al., 2019).

After all the data was gathered, the scraped data was cleaned, and the retrieved twitter data was sorted out the statistical analysis was performed, and the results of that analysis are presented in chapter 4 of this thesis. First, a descriptive statistical analysis was conducted to gather more data insight about the life cycles of movies and series in general. To test the hypotheses of this thesis, this study used a multivariate regression analysis with a log-log transformation for the dependent variable and the Twitter variables; this was done to increase interpretability.

The multivariate regression analysis is a great statistical tool that measures the effect that the explanatory variables and the moderator have on the dependent variable, in this case the duration of the lifecycle in the Netflix top ten of a movie or series. The statistical model for this study is defined the following way:

$$Log(Y_i) = \beta_0 + \beta_1 Log(PreVol_i) + \beta_2 Log(PreSentiment_i) + \beta_3 Log(PostVol_i) + \beta_4 Log(PostSentiment_i) + \boldsymbol{\gamma} Z + \varepsilon_i$$

Yi is the dependent variable with log transformation. The effect size of the variables of interest is indicated by β. The Twitter variables are log transformed, so the coefficient displays the elasticity. Meaning the a certain percentage change in the dependent variable for a 1 percent change in the independent variable (Pedace, 2016). $\boldsymbol{\gamma} Z$ is the set of control variables included in the model and ε_i is the error term.

Chapter 4 – Results

This chapter will start off with section 4.1 which contains the descriptive statistics of the initial dataset and will provide an overview of all the variables obtained during the data collection in chapter 3. Section 4.2 will discuss the assumptions of linear regression models and check if these are violated in this thesis. If they were violated a transformation will was performed to meet the assumptions. Section 4.3 will show the results of the analysis and discuss the outcomes. Section 4.4 will contain additional explorative analysis, mainly focusing on the effect of Twitter volume and sentiment on the debut rank of a show.

4.1 Descriptive Statistics

Table 2 lists the summary statistics of all the independent variables. The total dataset covers the year 2021 and covers 365 days. This resulted in 304 observations in total. However, as mentioned in section 3.2.1, due to censoring 5 observations were removed from the dataset. As mentioned in Section 3.2.3 due to the VADER lexicon output more observations had to be removed from the dataset. After removing the observations suffering from these problems 255 observations remained.

A production spends, on average, 11.36 days in the Netflix top ten with a standard deviation of 10.58 days. The distribution of the time a movie or tv show spends in the Netflix top ten is shown in Appendix 4a. The mean survival time for movies is 9 days and for TV shows it is 14 days.

The variables of interest for this research are the Twitter variables. The average number of pre-release tweets is 2206 and the average number of post-release tweets is 4496. The average sentiment pre-release is 5.99 which means that for every negative tweet there are almost 6 positive tweets on average. The average post-release sentiment is 4.52, meaning that for every negative tweet there are around 4.5 positive tweets on average. The average time in the top ten across the whole dataset is 11.36 days, meaning that productions spend on average a bit more than 11 days in the Netflix daily top ten list. Box plots of the distributions of the Twitter variables and the dependent variable Time in the top ten are added in Appendix 4.

Table 2. Descriptive Statistics

Variable	N	Mean	SD	Min	Max
Time_in_Top10	255	11.36	10.58	1	80
Debut_Rank	255	5.51	3.12	1	10
Days_2_peak	255	1.49	3.1	0	42
averageRating	255	63.01	17.58	6	91
VotesIMDb	255	81129.18	214949.27	123	2528373
NetflixExcl	255	0.73	0.45	0	1
Movie	255	0.51	0.5	0	1
Sequel	255	0.27	0.44	0	1
Prevol_tweets	255	2206.07	5114.65	3	48711
Pre_release_sentiment	255	5.99	8.83	0.01	77.28
Postvol_tweets	255	4496.09	9525.87	20	100025
Post_sentiment	255	4.52	5.26	0.05	43

4.2 Assumptions

Before performing the multivariate linear regression analysis some assumptions had to be checked. If these were violated the results of this type of regression can be incorrect. The assumptions tested for the linear regression in this thesis are linearity, homoscedasticity, influential cases, and multicollinearity. If one of these assumptions is violated, transformations will be performed to the model in order to meet the assumptions.

4.2.1 Linearity

The first assumption that is tested is the assumption of linearity. The linearity test results can be found in Appendix 5a. If the data is perfectly linear the red line should be horizontal, which is not the case for this model. As can be seen in Appendix 5a the linearity assumption is violated. However, if one outlier in the dataset is removed, the red line is more wrapped around the dotted line, and it becomes acceptable. This can be seen in Appendix 5b

4.2.2 Homoscedasticity

The second assumption that was checked is the assumption of homoscedasticity. Important for a linear regression model is equal variance of residuals, which was controlled with this assumption. If this assumption is violated it can cause underestimation of the standard deviation for the covariates. This can be checked in multiple ways. In this paper the Breusch-Pagan Test is used to identify homoscedasticity (Breusch and Pagan, 1979). The null hypothesis of this model is that homoscedasticity is present, and the alternative hypothesis states that heteroscedasticity is present. The Breusch-Pagan test performed on the model in this thesis resulted in a p-value higher than 0.05 which means that the null hypothesis is not rejected. The outcome of the Breusch-Pagan test is included in Appendix 6

4.2.3 Influential cases

The third assumption that was tested is the assumption of influential cases. Literature indicates that significant influential cases can impact the model negatively (Weisberg, 2013). To test for influential cases, Cook's D was used. Based on the research from Weisberg (2013) a Cook's D with a value higher than 1 is an influential case and this can influence the regression. As can be seen in Appendix 7 there is one clear influential case with Cook's D over 2. This is the same observation that is causing the linearity problems in section 4.2.3. Because this is the only observation with such a high Cook's level this observation was removed.

4.2.4 Multicollinearity

Lastly, the assumption of Multicollinearity was tested. It is important to control for this assumption as in the presence of multicollinearity the estimates of the standard errors of the regression increase. This can result in imprecisely estimation of the coefficients and a loss of power (Yoo et al., 2014). Multicollinearity increases the stand error in regression estimates, which creates wider confidence intervals and increases the chance to reject the significant test statistic. This results in imprecise estimation of the coefficients (Yoo et al, 2014).

To test for multicollinearity, first variance inflation factors (VIF) were examined in combination with tolerance. In line with previous research a VIF score above 10 is a sign of too much multicollinearity (Hair, Black, Babin and Anderson, 2014; Franke, 2010). In addition to that the tolerance should be above 0.2. If a variable exceeds these limits, the variable has to be excluded from the analysis. As can be seen in Appendix 8 the highest VIF value is 3.9, which means that no VIF is exceeding the value of 10, also the tolerance values are all above 0.2.

To further check for multicollinearity a correlation matrix was made. This matrix shows how two variables are related, and if that relationship is positive or negative. If two values correlate too much with each other it becomes difficult to estimate the true relationship of these independent variables and the dependent variable. if the correlation between two variables exceeds the threshold of 0.8, there is multicollinearity according to literature. As is shown in Appendix 9 the independent variables do not exceed the threshold, the model is not suffering from multicollinearity.

4.3 Empirical Results

A multivariate linear regression model was fit to the data. This was done with four models. Model 1 displays a linear regression with only the Twitter variables. In model 2 the control variables Netflix Exclusive, Movie, Sequel, IMDb votes and IMDb Rating were added. In model 3 the regression is extended with the genre dummies. In model 4 the Twitter sentiment variables were not included in the regression. The output of this model was added to control for potential selection bias as a substantial number of observations in the dataset used for model 1, model 2 and model 3 had to be removed due to incorrect values for the sentiment variables. The dataset for model 4 consists of 288 observations. Eight observations had to be removed from the dataset described in section 3.2.2, because for some observations the tweet volume was zero. Log (0) is undefined and thus not suited for analysis.

In Table 3, the results for the regressions are displayed. In Appendix 10 the full regression outputs are provided. In research it is common that a p-value below 0.05 signals significance, so a p-value below 0.05 is needed to accept or reject my hypotheses. Table 4 provides an overview of the tested hypothesis.

4.3.1 Pre- and post-release Tweet Volume

Interestingly, for all four models the pre-release tweet volume is significant. However, the result is contrary to what was expected in chapter 2. A one percent increase in pre-release tweet volume results in a 0.111 percent decrease in time spent in the Netflix top ten. In other words, there is a negative correlation between pre-release tweet volume and the duration a show or movie stays in the Netflix top 10. This means that hypothesis one is not supported.

