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Video quality downgrades in live-streaming: Net-neutrality Implications for platforms

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Abstract

This research aims to empirically estimate the actual impact on service end-users amid an emerging debate on net neutrality. Without net neutrality, internet service providers can require content providers to pay extra for their internet traffic usage. To save costs on network usage fees, Twitch, a live streaming platform, implemented a policy of limiting video quality (i.e., resolution of video), which is the form of an indirect cost to the users. Given that video quality is a critical factor in live streaming, we examine the effect of this policy on the behavior of the platform's users. The findings confirm that limiting video quality has a negative impact on both the suppliers and buyers of the platform, i.e., streamers and viewers. However, the effect is heterogeneous across channel popularity, as more popular channels have higher switching costs, making it challenging for users to switch platforms or leave easily.

Keywords: net neutrality, live streaming, video quality limitation, switching cost, difference-in-difference (DID)

1. Introduction

With the development of the Internet, the amount of content that can be consumed over the Internet has grown exponentially. This content diversification naturally leads to increased traffic on the Internet network, which is costly for Internet service providers (ISPs). ISPs have invested substantial amounts of capital in facilities and installed internet networks. ISPs claim that content providers (CPs) who have not contributed to the infrastructure investment use the property without sharing the cost. When looking at global internet traffic in 2022, the top six CPs (Facebook, Amazon, Google, Apple, Netflix, and Microsoft) account for nearly half of the traffic (Sandvine, 2022). With a few CPs consuming most of the internet traffic, ISPs would want to charge them extra. CPs, on the other hand, argue that the network is public infrastructure, like electricity or railroads, and that the interests of the public should be prioritized over the interests of specific companies. They further claim that ISPs charge internet users for their services, so asking CPs for additional usage fees is double billing.

This debate ultimately leads to the concept of net neutrality. Net neutrality means that all network operators and governments must treat all data on the Internet equally and not discriminate against any user, content, platform, equipment, or method of transmission. Without net neutrality, if CPs use too much internet traffic, as ISPs claim, they can arbitrarily block traffic or request CPs to pay extra for their usage. In particular, video streaming services, prominent users of internet traffic, which account for approximately 65% or more[1], are not safe from the net neutrality debate (Sandvine, 2022). Such an astronomical traffic usage burden on ISP has led a Korean ISP to file a lawsuit against Netflix over network usage fees, which shows the intensity of conflict between ISPs and CPs on net neutrality.

In the midst of this ongoing conflict between ISPs and CPs, a live streaming platform in South Korea has limited video quality (i.e., resolution of video) in order to reduce the cost of network usage fees. Twitch, one of the world's largest live streaming platforms, lowered the maximum video quality from 1080p (1920x1080) to 720p (1280x720) for Korean viewers starting September 30, 2022. They claim that "Twitch has consistently complied with local regulations and requirements in South Korea and has diligently paid all network fees and related costs. However, as the cost of providing our services becomes increasingly more expensive, Twitch must find *alternative* solutions to continue operating our services in South Korea." This is the reasoning behind the policy, and it is related to net neutrality.

Live streaming has emerged as a new form of entertainment and has become a widely utilized service even in e-commerce and education. With video streaming platforms supporting full-high-definition

[1] This is the amount of internet traffic that entire business uses for video streaming services.

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(1080p) video quality and even 4K (3840×2160) or 8K (7680x4320)[2], video quality has become a critical component of live streaming services. Although video quality becomes increasingly important and live streaming emerges as a new market, the network usage fees related to net neutrality issues are forcing platforms to make a buck-passing choice: limit video quality.

The announcement that the platform was implementing a video quality limitation policy came unexpectedly without any warning the day before the implementation. The announcement was a shock to the platform's users, both streamers and viewers, and no one knew what impact it would have on its users as video quality limitations had never been implemented before.

