The Impact of Movie and TV Show Quality on Streaming Service Subscriber Growth

Jack Neely
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Prof. Gary Smith

Abstract:

The purpose of this study is to create a regression function in order to investigate the impact that the quality of a streaming service's movie and TV series catalog has on their subscriber count. Specifically, this study hopes to answer the question, "Do quality movies and shows impact subscriber growth for streaming services?". The variables within the regression are release year, rotten tomatoes score, IMDb score, month collected, a dummy variable for if it is a movie or a TV series, a dummy variable for if it is a 'service original' or not, what service the content belonged to at the time of collection, and finally, the number of subscribers the streaming service has at various quarterly intervals. While the main goal of the study is to research quality's impact the study will also pursue tangential questions along the lines of if service originals also contribute to subscriber growth. After running the main regressions, the study did not show that quality metrics have any statistically significant impact on streaming service subscriber growth. Though the secondary concern in the impact of service originals was found to be statistically significant, where an original garners 3.28 million more subscribers than its unoriginal counterpart.

Introduction:

Originally launched as an alternative to DVD delivery, Netflix's 2007 choice to offer online video streaming permanently changed the media industry. Although the service grew slowly at first, before long, cable companies and DVD rental services were scrambling to maintain a consistent consumerbase. As the Netflix subscriber base grew, so did their catalog of available movies. Thirteen years later, Netflix remains at the top, boasting over 200 million monthly subscribers, yet the landscape is now full of countless competitors - each hoping to collect a monthly fee. Amazon Prime Video sits comfortably with 150 million subscribers, comfortably ahead of the Chinese giant Tencent, which has 115 million. While the industry's massive growth has cast doubt as to whether there is room for more businesses, Disney's recent emergence hints otherwise. After launching Disney+ in the final quarter of 2019, their service has already amassed 100 million monthly subscribers as of March 2021 - far outpacing even their own optimistic goals of 60 million subscribers by 2024. That said, they were able to enter the market with an extensive catalog of original content, negating any need to pay for movie and television rights. Though as it stands, Netflix's offerings far outnumber the various Walt Disney owned products on Disney+.

While the market continues to grow, there will certainly be a ceiling to how many streaming services can operate profitably, as consumers will ultimately remain with cable if that is the cheapest way to watch their desired content. As such, each service has to make a case as to why they are indispensable. Should they offer only the best shows and movies or should they try and amass an extensive catalog of original content? This paper will attempt to answer just that, through a careful analysis of streaming service subscriber count in relation to the size and quality of their respective content. More specifically, the paper will examine if quality movies and shows offered have more of an effect on subscriber growth than original content.

Most every streaming service offers their own original content, which they have invested money in creating, though some do more than others. As of July 2020, Netflix had 461 out of 726 original titles across all streaming services and Amazon had the second most at 91. Despite the top two streaming services boasting the most original content, HBO Max has acquired nearly 40 million monthly subscribers with only 14 original show titles.[1] Furthermore, creating original content is not cheap. Of the $15 billion Netflix spent on content in 2019, 80% went to their original titles, though their high expenditures are continually rewarded by an increasing subscriber base. As such, there is a clear optimal balance between quality of content and the sheer amount offered. With competition growing, individual services will have to find and maintain their corner of the market.

Literature Review:

Given the relative novelty of streaming services, there is little public market research available. That said, Waterman, Sherman, and Ji (2013) highlighted how the recent bundling of streaming services may help limit the number of new competitors. Akin to horizontal integration, each service within a bundle becomes slightly more indispensable as canceling one individual service becomes more complicated. Furthermore, subscribers feel the effect of getting more value for their dollar. Other than the obvious interest in streaming services for their convenience, they offered a specific subset of the media world for a fraction of the cost of traditional cable television. Though now with bundling, the industry seems to be moving backwards.

[1] HBO owns more content under the umbrella of WarnerMedia but they only have 14 produced shows.

