The Impact of Youtube's 2019 Child Protection Policy Changes on Youtuber Welfare

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Abstract: In 2019, YouTube, the most popular video sharing platform in the world, announced significant changes to its community guidelines in regards to creating content for children. These changes were formally made to protect the rights and privacy of children but will involve limiting the amount of advertisements shown and the disabling of key functions on videos. Therefore, these are expected to negatively affect youtubers, particularly those whose main demographic are children, as it severely limits their possible income via viewership, which is tied to advertisement revenue. Using SocialBlade, a social media analytics platform, we gathered weekly market data from the top 30 youtubers in the genres of children's videos, educational videos, and gaming videos, from 2019 to 2020 and investigated the effects of these changes on youtuber welfare using a two-stage least squares regression model. We found that the policy guidelines did have a significant positive effect on viewership for all three genres but when it comes to the subscription rate for youtubers, the results are highly varied not only between genres but also for individual youtubers. This means that the actual effects are highly dependent on the youtuber and the genre. The research provides important implications for policies on data privacy at the cost of another party. However, our results are limited not only by time, but also the opacity of the social media industry itself. Therefore, more information is needed to further expand on this topic.

Key Words: Youtube; Children; Advertisement; Data Privacy

1. INTRODUCTION

According to Stepanović (2018), platforms such as Youtube, can be defined as a new type of television that combines different types of traditional and non-traditional media. This raised debates on identifying whether it is considered as a media or technology company, therefore making it difficult to regulate. These new media platforms are threatening the distinction between the public and private sphere. Moreover, it is known to violate privacy in two ways: first, through the personal data of its users; and second, the content that is exposed for everyone on the internet to see. As a platform that allows anyone to upload a video without censorship nor editing, Youtube has the potential to violate privacy in both ways. YouTube earns millions of dollars by using cookies that gather personal user data to deliver targeted advertisements (here on as ads) to its viewers. It also enables a website to improve user-experience by providing user-specific features. However, the issue of data privacy rises from the collection of a user's data without consent, especially with regards to children.

That is why in 2019, YouTube announced massive changes to its community guidelines in regards to creating content for children, to be implemented in January 2020. This comes after Youtube was hit with a $170 million dollar fine by the U.S Federal Trade Commission (FTC) after it proved that the video service website failed to secure children's privacy on data. Thereafter, YouTube clamped down on content creators (herein as youtubers) and introduced new policy changes which made content creators choose between certifying their videos as either “for kids” or “not for kids”. In the former, the comment section will be disabled, targeted ads will be removed, and data on the young viewers will not anymore be collected. However, if the youtubers are caught showing content not made for younger audiences despite certifying otherwise, then they will receive heavy fines by YouTube. Meanwhile, the latter group will go on as usual but they will be cut off from younger audiences by Youtube’s search engine (Solsman & Nieva, 2019).

Note that, Youtubers earn money from a number of sources including advertisement (ad) revenue, sponsorships, and selling of merchandise. For this study, the only method to be examined will be the ad revenue, since it makes up most Youtubers’ revenue stream via Google AdSense (Rosenberg, 2020).

This study investigates the impacts of the recent policy changes on a youtuber’s estimated income, subscriber count, and viewership. It is expected that policy changes will lead to lower viewership and therefore lower revenue due to the loss of interactions with the target market, as well as the loss of corporate sponsors (Evans, 2009). The insights accumulated will be able to aid the policy decision makers from regulatory and developmental agencies to further supervise viewerships among minors.

2. METHODOLOGY

2.1 Data collection

The data for the study is gathered from SocialBlade.com, a popular and trusted data collection website for social media. The data is mostly free to view and use, only showing the three most recent years’ worth of data, and is collected from Youtube’s public data interface. There is a paid subscription to see more detailed analytics but this was not included in the study.

2.2 Sampling framework

The researchers used stratified random sampling to get the sample needed for the evaluation. Specifically, the study uses the top 30 youtubers (according to SocialBlade) from 3 different genres: Kid’s shows (Kid’s), video gaming (Gaming), and Educational videos. These genres are expected to be the most affected by the policy changes, since most of their market is catered to minors.

The policy is evaluated using two groups: the treatment and comparison group. It is also based on the assumption that both groups have the same characteristics to identify the difference based on the program rather than the group.