Using this exogenous shock, this study employs a difference-in-difference (DID) approach to measure the effect of the policy. Unfortunately, since the video quality limitation was enforced simultaneously for all users on the platform, finding a suitable control group remains difficult. Therefore, we adopt a method similar to Fang et al. (2020) and Sim et al. (2022), and take the previous year of the treatment group as a control.

Most of the previous research on the impact of video quality on viewers has been survey-based rather than empirical, so it is clear what we want to find out from this study. Using weekly streaming data from Twitch, a live streaming platform that has implemented a video quality limitation policy, we want to show how it affects viewers and streamers who use the platform.

Our results reveal that these video quality restrictions have a negative impact on both viewers and streamers. For viewers, the average number of viewers decreases by 34.9%, and the peak number decreases by 31.4% after video quality limitation. Streamers also have similar results to those of viewers. Streamers decrease their streaming hours by 20.9% and their number of streams by 9.4%. One noteworthy finding is that the impact of video quality restrictions differs depending on the popularity of each channel.

These results are significant in that this is the first empirical study of the impact of video quality on platform users and have theoretical implications in that we have identified the mechanism to some extent. Managerially, the heterogeneous effect of popularity can be utilized to help companies improve their cost performance and attract new users.

This study is also meaningful in terms of the debate on net neutrality. Previous studies on net neutrality have focused on who benefits and harms from the perspective of Internet service providers or content providers. However, there has been no research on how the net neutrality debate and resulting policies affect users who consume services, thus making this a major contribution as it is the first study of its kind. In addition, the heterogeneous effect of popularity in the absence of net neutrality shows that the additional cost burden of CPs is indirectly passed on to users, resulting in inequality where the rich get richer. This shows that the net neutrality debate should not only consider ISPs and CPs but also the platform ecosystem.

2. Literature review

2.1. Net Neutrality

The article introducing the term described net neutrality as "the basic principle behind a net neutrality is to give users the right to use non-harmful network attachments or applications, and give innovators the corresponding freedom to supply them."(Wu, 2003). In other words, it is a norm of the internet ecosystem that data traffic should be provided equally and without discrimination based on its type, content, platform, mode of transmission, and user.

The debate over net neutrality has been fiercely contested between ISPs and CPs. ISPs oppose net neutrality, arguing that content provided by CPs consumes a significant amount of internet traffic and should be paid for. CPs, on the other hand, are in favor of net neutrality, arguing that the Internet is a public asset that anyone can use and that anyone who connects to the Internet network should be able to use the service equally without limiting or blocking any content or traffic.

Although it has been several years since the U.S. Federal Communications Commission (FCC) abolished its net neutrality policy in December 2017, the debate on net neutrality continues and is an essential issue for policymakers. Previous research on net neutrality has focused on how the retention or abolition of net neutrality would affect ISPs and CPs in a game-theoretic model.

If net neutrality is abolished, CPs will have to pay additional fees to ISPs, which will significantly benefit ISPs and considerably harm CPs. In addition, from the perspective of ISPs' investment in social infrastructure, if net neutrality is maintained, infrastructure investment will be made at an optimal level, but if net neutrality is abolished, there is a risk of under- or over-investment in infrastructure (Cheng et al., 2011). Other studies have shown that when there is competition for both ISPs and CPs, ISPs are more profitable when net neutrality is abolished, consistent with previous studies, but for CPs, the results are interestingly different depending on

[2] https://blog.youtube/news-and-events/4k-live-streaming-live-has-never-looked/

dominance: dominant CPs are more profitable when net neutrality is abolished, while less successful CPs are more profitable when net neutrality is maintained (Guo et al., 2017).

Since video quality limitation is a policy introduced as an extension of network neutrality, we would like to examine the actual impact of such policies on platforms' users in the context of the net neutrality debate.