Across all four models the post-release tweet volume displays a significant positive effect, and this is in line with hypothesis 2. The values of the effect change depending on the model. In model 3 an increase of 1 percent post-release tweet volume increases the time a Tv show, or movie spends in the Netflix top ten with 0.300 percent, which is quite substantial. The p-values are also below 0.05, so hypothesis 2 is supported. This is in line with the findings of Deer et al. (2019) who found that tweet volume after release is likely to increase awareness which stimulates demand in the subsequent weeks. The effect of post-release tweet volume was also larger than that of pre-release tweets. Therefore, hypothesis 3 is supported.

Table3: outcome of the regression

Dependent variable: Time in top ten (log)	Model 1	Model 2	Model 3	Model 4
Tweet Volume Pre-release (log)	-0.131***	-0.132**	−0.111**	−0.110**
Tweet Volume Post-release (log)	0.327***	0.331***	0.300***	0.297***
Tweet Sentiment Pre-Release (log)	0.028	0.027	0.005	
Tweet Sentiment Post-Release (log)	0.002	0.008	−0.029	
Netflix Exclusive		−0.195*	−0.163	−0.168
Movie		−0.227**	−0.245**	−0.317***
Sequel		0.022	0.005	−0.078
Average IMDb Rating		0.000	0.000	0.000
Number of IMDb Votes		0.000	0.000	0.000
Action			-0.003	0.041
Adventure			0.030	-0.042
Comedy			0.224**	0.241**
Documentary			0.046	0.010
Drama			0.193*	0.159
Horror			−0.322*	−0.309*
Romance			0.121	0.135
Thriller			0.127	0.207
N	254	254	254	288
R2	0.226	0.256	0.293	0.345
R2 Adj.	0.214	0.229	0.243	0.309

Note: The dependent variable is log-transformed. The standard errors and full model results can be found in Appendix 10
*P<0.1, **P<0.05, ***P<0.01

4.3.2 Pre-and post-release Tweet Sentiment

Across all three models pre-release tweet sentiment has a positive effect on the time a production spends in the Netflix top ten. However, the effect is not significant across the three models. So, that means that hypothesis 4 is not supported. Interestingly, post-release sentiment has a positive effect on the dependent variable in the first two models, but this changes to a negative relation in model 3. However, just as pre-release sentiment, none of these effects are significant. So, hypothesis 5 is not supported. This is contrary to the existing literature, but can perhaps be explained due to the fact that social learning is not taken into account in this research project. Because both pre- and post-release sentiment are not significant it can't be determined which effect is greater. Therefore, hypothesis 6 is not supported.

4.3.3 Relation between other independent variables and the dependent variable

The variable Netflix exclusive does not have a significant effect on the dependent variable, which is remarkable as Netflix is spending more and more money on Netflix Exclusive content (Statista, 2022). The control variable Movie had a negative effect on the dependent variable, which is not surprising when looking at the distribution in Appendix 4a. The control variable sequel did not affect the dependent variable according to the model output. This is an interesting outcome as companies produce sequels as they are seen as less risky, reduce uncertainty and on average perform better compared to non-sequels (Ellashberg, Leenders, & Elberse, 2006; Dhar, Sun, & Weinberg, 2012). Other research found that sequels perform better during the first week or in general demand (Dhar, Sun, & Weinberg, 2012; Jang, Baek & Kim, 2021; Kim and Kim, 2020).

Remarkably, only one genre does have a significant effect on the time spent in the Netflix top ten and that is the Comedy genre which increases the duration in the top ten with 0.224 percent.

Table 4: Hypothesis and Results

Hypothesis	Expected effect	Effect correct	Significant	Conclusion
H1: Pre-release Tweet volume	Positive	No	Yes	Not Supported
H2: Post-release Tweet volume	Positive	Yes	Yes	Supported
H3: Effect Post-release Tweet volume larger than the effect of pre-release tweet volume	Post-release volume effect is larger than pre-release volume	Yes	Yes	Supported
H4: Pre-release Tweet sentiment	Positive	Yes	No	Not Supported
H5: Post-release Tweet sentiment	Positive	No	No	Not Supported
H6: Effect post-release tweet sentiment is larger than that of pre-release tweet sentiment	Post-release sentiment effect is larger than pre-release tweet sentiment	No	No	Not Supported

4.4 Exploratory Research

Increasing pre-release tweet volume reflects larger amounts of consumer buzz and awareness which can increase the demand in the opening week (Deer et al., 2019). For the Netflix release, this probably can be measured in the debut ranking of productions as there is no sales data available or number of views. This was tested in this section, using a similar linear regression as described in section 3.3 only with debut rank now as the dependent variable and only including the pre-release Twitter variables. Model 1 is a simple model with only the Twitter variables. In model 2 the control variables Netflix Exclusive, Movie, Sequel, IMDb votes and IMDb Rating were added. In model 3 the regression included the genre dummies. In model 4 the tweet sentiment variable was not included; this allows to measure the effect of pre-release tweet volume in a larger dataset and was added to control for selection bias. The dataset for model 1, model 2 and model 3 is smaller due to missing values for tweet sentiment as is explained in section 3.2.3

Table 5: Effects of pre-release Tweets on Debut Rank

Dependent variable: Debut Rank (log)	Model 1	Model 2	Model 3	Model 4
Tweet Volume Pre-release (log)	−0.135***	−0.124***	−0.122***	−0.122***−
Tweet Sentiment Pre-Release (log)	0.157	0.168	0.176	
Pre-release Tweet Volume * Pre-release Tweet Sentiment (log)	-0.023	-0.025*	-0.022	
Netflix Exclusive		−0.212**	−0.220**	−0.149
Movie		−0.186*	−0.161	−0.171*
Sequel		−0.064	−0.057	−0.023
Action			−0.085	−0.128
Adventure			−0.073	0.011
Comedy			−0.206*	−0.152
Documentary			−0.215	−0.246
Drama			−0.194*	−0.187*
Horror			0.062	0.042
Romance			−0.337**	−0.260*
Thriller			0-0.060	-0.106
N	254	254	254	288
R2	0.161	0.184	0.217	0.202
R2 Adj.	0.151	0.164	0.171	0.167

Note: The dependent variable is log-transformed. The standard errors and full model results can be found in Appendix 11.
*P<0.1, **P<0.05, ***P<0.01

As can be seen in Table 5 the effect of tweet volume pre-release has a significant negative effect on the debut rank in all four models. Indicating that one percent more tweet volume decreases the rank with 0.122 percent. It should be noted however that although the unstandardized beta-coefficient states a negative number here, a lower ranking position signals better performance. So, the debut ranking position of a video title becomes better when pre-release tweet volume increases. Again, pre-release tweet sentiment does not have a significant effect on the dependent variable. Also, for the interaction between pre-release tweet volume and pre-release there is no significant effect.

In contrast to the findings displayed in Table 4, the control variable Netflix Exclusive did have a significant effect in this model. Indicating that Netflix exclusives have a better debut ranking than titles that are not a Netflix Exclusive. The control variable Movie was not significant in this model, signaling that there is no difference between movies and TV-shows for debut ranking. For genres only the romance dummy variable was significant, meaning that productions in the romance genre have a better debut ranking compared to productions with other genres.

Chapter 5 – Discussion and Recommendations

The final chapter will consist of discussing the results found in chapter 4 forming an answer to the problem statement stated in chapter 1, the theoretical and managerial implications, limitations, and potential ideas for future research.

5.1 Discussion

The goal of this research was to gain more insights in what influences the Netflix top ten and if Twitter WoM influences which shows and movies appear in the Netflix top ten. To study how Twitter WoM influenced the Netflix top ten, six theoretical research questions and two empirical research questions were formulated.

The first empirical research question was: What is the effect of Twitter WoM volume on placement in the Netflix top ten pre-release and post-release? For pre-release it was hypothesized that because of the awareness effect and product 'buzz' established by the number of tweets (tweet volume) that the pre-release volume has a positive impact on how long a title stays in the Netflix top ten. However, the results in chapter four do not support this hypothesis. On top of that, the pre-release tweet volume had a significant negative effect on the time a show or movie spends in the Netflix daily top ten.

Moreover, the analysis in section 4.4 pointed out that higher pre-release tweet volume resulted in a better debut ranking. Meaning that a higher amount of pre-release tweet volume results in a higher debut ranking, but a shorter lifecyle in the Netflix top ten. The effect of pre-release tweet volume on debut ranking is in line with previous research. Previous research found that buzz and awareness are important drivers for initial sales (Divakran et al., 2017; Housten et al., 2018; Deer et al., 2019). Sim et al. (2022) mentioned that since the marginal costs in the streaming market are zero, meaning that there is almost no risk for the consumer, it can result in the consumer wanting to see for themselves what this 'buzz' is all about. These two effects can explain why pre-release tweet volume increased the debut ranking position of a video title.

