Research Article

Citation date: 2017/11/06

Inverted u-shaped impact of social media posting frequency on engagement and sentiment ratio

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How to cite:

Salazar, J. M. R. (2017) 'Inverted u-shaped impact of social media posting frequency on engagement and sentiment ratio', *Empirical Quests for Management Essences*, 1(1), pp. 1–15.

Article history:

Received: 2017/03/22
Available online: 2017/11/06

Abstract

The frequency with which companies should publish on social media is one of the most often asked topics. It has been hypothesized that there is an optimal frequency of posting on social media networks that improves a business's capacity to engage with followers and to increase positive brand mentions. Surpassing this quantity and posting too often will leave followers feeling overwhelmed. Thus, it is important to figure out what frequency level is optimal for content posting in social media to increase follower engagement and positive brand mentions. The objective of this research is to verify this hypothesis and to find out the optimal frequency level for content posting on social media. Several quadratic longitudinal models have been implemented. The dataset contains weekly data from 2016 to 2017 for 5 companies, making 525 sample longitudinal data points. According to the findings of this research, the optimal frequency for social media content posting is 6-7 posts in a week. Publishing more than that reduces engagement and positive brand mention. The findings of this research will assist companies and social media executives in incorporating optimal frequency levels into their social media marketing plan.

Keywords: Follower Engagement, Inverted U-shape, Longitudinal models, Positive brand mention, Social media

Declarations

Competing interests:

The author declares no competing interests.

1. Introduction

In the previous decade, social media has emerged as the defining trend, reshaping communication and relationships between people, communities, governments, and corporations (Zarrella, 2009). Researchers and marketers are grappling with the rapidly changing landscape for developing business cases to proactively engage with stakeholders, as well as the profound impact of rapidly evolving social media on viral user-generated content, its impact on shaping consumer perceptions, and the impact of rapidly evolving social media on shaping consumer perceptions (Sajid, 2016) (Brown, 2012)

Communication has always aided the interaction between sellers and buyers, with merchants use words, signs, and symbols to capture prospective consumers' attention to their items and persuade them to purchase them. While the core aims of marketing communications—differentiate, recall, educate, and convince —have remained constant, the structure of marketing communications has evolved as new media systems have grown in breadth and complexity (Augustini, 2014) (Odden, 2012).

Social media marketing may help a firm in a variety of ways. A corporation may reach a large audience by organizing marketing campaigns. Consumers are not the only ones who make up the mass audience; stakeholders, workers, bloggers, and future customers may also be included (Brown, 2012). The ability to reach a larger audience is another advantage of social media marketing. When compared to offline sources, the materials on social media platforms are greater and more diverse. In addition, social media improves the company's openness. Because social media draws a large audience that is directly or indirectly related or affiliated with the firm, companies involved in social media marketing are required to be open (Funk, 2014). Moreover, everyone affiliated with the organization wants to know all there is to know about it. Another benefit of social media marketing is that marketers can listen to, monitor, and measure what is being published on social media sites, and utilize this information to improve products and services while also adjusting everything to the demands of customers (Felix, Rauschnabel and Hinsch, 2017). The influence of social media on a company's marketing plan may be assessed very readily using social media analytics and metrics.

When it comes to discovering new consumers, more businesses are understanding the value of social media. For marketers, social media has emerged as a viable alternative to search engines for reaching their target customers. Not to mention, having a strong social media presence helps with search engine optimization (Odden, 2012).

However, since many companies are new to the world of social media, there are a lot of questions and concerns about the platform. One of the most typical stumbling blocks is determining the optimal frequency of social media posting.

The issue with "optimal frequency", however, is that it ignores different business verticals, geographic areas, and audience demographics. If the optimal posting frequency is three posts per day, for example, it may work for an e-commerce or news business, but it may be disruptive to a B2B firm's audience. Rather of striving for perfect times, days, or frequency numbers, they are advised to focus on consistency allowing the audience to understand that after a certain amount of time, they will be able to discover something new on their favorite brand's social media profile.

Many social media platforms have changed their algorithms to prevent brand postings from appearing in the news feeds of all members of their audience (Tuten, 2008). If firms do not want to pay for social marketing to get through this barrier, another option is to create intriguing and engaging content. If farms' audience considers posted material useful or amusing, they will intentionally return to firms' website to see if there have been any improvements

Methodology

Model 1.