Although piracy is slightly outside the realm of this paper, there is no doubt that it remains one of the streaming services biggest obstacles. Norway's Department of Telematics 2015 study on the matter emphasized the prevalent nature of illegal streaming, despite the growth of streaming services. Although not everyone is willing to pay for their content, streaming services and television networks must employ counter measures to piracy. Furthermore, original content has perks in that the service is often the sole owner. As such, legal battles are neater and potential pirates may want to subscribe in order to access future titles. Though tackling piracy is no simple task, as not only does it predate the entire streaming industry but millions of individuals combine to make it an issue. You can't simply plug a few leaks, you would have to make piracy impossible. Services can take more localized steps towards mitigating revenue loss by preventing account sharing. A Michael Levenson New York Time article alluded to Netflix's CEO hopes to end account sharing, citing the practice as massive subscriber losses. They are currently testing a system where users are forced to verify their login with a code sent to a phone or email associated with the account owner. Both piracy and account sharing point towards additional hurdles within the streaming industry, not only must services compete with each other but they have to ensure everyone watching their content is a paying customer.

A Forbes article with data provided by an emerging streaming service analytics company Antenna highlights the increased growth within the business over the course of the pandemic.[2] Disney plus subscriptions tripled in the week of March 14th-21st 2020, when the pandemic fever was just ramping up. Given the strong correlation between staying at home and increased

[2] https://www.forbes.com/sites/arielshapiro/2020/03/23/exclusive-disney-sees-huge-subscription-spike-as-homebound-audiences-clamor-for-content/?sh=7a94fd8f17c4

subscriptions, looking at growth numbers of the course of 2020 will be done with greater context.

Equation Theory:

The main regression of the paper combines data spanning 11 months from all three streaming services (Disney+, Hulu, and Netflix) in order to find out if quality affects their subscriber growth. With the main independent variables finalized, the following equation is an aggregate of known factors that should impact subscriber count:

(1) Subs = β0 + β1M1 + β2M2 + β2M3 + β4M4 + β5M5 + β6M6 + β7M7 + β8M8 + β9M9 + β10M10 + β11M11+ β12release + β13rtscore + β14imdb100 + β15movie + β16original + β17Disney+ + β18Hulu + β19Netflix + μ

The dependent variable Subs is simply the service's subscriber count at various dates in time, mainly derived from quarterly financial reports. Variables 1-11 are categoricals for the months that I recorded data, the earliest being May 2020 and the most recent being March 2021. Since much of the available subscriber count data was only for months that the companies released a quarterly report, I had to interpolate data for the months in-between using excel. For instance, if I had two known months separated by two unknowns, excel would equally space out the growth and fill the middle. The study includes β12release to see if older or newer products have any significant impact on subscriber growth, where a negative coefficient would mean that newer products would somehow hurt subscriber growth.

While this model attempts to show how each variable affects subscriber count, the main variables of interest are the quality scores. Rather than create my own rating system for movies and TV shows, I borrowed from long standing sources in Rotten Tomatoes (RT) and IMDb in order to best measure quality. Rotten Tomatoes offers a percentile rating from 0 to 100 based on the weighted average reviews of top industry critics while IMDb shows a 0-10 rating based on the average of consumer reviews. In order to simplify the differences in scale between the two metrics, I created a new variable IMDb100 by multiplying the original scores by 10. While both are still subjective, the high-brow careful curation of RT combined with IMDb's stamp of the masses limits biases and ensures consistency. I expect that both β13 and β14 are positive, in that higher quality movies and tv shows should lead to more subscriber growth.

Furthermore, there are two dummy variables included, ß15 is "1" if the product is a movie and "0" if it is a TV show and ß16 is "1" if it is a service 'original' or exclusive to that platform and "0" if the rights do not belong to the service. I am including the 'original' dummy variable as each streaming service lists product rights as one of their biggest risk factors, leading each service to invest millions of dollars each year into creating their own content. As such, the more originals a service has the more stable their subscriber count should be.