2.2. Visual Quality

Visual quality has a massive impact on viewer behavior. Especially the impact of image quality on viewers' perceived sense of presence has been widely researched in the related area. The term 'presence' can be described as the sensation of 'being there' that a viewer experiences, which is formed by the auditory and visual elements originating from the contents (Moon, 2014). The improved quality of images on television increased the level of presence over the same content, and this was represented by the credibility of the newscast. When the viewers were asked to measure the credibility of the newscast while watching TV, those who watched high-definition content rated the news as more credible than those who did not. Furthermore, the improved image quality may impact viewers' perceptions, such as a character's physical attractiveness, reality judgments, and the impact of the message on oneself (Bracken, 2006).

When we looked at the relationship between video quality and viewer engagement, the lower the video quality, the more likely viewers were to abandon a video, spend less time watching, and be less likely to revisit the same site (Krishnan & Sitaraman, 2013). Compared to VoD content, the average bitrate had a more significant impact on live content (Dobrian et al., 2013). Since the video quality utilized in those studies was mainly measured regarding network connection, such as startup delay, average bitrate, and buffering delay, it was difficult to identify direct video quality (resolution) effects that we wanted to address in this study.

A survey of multimedia content consumption via online streaming platforms revealed that video content was primarily consumed in Full-HD format (Falkowski-Gilski & Uhl, 2020), representing a resolution of around 1080p. Given that most consumers through live streaming platforms are consuming content with a resolution of 1080p (Full-HD), reducing video quality to a resolution of 720p (HD) might significantly impact reducing content consumption. Therefore, the first research question is proposed here,

RQ1: How does video quality limitation on live streaming platforms affect viewers' attitudes?

2.3. Live streaming

In the past, the term live streaming was simply a way to download and consume content simultaneously and had a high barrier to entry for individuals. However, as technology such as internet network speed and video quality has evolved, more and more people have been able to easily provide their own content via live-streaming, which has expanded live-streaming into a medium for delivering user-generated content (Sjoblom & Hamari, 2017). Unlike traditional television or one-way streaming services such as YouTube, live streaming is one of the new forms of multimedia entertainment in which viewers, as content consumers, and streamers, as content providers, interact with each other in real time. This interaction doesn't just happen between the viewer and the streamer but also between the viewers, making live streaming as a form of social media (Hilvert-Bruce et al., 2018).

Many people are interested in watching others do activities (such as playing computer games, traveling, or eating delicious food) rather than experiencing them themselves. Twitch, known as one of the largest live-streaming platforms in the world, was visited by an average of 31 million people nearly every day in 2022, with 21B hours of content watched (Twitch, 2022). This interest goes beyond just watching to commenting, liking, and higher engagement with monetary contributions and merchandise purchases.

In the existing media research on live streaming, there is a large body of research on what motivates viewers to consume and monetize such live-streaming content. Most studies argue that a stronger social and community basis is the primary motivation for viewers to consume live-streaming content (Gros et al., 2018; Gros et al., 2017; Hilvert-Bruce et al., 2018). Live streaming distinguishes itself by facilitating real-time interactivity between content creators and viewers. This dynamic interaction can foster social connections, which have been identified as a primary driver for engagement and consumption in live streaming. Beyond the socio-community appeal, other predominant motivations for live streaming consumption include the pursuit of information, the desire for entertainment, and the need for stress relief (Sjoblom & Hamari, 2017; Wohn et al., 2019).

On the streamer side, the motivation for live streaming is not much different from the viewer. The main motivations for streamers were boredom, socialization, the desire to belong to a specific group, communication, and fun (Friedlander, 2017; Zimmer & Scheibe, 2019). One of the key factors in continuous live streaming for streamers is the expectations they have of the platform. According to the united theory of acceptance and use of technology, performance expectancy is the strongest predictor when illustrating users' intentions (Pavlou, 2003). If the platform could meet the performance expectancies of the streamers, it could boost their intentions to continue their streaming (Zhao et al., 2018). However, there is little research on how creators are affected when their expectations of the platform are not met, so our second research question is as follows,

RQ2: How does video quality limitation on live streaming platforms affect streamers' attitudes?