The negative effect on total time spent in the Netflix daily top ten is difficult to explain, due to a lack of research as most research studies the effect of pre-release buzz on initial sales. The higher debut ranking indicated a higher number of views immediately after release. What could be the case is that, because of the higher pre-release tweet volume, more people decided to immediately binge-watch the production. This might translate to an increased view count in the first few days and a lower number of views after a couple days. Amazon data showed that social media buzz drops more drastically for shows that can be binge-watched in comparison to shows that air week to week (West, 2013). However, this is not empirically researched and therefore just speculation. Another reason that might explain the negative effect of pre-release tweet volume is that the production does not meet the expectations of consumers created by the tweets. For example, based on the pre-release tweets a consumer expected the production to be of a certain genre and contain a compelling storyline. If this is not the case after a couple episodes and the video title is not what they expected, the customer might be dissatisfied and stop watching. In other industries there is a positive relation between satisfaction and repurchase behavior (Pappas et al., 2013). It could be the case that the viewer was disappointed, because the production did not meet expectations set by the pre-release tweets. This might have created dissatisfaction and the number of consumers stopped watching. These two explanations might explain why pre-release tweet count had a negative effect on the lifecycle of a title in the Netflix top ten, however more research towards this subject is needed.

For post-release tweet volume, it was hypothesized that post-release tweet volume has a positive impact on how long a title stayed in the daily Netflix top ten, because tweet volume increases the awareness level in consumers and might trigger their curiosity. The empirical analysis showed a significant effect of post-tweet volume on the time a production spends in the Netflix top ten. This is in line with research findings in the movie industry from Deer et al. (2019) and means that increasing customer awareness post-release is important for sustained success.

The second empirical research question was: What is the effect of Twitter sentiment in tweets on placement in the Netflix top ten pre-release and post-release? It was hypothesized that pre-release tweet sentiment does impact the time a show or movie stays in the Netflix top ten positively. Previous research found that negative Twitter WoM influences purchase intentions (Hennig-Thurau, 2015). However, according to the analysis in this research, there was no significant relationship between pre-release tweet sentiment and duration in the Netflix top ten. The effect was also very small. Moreover, there was no significant relationship between the debut rank of a production in the top ten and pre-release sentiment. This finding is in line with research from the movie industry that also states that pre-release sentiment is likely to be neutral due to lack of information (Deer et al, 2019). Furthermore, there was no significant interaction effect between pre-release tweet sentiment and pre-release tweet volume.

Lastly, for post-release sentiment it was hypothesized that the sentiment does impact the time a show or movie remains in the Netflix top ten positively. According to previous research, post-release sentiment has a positive effect on the demand for movies (Deer et al., 2019). However, according to the research in this thesis post-release tweet sentiment did not affect the time duration of a production in the Netflix top ten. A possible explanation for this can be the low marginal costs for a consumer. In contrast to the movie industry where a customer has to buy a ticket, watching an additional show on a video streaming market does not add additional costs. This means that the risk is much lower in the SVOD market. Because of that, customers might be paying less attention to the opinions of others about the quality of a movie or TV show and just want to see for themselves why there is so much 'buzz' for a certain production. This outcome is in line with the findings of Shibab and Putri (2019). They concluded that sentiment is not affecting sales if the product is popular.

To conclude, an answer to the problem statement stated in section 1.2 can be formed based on these findings. Twitter WoM seems to have a significant effect on what is in the Netflix top ten as pre-release tweet-volume influences the debut ranking of productions and there is also a positive effect between the post-release tweet volume and how long a production stays in the Netflix top ten. However, more research is needed on this subject to completely understand the effects that Twitter has on the popularity of video titles in the SVOD industry.

5.2 Theoretical and Managerial Implications

The outcome of this study has several theoretical and managerial implications. First, this research adds understanding of the effect Twitter WoM volume has on the popularity of shows and productions that are available on SVOD platforms. Prior literature focused mainly on the effects of Twitter WoM on sales in the movie industry (Divakaran et al., 2017; Deer et al., 2019). This study showed that post-release tweet volume does also positively impact the time a production spends in the Netflix top ten. Interestingly, pre-release tweet volume impacted the amount of time a TV-show or movie spends in the Netflix top ten negatively and influenced the initial ranking positively. This was something that, prior to this research, was not investigated. Although the exact reasoning why pre-release tweet volume has this effect remains unclear, this might be an interesting topic for future research.

Secondly, this literature adds more understanding of the effect of tweet sentiment on SVOD platforms. This research found that similar to the movie industry pre-release sentiment does not affect the popularity of a movie or Tv-show, which is in line with the findings of Deer et al. (2019) in the movie industry. This indicates that the popularity of shows and movies on a SVOD platform is not affected by the sentiment, in contrast to other markets (Hennig-Thurau et al., 2015). Lastly, this literature expands the current literature by discovering that post-sentiment does not affect the popularity of a production in the video streaming market. This is contrary to the findings in the movie industry (Deer et al., 2019).

The findings of this research have some implementations for managers of streaming platforms and production houses that use online WoM to generate demand. The results suggest that if the managers want to increase the initial demand for the product and reach the highest possible debut ranking, they should focus on increasing the online WoM in the pre-release phase. However, managers should be cautious with this as more Twitter WoM in the pre-release phase can negatively impact the long-term success of a product. Secondly, for long-term success, marketing activities should focus on increasing post-release Twitter WoM as much as possible as this can prolong the time a video title spends in the popularity charts. This can be achieved through posting tweets with highlights, funny moments in the video title and by responding to fans.

5.3 Limitations and further Research.

The first limitation of this study is that it is focused on the United States. SVOD platforms are available in a lot of countries. There might be differences between regions and also the effects of Twitter WoM might differ across countries. Netflix is also investing more money in non-English production and is focusing more and more on global expansion (Goldbart, 2021; Richter, 2021). So, taking the top ten of multiple countries can be a great addition to get a better understanding of the effect of Twitter WoM on Netflix popularity. It should also be noted that Twitter WoM does not measure all the social media word of mouth. Future research might possibly want to use the data from other social media websites.

Another limitation of this research is that only tweets written in English were used for this project. About 32 percent of all tweets are written in English (Vicinitas, 2018). To get a better understanding of the effect Twitter WoM has on video streaming popularity, it might be worth it to include more languages.

A third limitation to this research is that it was focusing on the Netflix top ten in 2021. Because the Netflix top ten is out since March 2020, and we are now in June 2022 more observations are available. Adding more observations can improve this research and might provide more insight in the effects of Twitter WoM on video streaming platforms.

A fourth limitation is the possible selection bias because some observations were removed from the dataset because the sentiment score was incorrect. Models without the sentiment variables were used to showcase that with additional observations the effects of the other variables remained similar. Future research should try to prevent this from happening by using a more sophisticated method to classify the tweets.

Another limitation for this research is that social learning was not included for post-release tweet sentiment. Research looking into the effects of Twitter WoM on movie sales found that this is an important factor and has a significant effect on ticket sales (Deer et al., 2019). It might be interesting to discover the potential effect of social learning in Twitter WoM on the lifecycle of a show or movie in the Netflix top ten chart.

Further research might also want to look into discovering what causes the relation between tweet volume pre-release and the time a video title spends in the Netflix top ten.

References

Aguiar, L., & Waldfogel, J. (2018). Platforms, Promotion, and Product Discovery: Evidence from Spotify Playlists. *National Bureau of Economic Research*.

Banerjee, A. V. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics*, 797-817.

Barlow, W. E., & Prentice, R. L. (1988). Residuals for relative risk regression. *Biometrika*, 65-74.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 992-1026.

Bloomberg. (2019, January 18). *Financial Express*. Retrieved from Netflix needs to grow; why it has no choice: https://www.financialexpress.com/industry/technology/netflix-needs-to-grow-why-it-has-no-choice/1447311/

Breen, M. (2016, February 19). *Netflix Knows it Only Has About a Minute to Grab Your Attention*. Retrieved from NBCNews: https://www.nbcnews.com/business/business-news/netflix-knows-how-long-you-ll-search-they-lose-you-n521766

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometria*, 1287-1294.

BroadbandSearch. (2022). *The Most Visited Internet sites of 2022*. Retrieved from BroadbandSearch: https://www.broadbandsearch.net/blog/most-visited-popular-websites

Burch, S. (2021, April 5). *Netflix Lost 31% of Market Share in the Last Year as Streaming Rivals Gained Ground | Charts*. Retrieved from Yahoo: https://www.yahoo.com/entertainment/netflix-lost-31-market-share-130058085.html?guce_referrer=aHR0cHM6Ly93d3cuYmxvb21iZXJnLmNvbS9uZXdzL25ld3NsZXR0ZXJzLzIwMjEtMDQtMTgvbmV0ZmxpeC1pcy1sb3NpbmctbWFya2V0LXNoYXJlLWJ1dC1pcy1pdC1sb3NpbmctY3VzdG9tZXJz&guccounter=2

Business_Strategy_Hub. (2019, October 12). *Business Strategy Hub*. Retrieved from Netflix Business Model (2022) | How does Netflix make money: https://bstrategyhub.com/netflix-business-model-how-does-netflix-make-money/

Cai, H., Chen, Y., & Fang, H. (2009). Observational Learning: Evidence from a Randomized Natural Field Experiment. *The American Economic Review*, 864-882.