Table 1. Groups for evaluation

Group	Year and number of Youtubers
Treatment group	Number of viewers, subscribers, and earnings of 30 Youtubers in 2020
Comparison group	Number of viewers, subscribers, and earnings of 30 Youtubers in 2019

2.3 Empirical estimation

The researchers made use of the Instrumental Variable (IV) model, a quasi-experimental statistical technique used for estimating impacts (Genetian et al., 2002),. The number of weekly viewers and subscriptions are used to explain the estimated earnings of Youtubers, hereon mentioned as Youtuber welfare. The higher the estimated earnings, the higher the youtuber welfare. This is because specific numbers on earnings are not publicly available (Berg, 2020). Furthermore, it could also determine a possible causal relationship in scenarios that are not controlled experiments and there may be incidents of non-compliance.

To compute ad revenue, a measure called Cost Per Mille (CPM) is charged towards advertisers and is calculated as 1000 views per unit of CPM (Rosenberg, 2020). According to SocialBlade (2020), the average CPM ranges from \$2-\$4 per 1000 views, but it can theoretically go higher depending on the advertiser’s preferences. However, the money will be split between Youtube and the Youtuber, with 45% going to the former. To get the estimated earnings, we divided the total weekly views by 1000 then multiplied to 2.215 (the median average CPM from SocialBlade) then multiplied again to 0.55 (the youtuber’s share).

In order to determine the relationship between the variables, the regression method used will be two-stage least squares (2SLS) wherein the instrument should explain the earnings of Youtubers while dissociating other factors that can influence subscriptions, views, pre that are not included in the study, also known as the error term. The first stage involves regressing each instrumental variable *(subscriptions, views, pre)* to the dependent variable, which is earnings. The second stage involves an OLS estimation that will confirm if the instrumental variables are correlated with the dependent variable (Kenkel, 2016). Therefore, the study makes use of the following econometric model:

$$Earnings = \beta_0 + \beta_1 Views + \beta_1 Subscriptions \beta_1 Pre$$

wherein:

Earnings is the total estimated weekly earnings of the youtuber, Views is the estimated weekly views of the youtuber, Subscriptions is the estimated weekly subscription gains (or losses) of the youtuber, and Pre is a dummy variable where 0 means the week is in 2019 (before implementation) while 1 means the week is in 2020 (after implementation).

3. RESULTS AND DISCUSSION

The top 3 youtubers of the kids show genre were used to test the model (Cocomelon, Kid's Diana, & Like Nastya). Based on the tables below, findings show that views are a significant factor when determining earnings with a p-value of 0.00, but their coefficients are only consistently listed as 0.0011. This could mean that for every increase in views, earnings will also increase by $0.0011. However, subscriptions see a negative albeit tiny coefficient of at least 1.4^-8 power and with very high p-values. This means that although negative, the real extent of the decrease is highly dependent on the youtubers themselves. Meanwhile, with the dummy variable pre-, results differ on the coefficient and p-value.

Table 2. Initial test results for Cocomelon

totalearni~s	Coef.	Std. Err.	t	P >|t|
totalviews	.0011687	1.37e-11	8.6e+07	0.000
totalsubs	9.54e-09	2.01e-08	0.47	0.637
pre	-.0003573	.037409	-0.01	0.992
_cons	.0049593	.1173947	0.04	0.996

Table 3. Initial test results for Kid's Diana

earnings_kids~a	Coef.	Std. Err.	t	P >|t|
kidsdianaviews	.0011687	2.36e-12	4.9e+08	0.000
kidsdianasubs	-1.60e-08	1.09e-08	-1.47	0.144
pre	-.011641	.0028776	-4.05	0.000
_cons	.019288	.00584	3.30	0.001

Table 4. Initial test results for Like Nastya

earnings_nastya	Coef.	Std. Err.	t	P >|t|
likenastyaviews	.0011687	1.37e-11	1.37e-11	0.000
likenastyasubs	4.14e-09	5.19e-09	0.80	0.427
pre	.011794	.0032094	0.37	0.714
_cons	.0000798	.0059499	0.01	0.989

The same regression but this time using the consolidated scores of all youtubers in the Kid's genre. As seen on *Table 5*, the consolidated regression still came up with the same coefficient for views at p-value = 0. Also, the subscription rate and the dummy variable pre is negative and have very insignificant p-values, meaning they are insignificant to earnings and their effects on each youtuber is highly variable with a given youtuber.

Table 5. Regression results for kids shows

totalearni~s	Coef.	Std. Err.	t	P >|t|
totalviews	.0011687	1.37e-11	8.6e+07	0.000
totalsubs	9.54e-09	2.01e-08	0.47	0.637
pre	-.0003573	.037409	-0.01	0.992
_cons	.0049593	.1173947	0.04	0.996

The same regression on the consolidated data of the Education genre and there have been similar answers wherein the total earnings increased by 0.0012 for every unit of increase of views, with a p-value of 0.00. The total subscription count and dummy variable pre also have very high p-values and therefore are not significant, but the dummy variable pre has a positive coefficient of 0.103.