Audience/fans engagement is the dependent variable in model 1. Audience Engagement refers to the percentage of visitors who engage in a marketing campaign by leaving comments, sharing, or referring back to it (Evans, 2010) (Carboni and Maxwell, 2015). Audience engagement is expected to remain constant for organizations with a big number of followers. Then, depending on advertising, search efforts, and promotional activities, expectations may be adjusted appropriately (Hall-Phillips et al., 2016). To determine the regular level of discussion inside a single channel, audience engagement should be studied over time. A squared term of frequency has been included in the model to investigate existence of an inverted u-shaped curve.

$$(Engagement)_i = \alpha + \beta_1 Frequency_i + \beta_2 Frequency_i^2 + \varepsilon_i$$

Where,

$$(Engagement)_i = \frac{Comments + shares + likes}{Total\ views}$$

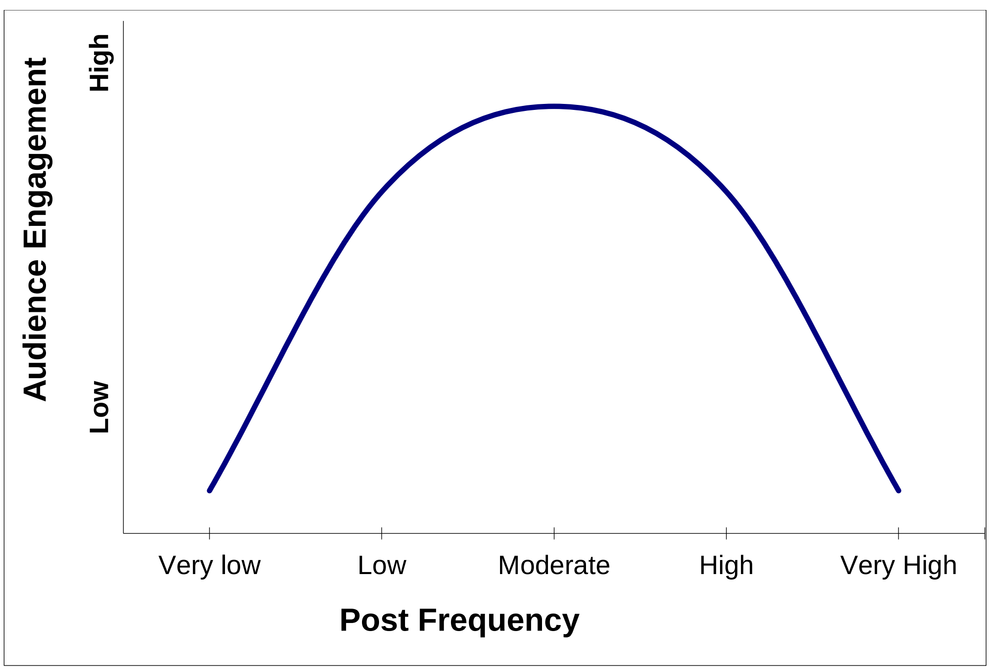

Figure 1. Inverted U-shaped relationship between audience engagement and post frequency

The figure implies that audience engagement increases when post frequency increases up to a certain point. After that point, an increase in post frequency decrease the audience engagement.

Model 2.

Positive sentiment ratio is the dependent variable in model 2. Positive sentiment ratio is the ratio of positive brand mentions concerning certain goods or services over a specified time period (Vidya, Fanany and Budi, 2015). Because sentiment ratios may vary fast, they should be trended across time and portrayed in the context of positive, neutral, and negative. The capacity to detect and address these issues will improve company's ability to innovate (Lawrence, 2014).

$$(Sentiment\ Ratio)_i = \delta + \gamma_1 Frequency + \gamma_2 Frequency_i^2 + \varphi_i$$

Where,

$$(Sentiment\ Ratio)_i = \frac{Positive\ brand\ mentions}{All\ brand\ mentions}$$