2.4. Switching Cost

In the case of a streamer, they must create and share the content, so they are positioned as a provider (or supplier) in terms of content, but from a platform perspective, they are consumers who utilize the platform just like viewers. Just as viewers choose which streamers to view, streamers choose to stream on one of many different live streaming platforms, and they can move to another at any time. If a streamer wants to move from an existing platform to a new one, they must consider the switching cost.

Switching costs are the one-time costs that customers associate with the process of switching from one provider to another (Burnham et al., 2003). Previous research shows that consumers might be reluctant to leave their current provider due to high switching costs (Jones et al., 2002). In the context of blog services, consumers' decision to switch service providers is influenced negatively by satisfaction with the current service and sunk costs and positively by the existence of attractive alternatives. Especially, sunk costs include the irrecoverable time and effort invested in using the existing service. In the case of blog services, these sunk costs include the time and effort bloggers put into writing content, uploading photos, tagging items, filtering information, and linking resources to the Internet (Zhang et al., 2012). This is similar to live streaming services. The audience they've built up, the unique community and culture of their channel, their relationships with other streamers, and their streaming history can all be sunk costs for streamers using a live streaming service, and the more sunk costs they have, the harder it is to switch service providers. This sunk cost factor for live streaming will be more significant for more popular channels. Thus, the third research question is proposed here,

RQ3: How will the effect of video quality limitation be impacted differently depending on the channel's popularity?

3. Method

This section will provide the data used in this study and the model specification. On September 30, 2022, Twitch, one of the world's leading live streaming platforms, limited the maximum video quality from 1080p to 720p for South Korean viewers only. The announcement was a shock to viewers and streamers, as it was announced the day before. Given the sudden nature of this significant change, we aimed to employ a Difference-in-Differences (DID) methodology to discern the implications of this video quality limitation on both viewers and streamers.

3.1. Data

The data used in this study was crawled from a site[3] that collects records of streams on Twitch, including the average number of viewers, peak viewers, and stream duration at a daily level. Since the video quality limitation issue was targeted at Korean viewers, we limit our analysis to Korean-language streamers and initially collect data on 5,100 streamers from April 30, 2021, to April 27, 2023. From the analysis, we aggregate the daily streaming data of 5,100 streamers to weekly and exclude streamers who started live streaming after April 30, 2021, the start date of the data collection point. We also limit our analysis to channels operated by individuals, as there are channels on Twitch that organize esports, and the nature of these channels may differ from those operated by individuals (Sjoblom et al., 2019). As a result, a total of 2,701 unique streamers' live streaming data is used as the analysis for this study.

Table 1. Data description

Variable	Description	Number of Observations	Mean	Standard Deviation	Min	Max
Avg Viewers	Total daily average number of viewers in a week	280,904	1,013	4,656	0	183,599
Peak Viewers	Highest number of viewers in a week	280,904	394.9	1,790	0	103,431
Stream Hours	Total number of hours streamed during the week	280,904	26.59	20.67	0	203.8

[3] https://sullygnome.com/

Streams	The number of times streamer streamed in a week	280,904	4.686	2.267	0	7
Treated	1 if a year is the treated year, 0 otherwise	280,904	0.500	0.500	0	1
After	1 if a week of year is later than September 30, 2022 (October 1, 2021) for the treated year (the control year)	280,904	0.577	0.494	0	1