Campbell, M. C., & Keller, K. L. (2003). Brand Familiarity and Advertising Repetition Effects. *Journal of Consumer Research*, 292-304.

Carare, O. (2012). The Impact of Bestseller Rank on Demand: Evidence from the App Market. *International Economic Review*, 717-742.

Chakravarty, A., Liu, Y., & Mazumdar, T. (2010). The differential effects of online word-of-mouth and critics' reviews on pre-release movie evaluations. *Journal of Interactive Marketing*, 185-197.

Chen, Y., Wang, Q., & Xie, J. (2011). Online social interactions: a natural experiment on word of mouth versus observational learning. *Journal of Marketing Research*, 238-254.

Chu, S.-C., & Kim, Y. (2011). Determinants of consumer engagement in electronic word-of-mouth (ewom) in social networking sites. *International Journal of Advertising*, 47-75.

Cook, S. (2021, December 9). *50+ Netflix statistics & facts that define the company's dominance in 2022*. Retrieved from Comparitech: https://www.comparitech.com/blog/vpn-privacy/netflix-statistics-facts-figures/

Datta, H., Knox, G., & Bronnenberg, B. J. (2018). Changing their tune: How consumers' adoption of online streaming affects music consumption and discovery. *Marketing Science*, 5-21.

Davison, A. C., & Gigli. (1989). Deviance residuals and normal scores plots. *Biometrika*, 211-221.

Deer, L., Chintagunta, P. K., & Crawford, G. (2019). Online Word of Mouth and the Performance of New Products.

Dekimpe, M. G., Steenkamp, J.-B. E., Mellens, M., & Abeele, P. V. (1997). Decline and variability in brand loyalty. *International Journal of Research in Marketing*, 405-420.

Dhar, T., Sun, G., & Weinberg, C. B. (2012). The long-term box office performance of sequals. *Marketing Letters*, 13-29.

Divakaran, P. K., Plamer, A., Søndergaard, H. A., & Matkovskyy, R. (2017). Pre-launch Prediction of Market Performance for Short Lifecycle Products Using Online Community Data. *Journal of Interactive Marketing*, 12-28.

Dowling, G. R., & Staelin, R. (1994). A Model of Perceived Risk and Intended Risk-Handling Activity. *Journal of Consumer Research*, 119-134.

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter? An emperical investigation of panel data. *Decision Support Systems* , 1007-1016.

Eliashberg, J., & Shugan, S. M. (1997). Film Critics: Influencers or Predictors? *Journal of Marketing*, 68-78.

Eliashberg, J., Elberse, A., & Leenders, M. A. (2006). he motion picture industry: critical issues in practice, current research, and new research directions. *Marketing Science*, 638-661.

Fisher, S. (2021, February 5). *What is IMDb?* Retrieved from Lifewire: https://www.lifewire.com/internet-movie-database-3482288

Fortune Business Insights. (2021, December 15). *Video Streaming Market Share to Touch USD 932.29 Billion by 2028; Video Streaming Market Size 2021 to 2028.* Retrieved from Fortune Business Insights: https://www.globenewswire.com/news-release/2021/12/15/2352238/0/en/Video-Streaming-Market-Share-to-Touch-USD-932-29-Billion-by-2028-Video-Streaming-Market-Size-2021-to-2028.html

Franke, G. R. (2010). Multicollinearity. *Marketing Research*.

Gandour, R. (2016, September 19). *Study: Decline of traditional media feeds polarization*. Retrieved from Columbia Journalism Review: https://www.cjr.org/analysis/media_polarization_journalism.php

Gelper, S. E., Peres, R., & Eliashberg, J. (2018). Talk bursts: The role of spikes in prerelease word-of-mouth dynamics. *Journal of Marketing Research*, 801-817.

Gilbert, E., & Hutto, C. (2014). VADER: A Parsimonious Rule-baded Model for Sentiment Analysis of Social Media Text. *Eighth International AAAI Conference on Weblogs and Social Media*.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word of mouth communication. *Marketing Science*, 545-560.

Goldbart, M. (2021, December 21). *The 'Squid Game' and 'Lupin' Effect: 50% Of European Netflix And Amazon Viewing Could Be To Non-English Language Shows By 2030*. Retrieved from Deadline.com: https://deadline.com/2021/12/digital-i-report-netflix-amazon-non-english-language-viewing-1234900060/

Goldsmith, R. E., & Horowitz, D. (2006). Measuring Motivations for Online Opinion Seeking. *Journal of Interactive Advertising*, 2-14.

Gomez-Uribe, C. A., & Hunt, N. (2015). The Netflix Recommender System Algorithms, Business Value, and Innovation. *ACM Transactions on Management Information Systems*, 1-19.

Gopinath, S., Chintagunta, P. K., & Venkataraman, S. (2013). Blogs, Advertising, and Local Market Box Office Performance. *Management Science*, 2635-2654.

Hair, J. F., Black, W. C., Black, B., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis. In J. F. Hair, W. C. Black, B. Black, B. J. Babin, & R. E. Anderson, *Multivariate Data Analysis: Global Edition, 7th Edition.* New York City: Pearson.

Hennig-Thurau, T., & Wiertz, C. (2015). Does Twitter matter? The impact of microblogging word of mouth on consumers' adoption of new movies. *Journal of Academic Marketing Science*, 375-394.

Heo, S., & Park, J. (2021). Are you satisfied or satiated by the games you play? An empirical study about game play and purchase patterns by genres. *Telematrics and Informatics* .

Ho, Y.-C. (., Wu, J., & Tan, Y. (2017). Disconfirmation Effect on Online Rating Behavior: A Structural Model. *Information System Research*, 626-642.

Holleran, T. (2021, April 13). *Streaming Subscriptions in US Overtake Number of People*. Retrieved from Ampere Analysis: https://www.ampereanalysis.com/insight/streaming-subscriptions-in-us-overtake-number-of-people

Insights, F. B. (2021). *Video Streaming Market Size, Share & Covid-19 impacht Analysis.* Retrieved from Fortune Business Insights: https://www.fortunebusinessinsights.com/video-streaming-market-103057

Iqbal, M. (2022, January 11). *Twitter Revenue and Usage Statistics*. Retrieved from BusinessofApps: https://www.businessofapps.com/data/twitter-statistics/

Jang, M., Baek, H., & Kim, S. (2021). Movie Characteristics as determinants of download-to-own performance in the Korean video-on-demand market. *Telecommunications Policy*.

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology*, 2169-2188.

Jarvey, N. (2014, July 24). *Twitter Survey Explains Why Movie Tweets Matter*. Retrieved from The Hollywood Reporter: https://www.hollywoodreporter.com/news/general-news/twitter-survey-explains-why-movie-720831/

Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica*, 263-291.

Kalra, A., & Mathur, S. (2000). When Should Firms Reveal their Bestsellers? *Academia*.

Kanouse, D. E. (1984). Explaining negativity biases in evaluation and choice behavior: theory and research. *The association for Consumer Research*, 703-708.

Keck, C. (2022, January 20). *Netflix stock plunges as company misses growth forecast*. Retrieved from The Verge: https://www.theverge.com/2022/1/20/22893950/netflix-stock-falls-q4-2021-earnings-2022

Kim, D. H., & Kim, S. (2018). A comparative study: Performance of Hollywood and Korean sequel films in Korea. *Journal of Media Economics*, 39-46.

Kim, H., & Hanssens, D. M. (2017). Advertising and Word-of-Mouth Effects on Pre-launch Consumer Interest and Initial Sales of Experience Products. *Journal of Interactive Marketing*, 57-74.

Kirmani, A., & Rao, A. R. (2000). No pain, no gain: a critical review of the literature on signaling unobservable product quality. *Journal of Marketing*, 66-79.

Koh, Y. (2014, April 11). *Report: 44% of Twitter Accounts Have Never Sent a Tweet*. Retrieved from The Wall Street Journal: https://www.wsj.com/articles/BL-DGB-34255

Lamare, A. (2018, July 31). *How streaming started: YouTube, Netflix, and Hulu's quick ascent*. Retrieved from The Business of Business: https://www.businessofbusiness.com/articles/a-brief-history-of-video-streaming-by-the-numbers/

Lee, J. H., Jung, S. H., & Park, J. (2017). The role of entropy of review text sentiments on online WOM and movie. *Electronic Commerce Research and Applications*, 42-52.