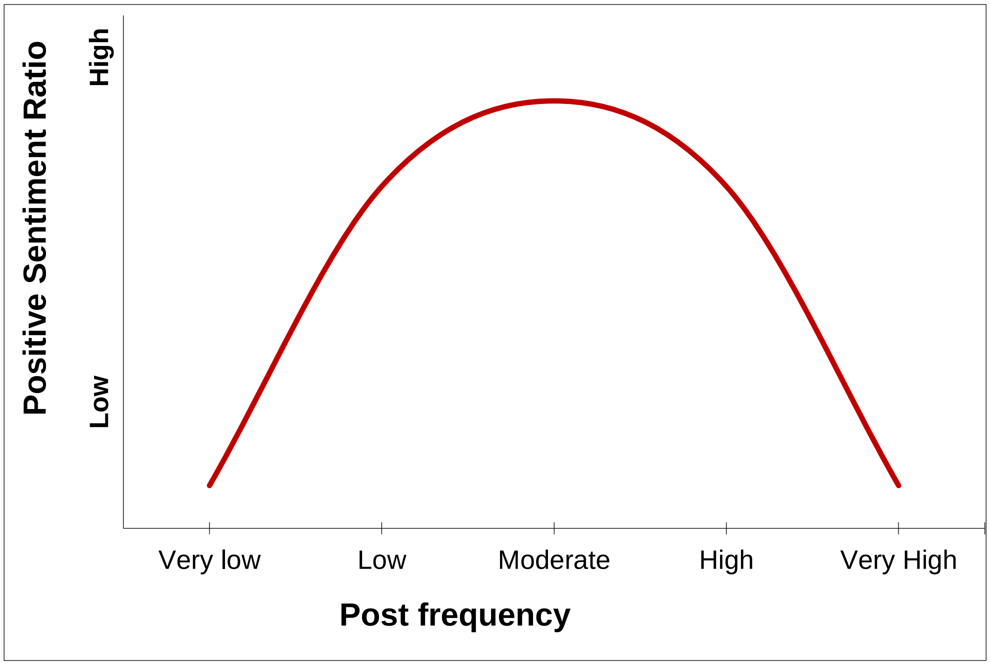

Figure 2. Inverted U-shaped relationship between audience engagement and post frequency

The graph shows that when the frequency of posts increases up to a certain degree, positive sentiment ratio rises. After that, increasing the number of posts decreases positive sentiment ratio.

Longitudinal models

Longitudinal models are a kind of model in which data is collected across time for cross sections. When the unit of analysis involves repeated data throughout time, longitudinal models, also known as panel models, are utilized (Park, 2010). Because data points from each unit of analysis are likely to be strongly linked over time (i.e. they represent the same unit of analysis), methods must account for the data's clustered structure (Singer, Willett and Willett, 2003) . Municipalities in this research contain yearly data, allowing for longitudinal data analysis.

Depending on the assumptions established, such as whether to use random or fixed effects, there is a lot of flexibility when it comes to analysing longitudinal datasets. Fixed- and random-effects assumptions in the econometric literature relate to assumptions regarding the associations of error elements inside the model.

For both fixed and random effects, the generic model is as follows (Diggle et al., 2002):

$$y_{it} = x_{it}\beta + \alpha_i + \varepsilon_{it}$$

Where yit is the response variable for unit I at time t and xit is the independent variable with coefficient for unit I at time t. Both are error terms, with I denoting random individual-specific effects (time invariant) for unit I and it denoting an idiosyncratic error (time variant) for unit I at time t.

In random-effect models, it is presumed that at any one moment, I is uncorrelated with any of the independent variables xit (Singer, Willett and Willett, 2003). To put it another way, unobserved effects in the model are only connected with explanatory variables at random. This is a big assumption to make, and it'll almost certainly be broken — particularly in models with few explanatory variables.

In fixed-effect models, I is allowed to associate with independent variables xit (unobserved qualities may be linked to explanatory factors), which is a less rigorous assumption. Fixed-effect models can account for these unobserved constant (or stable) qualities throughout time, resulting in estimates that are unbiased of any correlations between mistakes and explanatory factors (Hedeker and Gibbons, 2006). The Hausman specification test, which analyses error terms across models, may also be used to determine whether fixed-effects or random-effects models should be used (Hand and Crowder, 2017) (Diggle et al., 2002).

Results

Model 1 results

The results of different longitudinal estimation techniques under model 1 are reported in table, 1, 2 and 3. Engagement is the dependent variable, whereas frequency and frequency squared are the independent variables.

The regression coefficient for frequency is 0.9989. A regression coefficient significance test is also included in the table. The t-statistic is 22.9, with a p-value of less than 0.05. The coefficient value of 0.9989 is deemed significant since the p-value is less than 0.05. This suggests that frequency has a significant positive impact on engagement. The regression coefficient for squared frequency is -0.994. A regression coefficient significance test is also shown in the table. The t-statistic is -33.60, with a p-value of less than 0.05. The coefficient value of -0.994 is deemed significant since the p-value is less than 0.05. This indicates that there is an inverted u-shaped relationship between frequency and engagement. The almost similar results can be seen in table 2 and table 3. These results validate our hypothesis that When the frequency of posts is increased up to a certain degree, audience engagement rises. After that, increasing the number of posts decreases audience engagement. Additionally, we calculated the maximum point using optimization rule. The results showed that 5 posts per week is the optimal frequency. This implies that if the posting frequency exceeds 5 posts per week, the engagement level of the company's social media follower decreases.