3.2. Econometric Models

To account for the growth and seasonality of live streaming, we compare each streamer's weekly streaming data to a similar week a year ago (Sim et al., 2022). The data period is divided into two one-year periods. The two one-year periods are each comprised of 52 weeks, with the first year from April 30, 2021, to April 28, 2022, and the second year from April 29, 2022 to April 27, 2023. In this setting, we employ the difference-in-difference (DID) approach to address the research questions of this study, using the first year as the control group and the second year as the treatment group. This can be expressed as

$$\ln(y_{ijt}) = \alpha_i + \beta_1 \cdot Treated_j + \beta_2 \cdot After_t + \beta_3 \cdot Treated_j \cdot After_t + \sum_t \delta_t + \varepsilon_{ijt} \quad (1)$$

$$\ln(y_{ijt}) = \alpha_i + \beta_1 \cdot Treated_j + \beta_2 \cdot After_t + \beta_3 \cdot Treated_j \cdot After_t + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \varepsilon_{ijt} \quad (2)$$

where $i = 1, 2, \ldots, n$ indexes of streamers; $j = 1, 2$ indexes of two one-year periods, $t = 1, 2, \ldots, 52$ indexes of the week of year, y_{ijt} is the dependent variable of this study (avg viewers, peak viewers, stream hours, streams) for streamer *i* in year *j*, and week *t*; $Treated_j$ indicates 1 if $j = 2$ (treatment group), 0 otherwise (control group); $After_t$ indicates 1 if week of the year *t* is later than September 30, 2022, when the video quality limitation began, 0 otherwise; The model also include streamer fixed effect (α_i), week-of-the-year dummy variable (δ_t), period dummy variable (γ_j), and ε_{ijt} is an error term clustered at the streamer level to take account of autocorrelation in the data (Bertrand et al., 2004).

We control the week-of-year fixed effect ($\sum_t \delta_t$) in equation (1), and streamer-specific period fixed effects ($\sum_i \sum_j \alpha_i \cdot \gamma_j$) and streamer-specific week-of-the-year fixed effects ($\sum_i \sum_t \alpha_i \cdot \delta_t$) in equation (2) for annual growth of streaming and seasonality. In both equations, β_3 captures the impact of video quality limitation in live streaming platform.

We want to utilize the DDD approach further to understand the mechanisms behind the impact of video quality limitation on streamers and viewers. Since previous studies on live streaming have analyzed viewer motivation by dividing the size of the channel, and the size of the channel represents the popularity of the channel, we construct the DDD term by adding the popularity of the channel as a variable (Hilvert-Bruce et al., 2018). The popularity of a channel is divided by the average number of viewers for each streamer before the start of the quality limit (before September 30, 2022). We categorize the popularity of channels into the top 1%, 5%, and 10% based on previous studies that show that the top 10% of streamers account for 95% of viewers (Kaytoue et al., 2012). This can be expressed as

$$\ln(y_{ijt}) = \alpha_i + \beta_1 \cdot Treated_j \cdot After_t + \beta_2 \cdot Treated_j \cdot After_t \cdot Top\_n_i + \sum_i \sum_j \alpha_i \cdot \gamma_j + \sum_i \sum_t \alpha_i \cdot \delta_t + \varepsilon_{ijt} \quad (3)$$

where Top_n_i indicates 1 if streamer *i* is the channel in top n%, 0 otherwise.

4. Result

4.1. Impact of video quality limitation on viewers and streamers

To examine how the video quality limitation affected both viewers and streamers, we analyze the average number of viewers and the peak number of viewers as dependent variables on the viewer side, and the total streaming hours and number of streams as dependent variables on the streamer side. As seen from Table 1 and Table 2, the coefficients of DID term (Treated x After) are negative and significant, and those coefficients remain unchanged across the models.

For viewers, the average number of viewers decreases by 34.9%, and the peak number decreases by 31.4% after video quality limitation. Streamers also have similar results to those of viewers. Streamers decrease their streaming hours by 20.9% and their number of streams by 9.4%.

These results indicate that video quality limitation on live streaming platforms negatively impacts viewers and streamers. The results show that this impact can lead to direct attitudes, such as viewers watching less and streamers reducing their streams or even leaving the platform.