Lee, K., Park, J., Kim, I., & Choi, Y. (2018). Predicting movie success with machine learning techniques: ways to improve accuracy. *Information Systems Frontiers*, 577-588.

Lee, Y.-J., Hosanagar, K., & Tan, Y. (2015). Do I follow my friends or the crowd? Information cascades in online movie ratings. *Management Science*, 2241-2258.

Li, Q., Zeng, D. D., Xu, D. J., Liu, R., & Yao, R. (2020). Understanding and Predicting Users' Rating Behavior: A Cognitive Perspective. *INFORMS Journal on Computing*, 996-1011.

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*, 74-89.

Luo, X., & Homburg, C. (2007). Neglected outcomes of customer satis- faction. *Journal of Marketing*.

Macmillan, G. (2015, September 29). *People on Twitter love television, often have two screens going as they watch, and are influencers on all things TV-related*. Retrieved from Marketing Twitter: https://marketing.twitter.com/en/insights/8-reasons-why-twitter-is-the-home-of-tv-conversation

Mishra, M. K., Kesharwani, A., & Das, D. (2016). The relationship between risk aversion, brand trust, brand effect and loyalty: Evidence from the FMCG industry. *Journal of Indian Business Research*, 78-97.

Moody, R. (2022, January 20). *Comparitech*. Retrieved from Which countries pay the most and least for Netflix?: https://www.comparitech.com/blog/vpn-privacy/countries-netflix-cost/

Moore, K. (2021, February 9). *What Movie & TV Genres Perform Well in the Netflix Top 10s?* Retrieved from What's on Netflix: https://www.whats-on-netflix.com/news/what-movie-tv-genres-perform-well-in-the-netflix-top-10s/

Nguyen, L. T., Wu, P., Chan, W., Peng, W., & Zhang, Y. (2012). Predicting Collective Sentiment Dynamics from Time-series Social Media. *Wisdom '12: Proceedings of the First international Workshop on Issues of Sentiment Discovery and Opinion Mining*.

Pedace, R. (2016, March 26). *Econometrics and the Log-Log Model*. Retrieved from Dummies.com: https://www.dummies.com/article/business-careers-money/business/economics/econometrics-and-the-log-log-model-156386/

Reinstein, D. A., & Snyder, C. M. (2005). The Influence of Expert Reviews on Consumer Demand for Experience goods: A case study of Movie Critics. *The Journal of Industrial Economics*, 27-51.

Reinstein, D. A., & Snyder, C. M. (2005). The Influence of Expert Reviews on Consumer Demand for Experience goods: A case study of Movie Critics. *Journal of Industrial Economics*, 27-51.

Richter, F. (2021, January 21). *Global Expanion Fuels Netflix's Growth*. Retrieved from Statista: https://www.statista.com/chart/20345/netflix-subscriber-growth-by-region/

Robehmed, N. (2015, April 27). *For Movies, Twitter Users Are A Key Audience*. Retrieved from Forbes: https://www.forbes.com/sites/natalierobehmed/2015/04/27/for-movies-twitter-users-are-a-key-audience/?sh=14d7dd305300

Rosen, A. (2017, November 7). *Tweeting made Easier*. Retrieved from Twitter: https://blog.twitter.com/official/en_us/topics/product/2017/tweetingmadeeasier.html

Rosentiel, T., Sonderman, J., Loker, K., Ivancin, M., & Kjarval, N. (2015, september 1). *How people use Twitter in General*. Retrieved from AmericanPress: https://www.americanpressinstitute.org/publications/reports/survey-research/how-people-use-twitter-in-general/

Rui, H., Liu, Y., & Whinston, A. (2013). Whose and what chatter matters? The effect of tweets on movie sales. *Decision Support Systems*, 863-870.

Schneider, C., Weinmann, M., Mohr, P. N., & Brocke, J. v. (2021). When the stars shine too bright: The influence of multidimensional ratings on online consumer ratings. . *Management Science*, 3871-3898.

Schoenfeld, D. (1982). Partial Residuals for The Proportional Hazards Regression Model. *Biometrika*, 239-241.

Seetharaman, P. B., & Chintagunta, P. K. (2003). The proportional hazard model for purchase timing: A comparison of alternative specifications. *Journal of Business & Economic Statistics*, 368-382.

Sharda, R., & Delen, D. (2006). Predicting box-office success of motion pictures with neural networks. *Expert Systems with Application*, 243-254.

Shaw, L. (2021, April 19). *Netflix is Losing Market Share. But is it Losing Customers*. Retrieved from Bloomberg: https://www.bloomberg.com/news/newsletters/2021-04-18/netflix-is-losing-market-share-but-is-it-losing-customers

Shi, M., Chiang, J., & Rhee, B.-D. (2006). Price Competition with Reduced Consumer Switching Costs: The Case of "Wireless Number Portability" in the Cellular Phone Industry. *Management Science*, 27-38.

Shibab, M. R., & Putri, A. P. (2019). Negative online reviews of popular products: understanding the effects of review proportion and quality on consumers’ attitude and intention to buy. *Electronic Commerce Research*, 159-187.

Si, J., Mukherjee, A., Liu, B., & Li, Q. (2013). Exploiting topic based twitter sentiment for stock prediction. *Conference paper* , 24-29.

Siegler, M. (2011, June 1). *At 1.6 Billion Queries per Day, Twitter finally aims to make search personally relevant*. Retrieved from Techcrunch: https://techcrunch.com/2011/06/01/new-twitter-search-relevant/?guccounter=1&guce_referrer=aHR0cHM6Ly93d3cuZ29vZ2xlLmNvbS8&guce_referrer_sig=AQAAAFo1hVbzUZLqq0-CxYv_5QgrlHBMQF5xcWoH26YDT_yVbngnN4rqt4uw_HfZ7aIe6de0ZwbMbOwpp7TrwqN98tLW8Wdq2Mj907jN6kN2nDP45xV

Sim, J., Park, J. G., Cho, D., Smith, M. D., & Jung, J. (2022). Bestseller lists and product discovery in the subscription-based market: Evidence from music streaming. *Journal of Economic Behavior and Organization*, 550-567.

Singh, A. (2009, August 24). *The Telegraph*. Retrieved from Inglourious Basterds a box office hit 'thanks to the Twitter effect'.: https://www.telegraph.co.uk/news/celebritynews/6081711/Inglourious-Basterds-a-box-office-hit-thanks-to-the-Twitter-effect.html

Smith, A. N., Fischer, E., & Yongjian, C. (2012). How Does Brand-related User-generated Content Differ across YouTube, Facebook, and Twiter? *Journal of Interactive Marketing*, 102-113.

Sood, S., & Drèze, X. (2006). Brand Extensions of Experiential Goods: Movie Sequel Evaluations. *Journal of Consumer Research*, 352-360.

Sorensen, A. T. (2007). Bestseller Lists and Product Variety. *The Journal of Industrial Economics*, 715-738.

Sorensen, A. T. (2017). Bestseller Lists and the Economics of Product Discovery. *Annual Review of Economics*, 87-101.

Soulo, T. (n.d.). *What do people tweet about & the Suprising Truth about what drives them*. Retrieved from Bloggerjet: https://bloggerjet.com/what-do-people-tweet-about/

Statista. (2022, May 21). Retrieved from Statista: https://www.statista.com/statistics/964789/netflix-content-spend-worldwide/

Statista. (2022, January). *Netflix's marketing expenses worldwide from 2017 to 2021*. Retrieved from Statista: https://www.statista.com/statistics/1097045/netflix-marketing-expenditure/

Sun, T., Youn, S., Wu, G., & Kuntaraporn, M. (2006). Online word-of-mouth (or mouse): An exploration of its antecedents and consequences. *Journal of Computer-Mediated Communication*, 1104-1127.

Suslak, M. (2014, November 7). *If it's happening at the movies, it's happening on Twitter*. Retrieved from Twitter: https://blog.twitter.com/en_us/a/2014/if-it-s-happening-at-the-movies-its-happening-on-twitter

Tassi, P. (2020, February 25). *Netflix's Top 10: What Is It, And Why Has It Shown Up Now?* Retrieved from Forbes: https://www.forbes.com/sites/paultassi/2020/02/25/netflixs-top-10-what-is-it-and-why-has-it-shown-up-now/?sh=1529c0fd3e61

the Numbers. (2022, May 19). Retrieved from The Numbers: https://www.the-numbers.com/market/genres

Toubia, O., & Stephen, A. T. (2013). Intrinsic vs. Image-Related Utility in Social Media: Why Do People Contribute Content to Twitter? *Marketing Science*, 368-392.