Table 1. Panel Least Squares

Dependent Variable: ENGAGMENT
Method: Panel Least Squares
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FREQUENCY	0.998987	0.043576	22.92542	0.0000
FREQUENCY_SQURED	-0.994257	0.029586	-33.60604	0.0000
C	-0.023040	0.056242	-0.409661	0.6822

R-squared	0.757950	Mean dependent var	-1.107042
Adjusted R-squared	0.757023	S.D. dependent var	2.128103
S.E. of regression	1.049000	Akaike info criterion	2.939249
Sum squared resid	574.4088	Schwarz criterion	2.963611
Log likelihood	-768.5528	Hannan-Quinn criter.	2.948788
F-statistic	817.2915	Durbin-Watson stat	1.944529
Prob(F-statistic)	0.000000		

Table 2. Fixed Effect

Dependent Variable: ENGAGMENT
Method: Panel Least Squares
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FREQUENCY	1.002924	0.043841	22.87657	0.0000
FREQUENCY_SQURED	-0.994538	0.029711	-33.47350	0.0000
C	-0.022784	0.056414	-0.403875	0.6865

Effects Specification			
Cross-section fixed (dummy variables)			
R-squared	0.758612	Mean dependent var	-1.107042
Adjusted R-squared	0.755816	S.D. dependent var	2.128103
S.E. of regression	1.051602	Akaike info criterion	2.951751
Sum squared resid	572.8395	Schwarz criterion	3.008596
Log likelihood	-767.8347	Hannan-Quinn criter.	2.974010
F-statistic	271.3200	Durbin-Watson stat	1.949785
Prob(F-statistic)	0.000000		

Table 3. Method: Panel EGLS (Cross-section random effects)

Dependent Variable: ENGAGMENT
Method: Panel EGLS (Cross-section random effects)
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FREQUENCY	0.998987	0.043684	22.86868	0.0000
FREQUENCY_SQURED	-0.994257	0.029659	-33.52285	0.0000
C	-0.023040	0.056381	-0.408647	0.6830

Effects Specification			S.D.	Rho
Cross-section random			0.000000	0.0000
Idiosyncratic random			1.051602	1.0000

Weighted Statistics			
R-squared	0.757950	Mean dependent var	-1.107042
Adjusted R-squared	0.757023	S.D. dependent var	2.128103
S.E. of regression	1.049000	Sum squared resid	574.4088
F-statistic	817.2915	Durbin-Watson stat	1.944529
Prob(F-statistic)	0.000000		

Unweighted Statistics			
R-squared	0.757950	Mean dependent var	-1.107042
Sum squared resid	574.4088	Durbin-Watson stat	1.944529