Table 6. Regression results for education

totalearni~s	Coef.	Std. Err.	t	P >|t|
totalviewseduc	.0012183	2.11e-11	5.8e+07	0.000
totalsubseduc	-1.46e-10	2.00e-10	-0.73	0.468
pre	.0103222	.0251532	-0.41	0.682
_cons	-.0310462	.05333507	-0.58	0.562

Meanwhile, The gaming genre also shows similar results, only that the subscription p-value is the highest among the results, and the pre dummy variable having the negative coefficient of -0.0133 with p-value of 0.179.

Table 7. Regression results for gaming

totalearni~s	Coef.	Std. Err.	t	P >|t|
totalviewsgaming	.0012182	1.84e-11	6.6e+07	0.000
totalsubsgaming	8.06e-10	6.15e-09	0.13	0.896
pre	-.0133717	.0098731	-1.35	0.179
_cons	.0186694	.0192415	0.97	0.334

4. CONCLUSIONS

Similar to other social network sites on the internet, YouTube thrives on high engagement such as subscriber count, likes, views, and most importantly, comments. It is highly important to engage and respond to the comments left by viewers on a Youtuber's channel. Higher levels of exposure and popularity will lead to larger amounts of income from posting videos whereas lower engagement and interaction would lead to lower levels of exposure and popularity. If YouTube were to apply the remove engagement functions for children-related content, there is a risk of YouTubers never meeting the criteria and consequently, decreasing their monthly revenue from little to nothing.

In all regressions, there are no endogenous regressors that can hamper the regression model. Based on the results, views are still generally positive regardless of the policy changes. This means that people still watch their videos despite the disabling of the comment section and other changes. Moreover, youtubers, at least on their end, can still gain a following to earn revenue. This is evident when we examine the database and find that for most youtubers, their view count increased since the implementation of the new policy changes. Interestingly, the coefficients and p-value of all three genres are the same, despite having different values in the database. This could mean that viewers are not negatively affected by the disabling of other functions and might have made a positive effect on them. Hence, this may vindicate the intentions of YouTube of providing an accessible platform for children while shielding them from negative influences such as targeted advertisements. Following the implementation of the new policy, data from children's content is now treated differently. The company initiated new practices for children's content to address these problems, which is focused on the creation of a new shared responsibility for child protection.

However, it can be also seen that subscriptions rates are negative but are highly insignificant according to the p-value. This means that for some youtubers, the policy changes may have affected them but for others, it may not. Also, the dummy variable pre is negative for the kids and education genre while the gaming genre has a positive coefficient for pre but they all have high p-values, with the lowest among them being the gaming genre. This means that although the changes in policy guidelines did have an effect on youtuber earnings, its effects are really dependent on the youtuber. As can be seen in the top 3 youtubers of the kids genre, some benefitted while others did not.

5. LIMITATION AND RECOMMENDATIONS

As shown in the previous section, it would seem that whether the new policy guidelines positively or negatively affected the youtuber, is still dependent on the youtuber himself and the genre that he is considered in.

This basic research can suggest a few policy implications. First, it can be suggested that since it does not affect everyone negatively, then it could be suggested as a good measure to protect the rights and privacy of children while also not significantly affecting Youtuber welfare, at least for the genres studied. TV rating agencies can use this as a basis for preparing and controlling shows and movies meant for children. Lastly, this may shed more light on how significant changes of policies in social media can affect its members and users.

Due to time constraints, we were only able to survey the top 30 youtubers in the Kid's, Gaming, and Education genres according to SocialBlade. It would be more comprehensive to not only include more youtubers to the survey but also add more specific genres and subgenres to the dataset. Additionally, there was a cost constraint when gathering information for the database. What the researchers gathered from SocialBlade was merely the "free" information on the website but it actually offers more specific details such as daily analytics behind a subscription paywall. Therefore, it is recommended to avail the subscription to gain more information for the database.

Nevertheless, we must admit that when it comes to the issue of advertising and social media, the industry is virtually opaque for research. As stated before, earnings are not public and Youtubers may have alternate sources of income such as sponsorships, which are not included in this study. Very few youtubers and Youtube company officers are open to divulging any specific information on how the whole industry works, especially on earnings (Baculi, 2019). There is also an absence of academic articles concerning Youtube, save for those related to information dissemination and education.

Hence, it is also suggested to have a fact-finding research study to solve this gap of knowledge such as personal interviews and documentation before trying more regression models, not only to help define and expand the topic, but also to help explain the results after a regression. Future research should try to find more information on each youtuber to determine any factors that can further affect earnings or even views and subscriptions.

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