Finally, the variables that stand in for each streaming service are included to ensure I isolate the specific impact of a streaming services catalog on itself, and not simply on the total subscriber numbers. This study includes a secondary regression without these variables, in order to see what happens when the quality metrics are not self-contained.

Data Analysis:

The data set for this paper is entirely original. Though rather than personally select a monthly collection of top movies and TV shows from each streaming service, I borrowed from various online lists that posted their selections. Some of the websites include the New York Times, Insider, Collider, ForTheWin, and the Verge. The other benefit of borrowing from such lists is they are heavily utilized by consumers, as each of them helps guide uncertain viewers to specific programs. Once I selected a collection of movies and TV shows from the lists, I added the other independent variables such as the release year, IMDb and Rotten Tomatoes scores, and their respective service and month of collection. While sample size was mainly marred by the manual nature of the collection, the further back in time I went, the fewer lists were available. The fewer lists coupled with each list's inherent biases towards certain TV shows and movies, lead to the same products appearing many times.

Although subscriber count is the main variable of interest, collecting accurate data on each service's subscriber metrics created an interesting challenge. The daily ebb and flow of paying customers is not publicly available. As such, the paper's data is limited by each company's willingness to share information with the public. There are two main sources of subscriber numbers for each service. They share metrics either when they want to boast massive growth / significant milestones or when they have a quarterly financial report. Netflix consistently offers regional metrics every fiscal quarter, which may lead to lagged effects. Although they may not be completely accurate, interpolating subscriber count data helped ensure that movie and show recommendations came from a variety of sources, as data on the recent months were more readily available.

Given the vastly different watch times for movies and TV shows, I included the dummy variable in order to capture any possible differing effects. The dummy for original is included because of the inherent exclusive nature of service originals. If a possible consumer wants to watch an original TV show or movie they must pay for that specific service. Furthermore, the service owns the rights to that product, eliminating the risk of customers leaving their service for a competitor.

Broken down by streaming services, there are 229 movies and 47 tv shows from Disney+, 246 movies and 66 tv shows from Hulu, and 267 movies and 67 tv shows from

Netflix. There are 212 original programs, 99 from Disney, 28 from Hulu, and 85 from Netflix. The majority of Disney's content is owned by them, which may be a large factor in their incredible growth in the last year. Netflix subscriber total rose from 118,902,000 in April 2018 to 203,663,000 in January 2021. Their North American market has grown at a slower pace over the same period, going from 60,909,000 to 73,939,000. They are currently the only single streaming service with over 200 million active subscribers. Disney+ launched in November of 2019, gaining 10 million subscribers that very same day. In March 2021, they announced they passed the 100 million subscriber mark. Finally, as of January 2021 Hulu has amassed 39.4 million subscribers.

Data:

With all control variables in effect, as seen in *Table 1*, none of the quality measures have a statistically significant impact on subscriber count. *Table 1* simply represents a simplified version of the main regression, where quality's effect on subscriber count is observed without the addition of individual streaming services. *Table 2* then looks at the full regression, including the three streaming services. The critic's metric in rtscore was the least statistically significant with a p-value of 0.581, followed by imdb100's p-value of 0.084. imdb100's p-value is low enough to be statistically significant at the 10% level, which would mean that for every 0.1 increase in score, subscriber count goes down by 54,400. All of the coefficients in *Table 1* and *Table 2* have essentially been divided by 1000 because that has been done to the dependent variable. Variables marked 'm' were all significant and represent the various months that the data was collected. The measure for release year was not found to be statistically significant on any level. The dummy variable movie, which notes of an observation is a movie or tv show, is also insignificant with a p-value of 0.520. Meaning, it does not matter to subscriber growth whether a product is a movie or a tv show. Serviceoriginal was the only significant variable of interest and was statistically significant at the one percent level. The regression shows that service originals provide an average of 3.28 million subscribers more subscribers than does content not owned by the streaming service. All three variables for the specific streaming services were also statistically significant at the one percent level. The negative coefficients associated with Netflix and Hulu are a result of them having lower subscriber numbers than Disney.