Tucker, C., & Zhang, J. (2011). How Does Popularity Information Affect Choices? A Field Experiment. *Management Science*, 828-842.

Twitter. (2017, January 26). *Twitter TV fans are tuning in live to their favorite shows. Tips for engaging them.* Retrieved from Twitter Marketing: https://marketing.twitter.com/en/insights/new-research-twitter-tv-fans-tune-in-live-to-their-favorite-shows

Uhlig, D. (2021, October 29). *How much is twitter worth?* Retrieved from GoBankingRates: https://www.gobankingrates.com/money/business/how-much-is-twitter-worth/

Vicinitas. (2018, March 12). *2018 Reserach on 100 Million Tweets: What it Means for Your Social Media Strategy for Twitter*. Retrieved from vicinitas.com: https://www.vicinitas.io/blog/twitter-social-media-strategy-2018-research-100-million-tweets

Weisberg, S. (2013). Applied linear regression. In S. Weisberg, *Applied Linear Regression.* New Jersey: Hoboken.

West, K. (2013, December 13). *Unsurprising: Netflix Survey Indicates People Like To Binge-Watch T*. Retrieved from Cinemablend: https://www.cinemablend.com/television/Unsurprising-Netflix-Survey-Indicates-People-Like-Binge-Watch-TV-61045.html

Wiegand, W. A. (2003). Making the List: A Cultural History of the American Bestseller, 1900-1999. *The Library Quarterly: Information, Community, Policy*, 218-220.

Wong, F. M., Sen, S., & Chiang, M. (2012). Why watching movie tweets won't tell the whole story. *Proceedings of the 2012 ACM workshop on Workshop on online social networks*.

Yoo, W., Mayberry, R., Bae, S., Singh, K., He, Q. (., & Lillard, J. W. (2014). A Study of Effects of MultiCollinearity in the Multivariable Analysis. *International Journal of Applied Science Technology*, 9-19.

Appendix

Appendix 1: Github link

The code for the Webscraper and the Twitter retrieval can be found via the following link:

https://github.com/QuintendePutter/MasterThesis

Appendix 2a: Raw data from the-numbers.com

The raw data from the-numbers.com can be found via the following link:

https://drive.google.com/drive/folders/1Hhi7D7SeXKgtI5QA0RVNGDJXPBmNEwh1

Appendix 2b: Raw Twitter Data

The raw data from twitter data retrieval can be found via the following link:

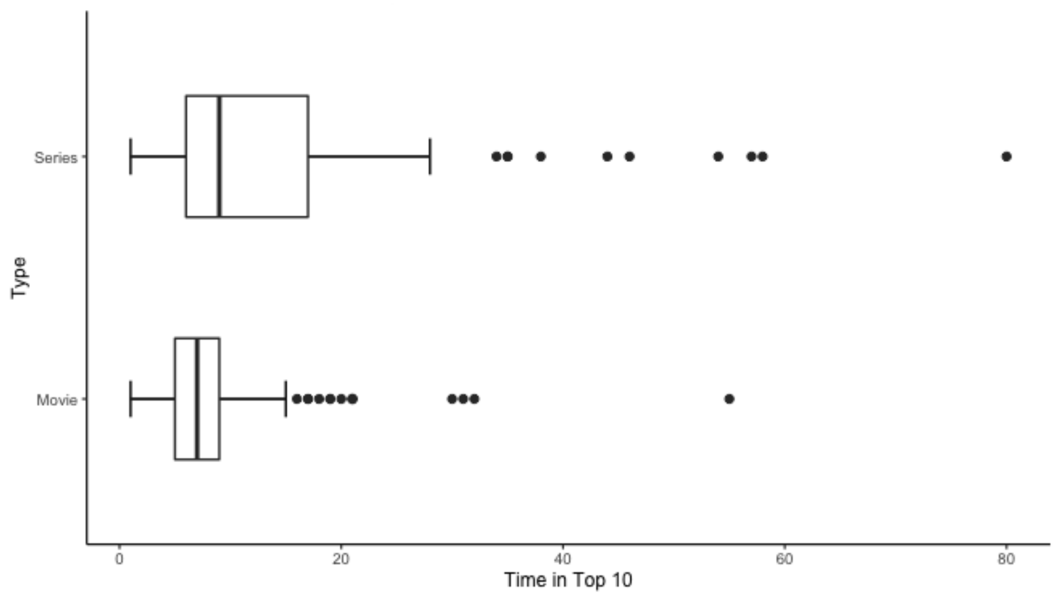
https://drive.google.com/drive/folders/1WN_0CDsM6ANf2pmovtcUmD22fJmZgEsy

Appendix 3: Complete Dataset

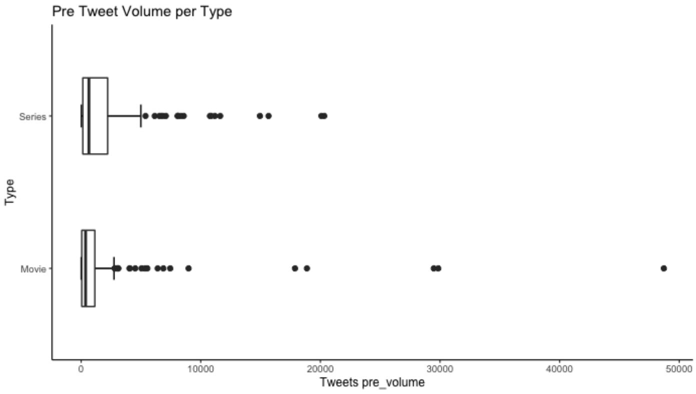
The complete cleaned dataset can be found via the following link:

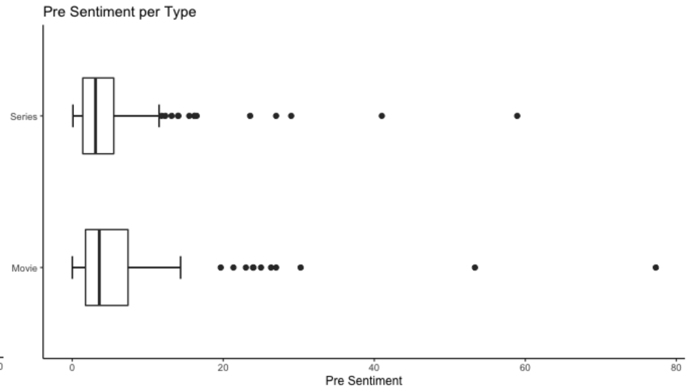
https://drive.google.com/drive/folders/1rjRFoOjQxlrXxnL6RebnIRpjGGBUQZLq

Appendix 4a: Distribution of Time spend in the daily Netflix top ten

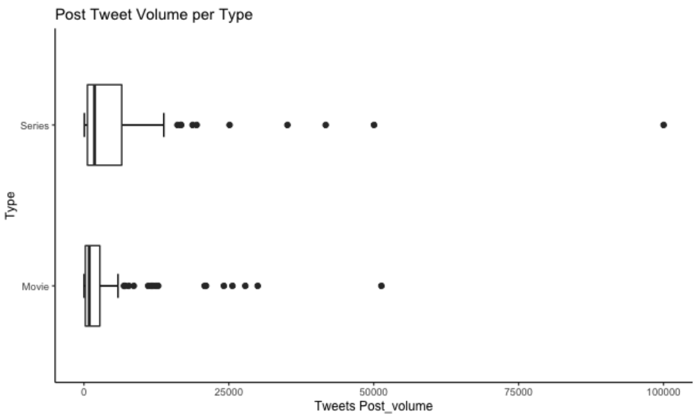


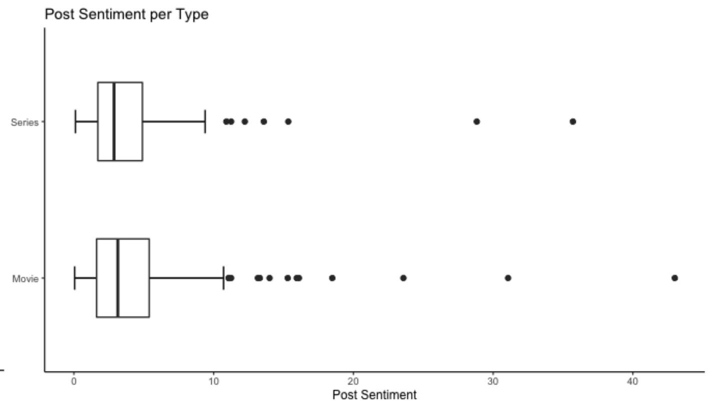
Appendix 4b: Distribution Pre-release Twitter Variables