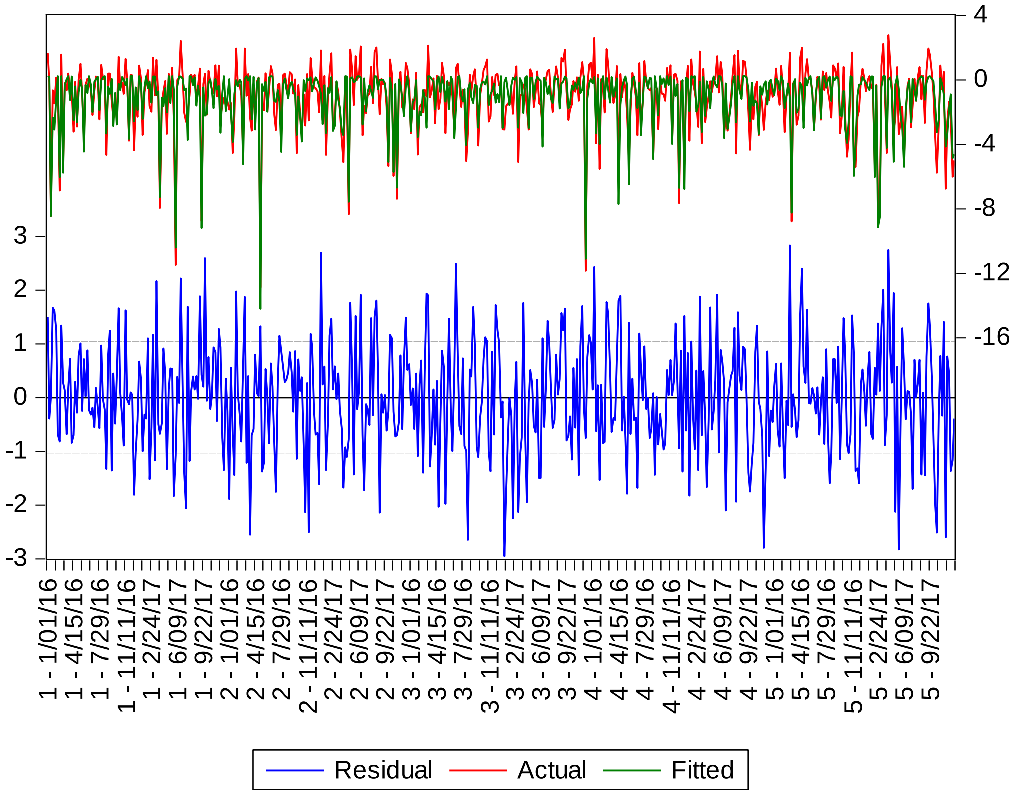

Figure 4. Residual, Actual, and fitted graph for model 1.

Model 2 results

Tables 4, 5, and 6 show the results of several longitudinal estimating strategies under Model 2. The dependent variable is positive sentiment ratio, whereas the independent variables are frequency and frequency squared.

According to the table 4, The frequency regression coefficient is 1.007. The table also includes a regression coefficient significance test. With a p-value of less than 0.05, the t-statistic is 84.366. Because the p-value is less than 0.05, the coefficient value of 1.007 is considered significant. This indicates that frequency has a favorable influence on positive sentiment ratio. The squared frequency regression coefficient is -1.004. The table also includes a regression coefficient significance test. With a p-value of less than 0.05, the t-statistic is -123.91. Because the p-value is less than 0.05, the coefficient value of -1.004 is considered significant. This suggests that frequency and engagement have an inverted u-shaped connection. Tables 5 and 6 show findings that are almost identical. These findings support our hypothesis that increasing the frequency of postings up to a certain point increases positive sentiment ratio or positive brand mentions. Increasing the number of posts after that reduces audience engagement. The residual and fitted graph show that the model does not have problematic outliers.

We also used an optimization algorithm to calculate the maximum point. The findings revealed that 6 postings per week is the best frequency. This means that if the company's social media posts exceeds 6 times per week, the company's positive brand mention decreases.

Table 4. Panel Least Squares

Dependent Variable: SENTIMENT
Method: Panel Least Squares
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FREQUENCY	1.007069	0.011937	84.36643	0.0000
FREQUENCY_SQURED	-1.004261	0.008105	-123.9135	0.0000
C	0.512225	0.015407	33.24726	0.0000

R-squared	0.977023	Mean dependent var	-0.582711
Adjusted R-squared	0.976935	S.D. dependent var	1.892089
S.E. of regression	0.287357	Akaike info criterion	0.349516
Sum squared resid	43.10370	Schwarz criterion	0.373879
Log likelihood	-88.74804	Hannan-Quinn criter.	0.359056
F-statistic	11098.00	Durbin-Watson stat	1.937669
Prob(F-statistic)	0.000000		

Table 6. Fixed effect

Dependent Variable: SENTIMENT
Method: Panel Least Squares
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FREQUENCY	1.008038	0.011931	84.49174	0.0000
FREQUENCY_SQURED	-1.004346	0.008085	-124.2159	0.0000
C	0.512306	0.015352	33.37000	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.977385	Mean dependent var	-0.582711

Adjusted R-squared	0.977123	S.D. dependent var	1.892089
S.E. of regression	0.286179	Akaike info criterion	0.348844
Sum squared resid	42.42334	Schwarz criterion	0.405690
Log likelihood	-84.57161	Hannan-Quinn criter.	0.371104
F-statistic	3731.245	Durbin-Watson stat	1.968705
Prob(F-statistic)	0.000000		

Table 6. Panel EGLS (Cross-section random effects)

Dependent Variable: SENTIMENT
Method: Panel EGLS (Cross-section random effects)
Date: 12/11/21   Time: 10:41
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FREQUENCY	1.007773	0.011919	84.55236	0.0000
FREQUENCY_SQURED	-1.004323	0.008082	-124.2726	0.0000
C	0.512284	0.025531	20.06529	0.0000