Table 2. Estimation result of the impact of video quality limitation on viewers

Dependent variable:	ln(avg viewers)			ln(peak viewers)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.0135 (0.0264)	-0.0135 (0.0264)	Absorbed	0.00667 (0.0224)	0.00667 (0.0224)	Absorbed
After	-0.00536 (0.0189)	Absorbed	Absorbed	0.00316 (0.0160)	Absorbed	Absorbed
Treated x After	**-0.429***** **(0.0353)**	**-0.429***** **(0.0353)**	**-0.429***** **(0.0353)**	**-0.377***** **(0.0295)**	**-0.377***** **(0.0295)**	**-0.377***** **(0.0295)**
Constant	5.000*** (0.0173)	4.997*** (0.0122)	4.990*** (0.0102)	4.206*** (0.0147)	4.208*** (0.0103)	4.211*** (0.00851)
Streamer fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-the-year fixed effect	No	Yes	Absorbed	No	Yes	Absorbed
Streamer-specific growth fixed effect	No	No	Yes	No	No	Yes
Streamer-specific week-of-the-year fixed effect	No	No	Yes	No	No	Yes
Streamers	2,701	2,701	2,701	2,701	2,701	2,701
Observations	280,904	280,904	280,904	280,904	280,904	280,904
R-squared	0.533	0.533	0.806	0.549	0.550	0.811

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Estimation result of the impact of video quality limitation on streamers

Dependent variable:	ln(stream hours)			ln(streams)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.0275* (0.0158)	-0.0275* (0.0158)	Absorbed	-0.0486*** (0.00822)	-0.0486*** (0.00822)	Absorbed
After	-0.0185 (0.0116)	Absorbed	Absorbed	-0.0336*** (0.00612)	Absorbed	Absorbed
Treated x After	**-0.234***** **(0.0214)**	**-0.234***** **(0.0214)**	**-0.234***** **(0.0214)**	**-0.0991***** **(0.0115)**	**-0.0991***** **(0.0115)**	**-0.0991***** **(0.0115)**
Constant	2.967*** (0.0104)	2.956*** (0.00733)	2.942*** (0.00618)	1.671*** (0.00541)	1.651*** (0.00385)	1.627*** (0.00331)
Streamer fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-the-year fixed effect	No	Yes	Absorbed	No	Yes	Absorbed
Streamer-specific growth fixed effect	No	No	Yes	No	No	Yes
Streamer-specific week-of-the-year fixed effect	No	No	Yes	No	No	Yes
Streamers	2,701	2,701	2,701	2,701	2,701	2,701
Observations	280,904	280,904	280,904	280,904	280,904	280,904
R-squared	0.419	0.420	0.757	0.382	0.383	0.738

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.2. Popular vs. Unpopular

To understand the mechanisms behind the impact of video quality limitation on streamers and viewers, we focus on the channel's popularity. Based on the existing research that service platform users cannot easily switch service providers due to switching costs, we wonder what the switching costs are for streaming platforms.

For viewers, the most critical switching cost is probably the presence or absence of a favorite streamer. Viewers who regard social connections as a top motivator for watching live streaming will prioritize their favorite streamers and continue to consume the platform streamers use. For streamers, on the other hand, there will be various sunk costs for the live streaming platform. The audience they've built up, their channel's unique community and culture, their relationships with other streamers, and their streaming history can all be sunk costs for streamers using a live streaming service. This sunk cost will be higher for more popular streamers, and the higher the sunk cost, the higher the switching costs, making it more challenging to switch from one platform to another.

Table 4 shows the heterogeneous effects of video quality limitation on streamers, contingent on their channel's popularity. As the popularity threshold narrows from the top 10% to 1%, the DDD term (Treated x After x Top_n) increases in both streaming hours and the number of streams. This indicates that high-popularity channels experience a less pronounced effect of video quality limitation on their streaming behaviors. These heterogeneous effects are similarly observed among viewers when examined with respect to channel popularity. The results in Table 5 show that as the popularity threshold narrows, the DDD term (Treated x After x Top_n) tends to increase for both the average and peak viewers. These findings collectively indicate that while the imposition of video quality limitation has an adverse effect on both viewers and streamers, these effects tend to diminish for top-tier channels, likely due to the associated switching costs. Consequently, the video quality limitation appears to be nearly negligible for highly popular channels.