In line with the streaming services being statistically significant, *Table 2* highlights the necessity for including them in the regression, as both one of the metrics for quality was found to have statistically significant impacts on subscriber growth. With a p-value of 0.013 and a coefficient of 245, for every 0.1 point increase in IMDb score subscriber count grows by 245 thousand. The 0.1 increase rather than 1 point increase is due to the fact that the IMDb scores have all been multiplied by 10. Furthermore, the dummy variables for movie and service original were also significant at the 1% level. Here, movies add 7.7 million subscribers and service originals add 15 million subscribers. Although these values are all significant, without including the different streaming services, they do not speak towards the driving question of the paper. *Table 2* shows how the quality of any movie or tv show affects the subscriber count on any streaming service and not how a service's catalog affects their own growth.

Conclusion:

This paper cannot conclude that film and tv quality has any significant impact on streaming service subscriber growth, despite select monthly findings showing otherwise. Both metrics for quality in IMDb score and Rotten Tomatoes did not consistently impact subscriber growth. In a competitive race to garner as much of the market share as possible, each streaming service must create the best possible catalog of content. As such, learning that quality may not be a leading growth driver is still impactful. Although quality was the main concern of the study, the inclusion of service originals alludes to other possible growth areas of streaming services - one of which being service originals. This study's substantial evidence that service originals leads to subscriber growth aligns with the basic truths of a good business model. In that there is room for increased profits anytime a service or product is exclusive to just one brand.

Disney's meteoric rise to 100 million subscribers was surely aided by their massive catalog of service originals. Of Disney's 276 recorded films and tv shows, 35.9% were original to the service, compared to just 8.9% for Hulu and 25.5% for Netflix. This study's controlled regression hints that service originals are the cause of subscriber growth and not simply correlated with the metric.

When looking at the main regression shown in *Table 1*, movies played no significant role in increasing subscriber metrics. Reading slightly past the numbers, movies might just not have the same staying power as tv shows. Customers often watch them in one or two sitting, which would go against the month to month subscriber count metrics. Whereas tv shows could take a user multiple months to watch, keeping them subscribed for a longer period of time. Movies also account for the majority of all observations in the study, as there were only 180 tv shows out of a total of 922 observations. That is partly due to the fact that the source material for the observations was somewhat biased towards movies. Some of the lists I recorded data from exclusively offered movie recommendations.

Movie bias in data collection was not the only setback of the study, as limited manpower, subjectivity, and limited access to data act as other prominent examples of constraining factors. Each streaming service has a catalog of hundreds or even thousands of tv shows and movies, as such collecting data on each one for every month would be nearly impossible. The decision to collect data from handpicked lists online saved valuable time while sacrificing a more complete dataset. Many of the sources updated their monthly recommendations, which eliminated the possibility of viewing archived lists. With less to choose from in earlier months, many of the monthly observations come from the same few available sources. As such the subscriber count for a service grew, yet the list of movies associated was quite similar. Furthermore, all of these streaming services are global entities, yet the data on movies and tv shows I was able to find was specific to the United States. Many of the titles included are only available to stream within the United States so their impact is limited to the set of subscribers residing in the US. Limiting Netflix's subscriber data to North America was helpful but Canadian and Mexican libraries were still out of reach. Data from Disney+ and Hulu suffer from the same setbacks. If I were to further the research on quality's impact on subscriber growth, a future study should include a more diverse set of observations that serves to best capture the entire service's catalog.

As alluded to earlier, an objective measure of quality with any subset of art is difficult. Movies and tv shows that critics find appealing may not matter to the general public. That could help explain why rotten tomatoes and IMDb scores offered differing impacts.