Effects Specification			S.D.	Rho
Cross-section random			0.045618	0.0248
Idiosyncratic random			0.286179	0.9752

Weighted Statistics

R-squared	0.977189	Mean dependent var	-0.304254
Adjusted R-squared	0.977101	S.D. dependent var	1.888033
S.E. of regression	0.285703	Sum squared resid	42.60894
F-statistic	11180.69	Durbin-Watson stat	1.960135
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.977022	Mean dependent var	-0.582711
Sum squared resid	43.10400	Durbin-Watson stat	1.937623

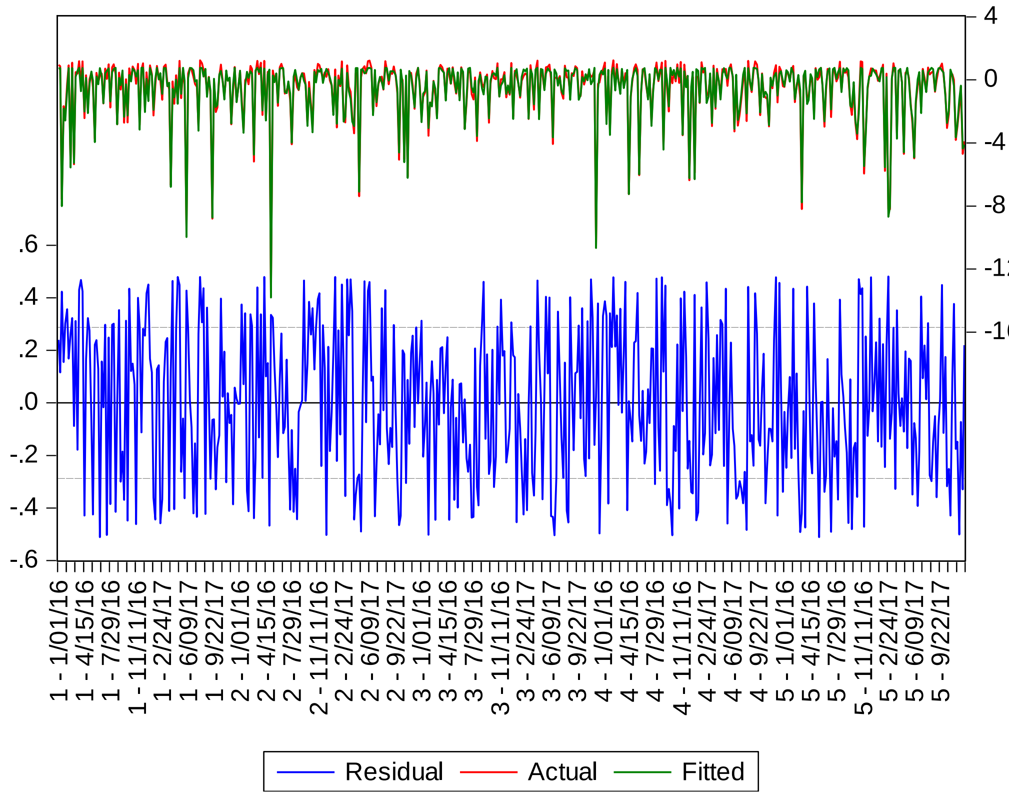

Figure 4. Residual, Actual, and fitted graph for model 2.

Conclusion

More individuals than ever before are seeking for relevant and consistent information in the era of social media. When it comes to the ongoing desire to publish, social media professionals continue to be perplexed. Brands often increase the frequency of their updates, driving away their fans. However, the regularity with which brands choose to publish on social media is a personal choice. It is determined by a company's demands and objectives. There are a number of strategies that might help a company enhance it engagement rate and positive brand mentions. Using statistical data and finding an optimal posting frequency is one of the strategies. The goal of this study is to determine the best frequency level for posting information on social media. According to the conclusions of this study, the best frequency for posting social media material is 6-7 times per week. When companies publish more than that, engagement and good brand mentions suffer. The outcomes of this study will aid businesses and social media executives in determining the best frequency level for their social media marketing strategy. It is crucial to remember, however, that quality always takes precedence over quantity. That implies that even if posting frequency is optimal for success, if content is not upgrades, it may not help the company reach its business objectives. Efforts of content managers will likely go undetected if they just keep producing low-quality material to fill their social media calendar.

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