Table 4. Heterogenous effect of video quality limitation upon popularity for streamers

Dependent variable:	ln(stream hours)			ln(streams)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Top 1%	Top 5%	Top 10%	Top 1%	Top 5%	Top 10%
Treated x After	-0.237***	-0.245***	-0.245***	-0.101***	-0.105***	-0.104***
	(0.0216)	(0.0223)	(0.0232)	(0.0116)	(0.0119)	(0.0124)
Treated x After x Top_n	**0.261*** **	**0.225*** **	**0.112** **	**0.146*** **	**0.117*** **	**0.0513* **
	(0.0669)	**(0.0644)**	**(0.0542)**	**(0.0395)**	**(0.0338)**	**(0.0291)**
Constant	2.942***	2.942***	2.942***	1.627***	1.627***	1.627***
	(0.00618)	(0.00618)	(0.00618)	(0.00331)	(0.00330)	(0.00331)
Streamer fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-the-year fixed effect	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Streamer-specific growth fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Streamer-specific week-of-the-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Streamers	2,701	2,701	2,701	2,701	2,701	2,701
Observations	280,904	280,904	280,904	280,904	280,904	280,904
R-squared	0.757	0.757	0.757	0.738	0.738	0.738

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

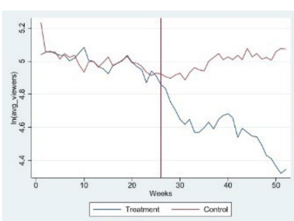
Table 5. Heterogeneous effect of video quality limitation upon popularity for viewers

Dependent variable:	ln(avg viewers)			ln(peak viewers)		
	(1)	(2)	(3)	(4)	(5)	(6)

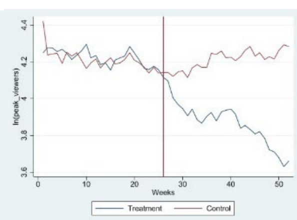
	Top 1%	Top 5%	Top 10%	Top 1%	Top 5%	Top 10%
Treated x After	-0.434***	-0.443***	-0.429***	-0.381***	-0.388***	-0.373***
	(0.0356)	(0.0363)	(0.0369)	(0.0297)	(0.0302)	(0.0306)
Treated x After x Top_n	**0.465****	**0.278***	**-0.00745**	**0.365***	**0.215**	**-0.0419**
	(0.216)	**(0.156)**	**(0.125)**	**(0.190)**	**(0.138)**	**(0.110)**
Constant	4.990***	4.990***	4.990***	4.211***	4.211***	4.211***
	(0.0102)	(0.0102)	(0.0102)	(0.00851)	(0.00851)	(0.00851)
Streamer fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-the-year fixed effect	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed	Absorbed
Streamer-specific growth fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Streamer-specific week-of-the-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Streamers	2,701	2,701	2,701	2,701	2,701	2,701
Observations	280,904	280,904	280,904	280,904	280,904	280,904
R-squared	0.806	0.806	0.806	0.811	0.811	0.811

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

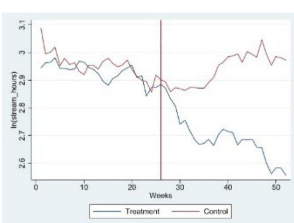
4.3. Robustness Check



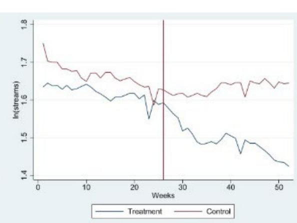
(a) ln(avg_viewers)



(b) ln(peak_viewers)



(c) ln(stream_hours)



(d) ln(streams)

Figure 1.Trend for dependent variables

Figure 1 presents the trends of viewers and streamers' behavior in the treatment and control group. We can observe that the treatment and control groups show parallel trends before the video quality restrictions were implemented. And after the video quality restrictions were implemented, we see a sharp decline in average viewers, peak viewers, streaming hours, and the number of streams. This confirms the validity of our main result, which was analyzed by empirically applying the difference-in-difference methodology.