While *Table 2* does not show a complete picture, as it lacks the differing streaming services, we can point towards interesting influencing factors when paired with *Table 8*. The regression in *Table 8* just shows the average IMDb scores associated with each streaming service, putting them in relation to one another. Although the metric for Rotten Tomatoes was not statistically significant at the 5% level, the negative coefficient could be due to the Disney+ observations. Not only did Disney+ have the most subscriber growth out of the three services but it also had the lowest rotten tomatoes scores, as seen by *Table 8*. Therefore, it is possible that their exceptional subscriber growth coupled with low ratings would lead the coefficient on rotten tomatoes to be negative.

Despite quality having minimal or no significant impact on streaming service subscriber growth, future studies could better measure the relationship between the two with a wider data selection. In addition to accounting for the global catalog of movies and tv shows, an interesting approach would be to take note of the most watched products on each service for a given week and record their quality metrics. Unlike third-party recommendations, the most watched category directly hints at what users are paying for. With the increasing competition between streaming services, each must tailor their catalog to best suit consumer demands. If quality is not significantly impactful on subscriber growth, they will surely find other business drivers. Given the positive impact of service originals in this somewhat limited sample, future studies could further the analysis so that streaming services have a better understanding on how to attract and keep paying customers.

Table 1: Regression for Quality on Subscriber Growth w Streaming Services

Subs	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
m1	-16100.000	1737.279	-9.29	0.000	-19600.000	-12700.000	***
m2	-12600.000	1689.489	-7.44	0.000	-15900.000	-9254.271	***
m3	-23800.000	2025.725	-11.76	0.000	-27800.000	-19800.000	***
m4	-9974.568	1651.093	-6.04	0.000	-13200.000	-6734.028	***
m5	-6908.083	1604.238	-4.31	0.000	-10100.000	-3759.503	***
m6	-8808.440	2019.240	-4.36	0.000	-12800.000	-4845.352	***
m7	-2850.154	1598.798	-1.78	0.075	-5988.056	287.748	*
m8	-1767.350	1607.970	-1.10	0.272	-4923.253	1388.554	
m9	-980.569	1565.660	-0.63	0.531	-4053.432	2092.294	
m11	9170.502	1630.246	5.62	0.000	5970.878	12370.126	***
release	-17.952	13.424	-1.34	0.181	-44.299	8.395	
rtscore	-8.656	15.670	-0.55	0.581	-39.411	22.100	
IMDb100	-54.452	31.448	-1.73	0.084	-116.173	7.269	*
movie	355.978	552.765	0.64	0.520	-728.914	1440.870	
serviceoriginal	3280.428	536.114	6.12	0.000	2228.217	4332.638	***
Disney+	0.000	.	.	.	.	.	
Hulu	-43200.000	570.734	-75.73	0.000	-44300.000	-42100.000	***
Netflix	-4585.627	557.390	-8.23	0.000	-5679.595	-3491.659	***
Constant	124000.000	27357.627	4.54	0.000	70619.407	178000.000	***
Mean dependent var	63476.791	SD dependent var					20053.151
R-squared	0.920	Number of obs					898.000
F-test	597.184	Prob > F					0.000
Akaike crit. (AIC)	18104.120	Bayesian crit. (BIC)					18190.523
Coefficients have been reduced by a factor of 1000							
****** p<0.01, ** p<0.05, * p<0.1***							