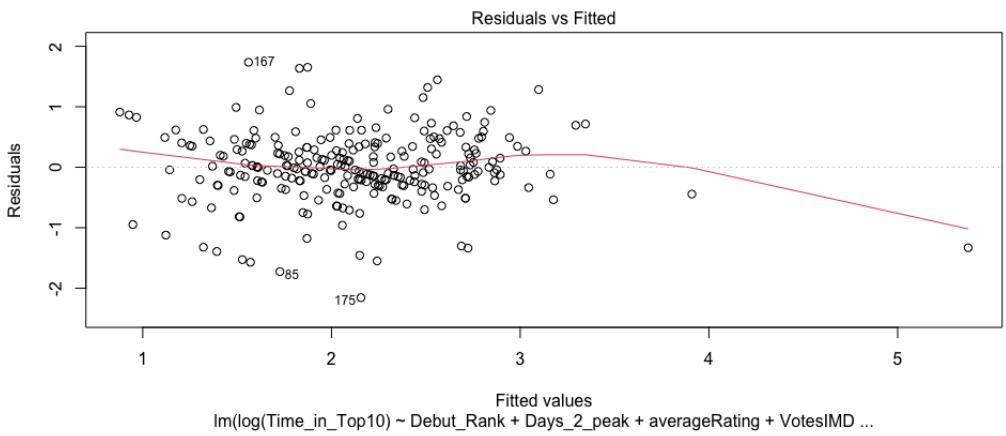


Appendix 4c: Distribution Post-release Twitter Variables

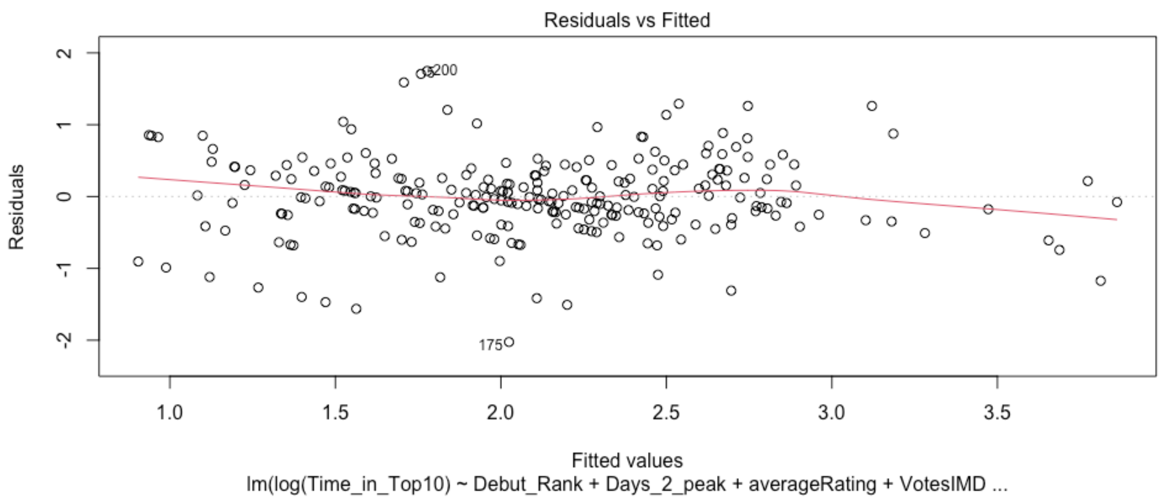




Appendix 5a: Linearity Test (with outlier)



Appendix 5b: Linearity Test (Outlier Removed)



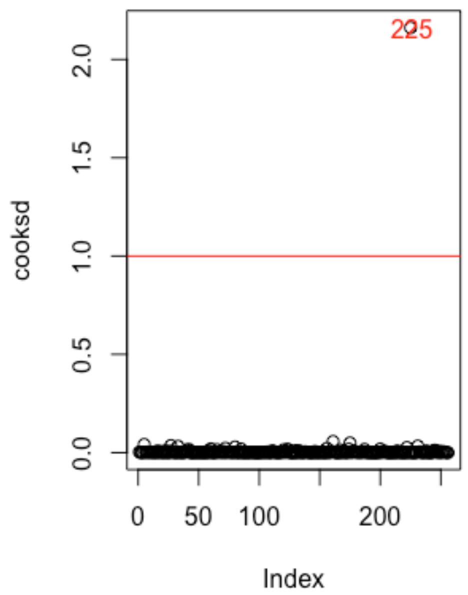
Appendix 6: Breusch-Pagan test

Breusch-Pagan test

studentized Breusch-Pagan test

data: loglogmodel
BP = 15, df = 8, p-value = 0.2

Appendix 7: Cook's Distance test



Appendix 8: VIF scores and Tolerance

Variables	Tolerance	VIF
Debut_rank	0.68	1.5
Days_2_peak	0.85	1.2
AverageRating	0.85	1.2
VotesIMDb	0.91	1.1
log(Prevol_tweets)	0.27	3.8
log(Pre_sentiment)	0.59	1.7
log(Postvol_tweets)	0.25	3.9
log(Post_Sentiment)	0.59	1.7

Appendix 9: Correlation Matrix

	Time in top ten	Debut Rank	Days_2_ peak	average Rating	Votes IMDB	Prevol	Pre Sentiment	PostVol	Post sentiment
Time in top ten	1								
Debut Rank	-0.37	1							
Days_2_peak	0.24	0.29	1						
averageRating	0.125	0.09	-0.07	1					
VotesIMDB	-0.03	0.13	0.04	0.25	1				
Prevol	0.10	-0.23	-0.05	0.13	0.09	1			
Pre Sentiment	0.11	0.04	-0.01	0.07	-0.08	-0.08	1		
PostVol	0.38	-0.18	0.06	0.18	0.04	0.62	0.03	1	
Post sentiment	-0.02	0.04	0	0.06	-0.04	-0.08	0.31	-0.06	1

Table 3: Correlation Matrix

Appendix 10a: Linear Regression Results (model 1)

```
lm(formula = log(Time_in_Top10) ~ log(Prevol_tweets) + log(Pre_release_sentiment) +
    log(Postvol_tweets) + log(Post_sentiment), data = Regression_data)

Residuals:
    Min      1Q  Median      3Q     Max
-2.5268 -0.3596  0.0199  0.4447  1.9375

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.54289    0.19631    2.77  0.0061 **
```

```
log(Prevol_tweets)        -0.13119    0.04077   -3.22   0.0015 **
log(Pre_release_sentiment)  0.02792    0.04311    0.65   0.5179
log(Postvol_tweets)         0.32668    0.04715    6.93  3.6e-11 ***
log(Post_sentiment)         0.00224    0.05636    0.04   0.9683
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7 on 249 degrees of freedom
Multiple R-squared:  0.226,    Adjusted R-squared:  0.214
F-statistic: 18.2 on 4 and 249 DF,  p-value: 3.95e-13
```

Appendix 10b: Linear Regression Results (model 2)

```
Call:
lm(formula = log(Time_in_Top10) ~ NetflixExcl + Movie + Sequel +
   averageRating + VotesIMDb + log(Prevol_tweets) + log(Pre_release_sentiment) +
   log(Postvol_tweets) + log(Post_sentiment), data = Regression_data)

Residuals:
   Min      1Q  Median      3Q     Max
-2.8091 -0.3183  0.0312  0.4210  2.1100

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                 7.70e-01   2.73e-01    2.82   0.0052 **
NetflixExcl                -1.95e-01   1.16e-01   -1.68   0.0946 .
Movie                      -2.27e-01   9.71e-02   -2.34   0.0203 *
Sequel                      2.21e-02   1.10e-01    0.20   0.8405
averageRating              -1.32e-04   2.76e-03   -0.05   0.9618
VotesIMDb                   5.59e-08   2.25e-07    0.25   0.8036
log(Prevol_tweets)         -1.32e-01   4.25e-02   -3.11   0.0021 **
log(Pre_release_sentiment)  2.71e-02   4.29e-02    0.63   0.5281
log(Postvol_tweets)         3.31e-01   4.98e-02    6.64    2e-10 ***
log(Post_sentiment)         7.82e-03   5.61e-02    0.14   0.8891
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.69 on 244 degrees of freedom
Multiple R-squared:  0.256,    Adjusted R-squared:  0.229
F-statistic: 9.35 on 9 and 244 DF,  p-value: 3.39e-12
```