Table 2: Regression for Quality on Subscriber Growth w/o Streaming Services

Subs	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
m1	22203.585	5324.950	4.17	0.000	11752.534	32654.636	***
m2	25365.700	5158.830	4.92	0.000	15240.685	35490.715	***
m3	17342.375	6190.722	2.80	0.005	5192.109	29492.642	***
m4	16950.387	5136.151	3.30	0.001	6869.882	27030.892	***
m5	16622.634	5004.118	3.32	0.001	6801.266	26444.003	***
m6	32552.503	6155.881	5.29	0.000	20470.618	44634.388	***
m7	17971.425	5002.517	3.59	0.000	8153.199	27789.651	***
m8	21521.014	5010.951	4.29	0.000	11686.235	31355.794	***
m9	19172.528	4897.681	3.92	0.000	9560.058	28784.998	***
o.m10	0.000	.	.	.	.	.	
m11	31242.395	5077.721	6.15	0.000	21276.569	41208.220	***
release	-62.546	41.966	-1.49	0.136	-144.910	19.819	
rtscore	-76.825	49.245	-1.56	0.119	-173.476	19.825	
IMDb100	245.008	98.925	2.48	0.013	50.853	439.163	**
movie	7752.318	1722.492	4.50	0.000	4371.656	11132.980	***
serviceoriginal	15026.557	1643.509	9.14	0.000	11800.911	18252.202	***
Constant	147000.000	85724.094	1.71	0.087	-21500.000	315000.000	*
Mean dependent var	63476.791	SD dependent var					20053.151
R-squared	0.199	Number of obs					898.000
F-test	14.620	Prob > F					0.000
Akaike crit. (AIC)	20171.434	Bayesian crit. (BIC)					20248.237
****** p<0.01, ** p<0.05, * p<0.1***							

Table 3: Disney+ Descriptive Quality Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
IMDb	276	7.591	.768	4.2	9.7
rtscore	276	84.37	16.527	8	100

Table 4: Hulu Descriptive Quality Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
IMDb	313	7.465	.831	4.2	9.3
rtscore	313	87.188	14.205	9	100

Table 5: Netflix Descriptive Quality Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
IMDb	334	7.58	.737	5.2	9.3
rtscore	334	88.415	12.153	8.7	100

Table 6: Summary Statistics - Total Quality

Variable	Obs	Mean	Std.Dev.	Min	Max
IMDb	923	7.544	.781	4.2	9.7
rtscore	923	86.789	14.348	8	100

Table 7: Regression of Rotten Tomatoes on Streaming Services

rtscore	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
Disney+	**0.000**	**.**	**.**	**.**	**.**	**.**	
Hulu (2.s)	**2.819**	**1.178**	**2.39**	**0.017**	**0.507**	**5.131**	**
Netflix (3.s)	**4.046**	**1.161**	**3.49**	**0.001**	**1.768**	**6.323**	***
Constant	**84.370**	**0.859**	**98.25**	**0.000**	**82.684**	**86.055**	***
Mean dependent var	**86.789**	**SD dependent var**					**14.348**
R-squared	**0.013**	**Number of obs**					**923.000**
F-test	**6.262**	**Prob > F**					**0.002**
Akaike crit. (AIC)	**7528.878**	**Bayesian crit. (BIC)**					**7543.361**
****** p<0.01, ** p<0.05, * p<0.1***							

Table 8: Regression of IMDb on Streaming Services

IMDb	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
Disney+	**0.000**	**.**	**.**	**.**	**.**	**.**	
Hulu (2.s)	**-0.126**	**0.064**	**-1.95**	**0.051**	**-0.252**	**0.001**	*
Netflix (3.s)	**-0.010**	**0.063**	**-0.16**	**0.870**	**-0.135**	**0.114**	
Constant	**7.591**	**0.047**	**161.81**	**0.000**	**7.499**	**7.683**	***
Mean dependent var	**7.544**	**SD dependent var**					**0.781**
R-squared	**0.005**	**Number of obs**					**923.000**
F-test	**2.468**	**Prob > F**					**0.085**
Akaike crit. (AIC)	**2162.162**	**Bayesian crit. (BIC)**					**2176.645**
****** p<0.01, ** p<0.05, * p<0.1***							

Table 9: Tabulation of ServiceOriginal & Services

Service Original	Service			
	Disney+	Hulu	Netflix	Total
0	177	285	249	711
1	99	28	85	212
Total	276	313	334	923

Table 11: Tabulation of Movie & Services

Movie	Service			
	Disney+	Hulu	Netflix	Total
0	47	66	67	180
1	229	246	267	742
Total	276	312	334	922

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