Appendix 10c: Linear Regression Results (model 3)

```
lm(formula = log(Time_in_Top10) ~ NetflixExcl + Movie + Sequel +
   averageRating + VotesIMDb + Action + Adventure + Comedy +
   Documentary + Drama + Horror + Romance + Thriller + log(Prevol_tweets) +
   log(Pre_release_sentiment) + log(Postvol_tweets) + log(Post_sentiment),
   data = Regression_data)

Residuals:
   Min      1Q  Median      3Q     Max
-2.5827 -0.3359  0.0456  0.3840  2.0736

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         7.32e-01   3.00e-01    2.44    0.015 *
NetflixExcl        -1.63e-01   1.19e-01   -1.37    0.172
Movie              -2.45e-01   1.04e-01   -2.36    0.019 *
Sequel              4.58e-03   1.13e-01    0.04    0.968
averageRating      -4.55e-06   2.76e-03    0.00    0.999
VotesIMDb           4.53e-08   2.27e-07    0.20    0.842
Action             -2.95e-03   1.12e-01   -0.03    0.979
Adventure           2.96e-02   1.27e-01    0.23    0.816
```

```
Comedy                    2.24e-01   1.14e-01    1.97    0.050 *
Documentary               4.59e-02   1.91e-01    0.24    0.810
Drama                     1.93e-01   1.07e-01    1.80    0.073 .
Horror                   -3.22e-01   1.78e-01   -1.82    0.071 .
Romance                   1.21e-01   1.64e-01    0.74    0.463
Thriller                  1.27e-01   1.52e-01    0.83    0.405
log(Prevol_tweets)       -1.11e-01   4.28e-02   -2.59    0.010 *
log(Pre_release_sentiment) 5.49e-03  4.39e-02    0.13    0.901
log(Postvol_tweets)       3.00e-01   5.11e-02    5.87  1.5e-08 ***
log(Post_sentiment)      -2.89e-02   5.85e-02   -0.49    0.621
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.69 on 236 degrees of freedom
Multiple R-squared:  0.293,    Adjusted R-squared:  0.243
F-statistic: 5.77 on 17 and 236 DF,  p-value: 6.04e-11
```

Appendix 10d: Linear Regression Results (model 4)

```
lm(formula = log(Time_in_Top10) ~ NetflixExcl + Movie + Sequel +
   averageRating + VotesIMDb + Action + Adventure + Comedy +
   Documentary + Drama + Horror + Romance + Thriller + log(Prevol_tweets) +
   log(Postvol_tweets), data = Total_data2)

Residuals:
   Min     1Q  Median     3Q    Max
-2.5895 -0.3585  0.0573  0.4011  2.1165

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)          7.71e-01   2.47e-01    3.12   0.0020 **
NetflixExcl         -1.68e-01   1.09e-01   -1.54   0.1249
Movie               -3.17e-01   9.75e-02   -3.25   0.0013 **
Sequel              -7.81e-02   1.05e-01   -0.74   0.4569
averageRating        4.74e-04   2.48e-03    0.19   0.8484
VotesIMDb            1.09e-07   2.22e-07    0.49   0.6219
Action               4.10e-02   1.04e-01    0.39   0.6946
Adventure           -4.17e-02   1.15e-01   -0.36   0.7176
Comedy               2.44e-01   1.04e-01    2.35   0.0197 *
Documentary          1.00e-02   1.75e-01    0.06   0.9544
Drama                1.59e-01   9.92e-02    1.60   0.1110
Horror              -3.09e-01   1.60e-01   -1.93   0.0544 .
Romance              1.35e-01   1.45e-01    0.93   0.3534
Thriller             2.07e-01   1.40e-01    1.48   0.1403
log(Prevol_tweets)  -1.10e-01   3.51e-02   -3.12   0.0020 **
log(Postvol_tweets)  2.97e-01   3.98e-02    7.46  1.2e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.68 on 272 degrees of freedom
Multiple R-squared:  0.345,    Adjusted R-squared:  0.309
F-statistic: 9.56 on 15 and 272 DF,  p-value: <2e-16
```

Appendix 11a: Explorative Results (model 1)

```
lm(formula = log(Debut_Rank) ~ log(Prevol_tweets) * log(Pre_release_sentiment),
    data = Regression_data)

Residuals:
   Min     1Q Median     3Q    Max
-1.828 -0.409  0.166  0.518  1.476

Coefficients:
                                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                                     2.2636     0.1610   14.06  < 2e-16 ***
log(Prevol_tweets)                             -0.1349     0.0239   -5.65  4.4e-08 ***
log(Pre_release_sentiment)                      0.1554     0.1023    1.52     0.13
log(Prevol_tweets):log(Pre_release_sentiment)  -0.0230     0.0143   -1.60     0.11
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.71 on 250 degrees of freedom
Multiple R-squared:  0.161,	Adjusted R-squared:  0.151
F-statistic:   16 on 3 and 250 DF,  p-value: 1.43e-09
```

Appendix 11b: Explorative Results (model 2)

```
lm(formula = log(Debut_Rank) ~ log(Prevol_tweets) * log(Pre_release_sentiment) +
    NetflixExcl + Movie + Sequel, data = Regression_data)

Residuals:
   Min     1Q Median     3Q    Max
-1.718 -0.386  0.149  0.502  1.399

Coefficients:
                                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                                     2.4658     0.1788   13.79  < 2e-16 ***
log(Prevol_tweets)                             -0.1245     0.0256   -4.86  2.1e-06 ***
log(Pre_release_sentiment)                      0.1676     0.1022    1.64    0.102
NetflixExcl                                    -0.2120     0.1066   -1.99    0.048 *
Movie                                          -0.1859     0.0949   -1.96    0.051 .
Sequel                                         -0.0636     0.1096   -0.58    0.562
log(Prevol_tweets):log(Pre_release_sentiment)  -0.0248     0.0144   -1.73    0.085 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7 on 247 degrees of freedom
Multiple R-squared:  0.184,	Adjusted R-squared:  0.164
F-statistic: 9.28 on 6 and 247 DF,  p-value: 3.52e-09
```

Appendix 11c: Explorative Results (model 3)

```
lm(formula = log(Debut_Rank) ~ log(Prevol_tweets) * log(Pre_release_sentiment) +
    NetflixExcl + Movie + Sequel + Action + Adventure + Comedy +
    Documentary + Drama + Horror + Romance + Thriller, data = Regression_data)

Residuals:
   Min     1Q Median     3Q    Max
-1.872 -0.390  0.145  0.499  1.238

Coefficients:
                                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                                     2.6710     0.2195   12.17  < 2e-16 ***
log(Prevol_tweets)                             -0.1220     0.0267   -4.57  7.7e-06 ***
log(Pre_release_sentiment)                      0.1761     0.1093    1.61    0.108
NetflixExcl                                    -0.2199     0.1098   -2.00    0.046 *
Movie                                          -0.1605     0.1012   -1.59    0.114
Sequel                                         -0.0568     0.1120   -0.51    0.613
Action                                         -0.0846     0.1143   -0.74    0.460
```

```
Adventure                          -0.0733     0.1291   -0.57    0.571
Comedy                             -0.2060     0.1150   -1.79    0.074 .
Documentary                          -0.2147     0.1943   -1.11    0.270
Drama                              -0.1941     0.1072   -1.81    0.072 .
Horror                             0.0615     0.1787    0.34    0.731
Romance                             -0.3366     0.1664   -2.02    0.044 *
Thriller                          -0.0598     0.1583   -0.38    0.706
log(Prevol_tweets):log(Pre_release_sentiment)  -0.0222     0.0150   -1.48    0.141
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7 on 239 degrees of freedom
Multiple R-squared:  0.217,    Adjusted R-squared:  0.171
F-statistic: 4.73 on 14 and 239 DF,  p-value: 1.24e-07
```

Appendix 11D: Explorative Results (model 4)

```
lm(formula = log(Debut_Rank) ~ log(Prevol_tweets) + NetflixExcl +
   Movie + Sequel + Action + Adventure + Comedy + Documentary +
   Drama + Horror + Romance + Thriller, data = Total_data)

Residuals:
  Min     1Q Median     3Q    Max
-1.792 -0.375  0.148  0.516  1.145

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)         2.6314     0.1626   16.18  < 2e-16 ***
log(Prevol_tweets)  -0.1221     0.0205   -5.95  8.2e-09 ***
NetflixExcl        -0.1489     0.1009   -1.48    0.141
Movie             -0.1714     0.0937   -1.83    0.068 .
Sequel            -0.0231     0.1019   -0.23    0.821
Action            -0.1283     0.1038   -1.24    0.217
Adventure           0.0110     0.1151    0.10    0.924
Comedy             -0.1518     0.1038   -1.46    0.145
Documentary        -0.2461     0.1748   -1.41    0.160
Drama             -0.1872     0.0978   -1.91    0.057 .
Horror             0.0418     0.1599    0.26    0.794
Romance            -0.2603     0.1440   -1.81    0.072 .
Thriller          -0.1057     0.1399   -0.76    0.451
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.68 on 275 degrees of freedom
Multiple R-squared:  0.202,    Adjusted R-squared:  0.167
F-statistic: 5.81 on 12 and 275 DF,  p-value: 5.83e-09
```