5. Discussion

Research on net neutrality conducted until now has been primarily confined to ISPs or CPs, focusing solely on their interests without illuminating the actual impact on end users who utilize the service. As the policy of video quality limitation, which is the focus of this study, was introduced as an extension of net neutrality, this study can make a significant contribution to policymakers thinking about maintaining or abolishing net neutrality. In fact, Twitch, a live streaming platform, also introduced such a policy to save the cost of internet traffic required to provide high-quality video due to the costly burden of additional network usage fees in the Korean market. In other words, the content provider is passing on their substantial network usage fees to the user as an indirect cost in the form of degraded quality of service. As the first study to examine the impact on actual users of policies implemented by platforms to minimize the burden of additional costs for content providers if net neutrality is abolished, this study may have important implications for policy makers.

Furthermore, from the perspective of live streaming platforms, the implications of this research are indeed substantial. Most of the existing research on video quality on live streaming focuses on technical aspects, such as how to prevent video quality from stuttering (Li et al., 2014; Ozcelik & Ersoy, 2020) or how to evaluate video quality (Shang et al., 2023; Tu et al., 2021). Even for the few studies on the impact of video quality on users, most of them are based on surveys. This is the first study to empirically examine the impact of video quality on platform users. In the unique setting of a live streaming platform abruptly implementing a video quality limitation policy, this study examines the effects of this policy on the platform's users, both viewers and streamers.

The first research question examined the impact of this video quality limitation on viewers in terms of average and peak viewers, and the second research question examined the impact on streamers in terms of streaming hours and number of streams. The results showed that the issue of video quality limitation had a negative impact on both viewers and streamers. Viewers watched less, and streamers streamed less or left the platform.

This makes sense since video quality is the most important aspect of live streaming. However, what is interesting here is the heterogeneous effect between popular and unpopular channels, which we want to see in our third research question. When comparing the effect of video quality limitation on popular and unpopular channels, we find that the policy had a negative effect on unpopular channels, but canceled out on popular channels. This is because, as existing research explains (Zhang et al., 2012), for popular channels, switching costs are higher for streamers, making it harder for them to choose to switch platforms or cut back on streaming easily. Viewers are locked into their favorite streamers, meaning that if a streamer continues to stream on their existing platform, they will remain on that platform.

However, these heterogeneous effects can be interpreted as inequality at the platform ecosystem level, where the rich get richer. Therefore, it is necessary to expand the net neutrality debate to discuss how platform users will be affected in terms of platform ecosystems instead of just considering ISPs and CPs. On the other hand, these effects can be viewed differently from a management perspective. Since platforms cannot apply infinitely high video quality due to cost issues, the finding that popular channels show little negative effect may imply that such video quality limitation policies can be implemented differently depending on the popularity or as an incentive to attract new streamers.

However, there are some limitations to this study. First, video quality limitation is based on access IPs from South Korea, which is difficult to measure precisely because the data collected is only from Korean-language streamers' channels, not IP-based. Second, we do not have data on whether streamers moved to other platforms after the video quality limitation. Third, we obtain data at the channel level, which limits our ability to measure direct effects at the individual viewer level, such as which streamer's channel they watched and how often they watched it. Finally, since it was challenging to set a proper control group in the DID approach, we set the year before the treatment group as the control group and analyzed it.

Since live streaming is an emerging market, there is much room for further research. For example, in the context of this study, it would be interesting to measure the economic impact of this video quality limitation on platforms. For platforms, the costs associated with higher video quality increase exponentially, so limiting video quality to a certain extent while retaining users could result in cost savings. Another possible direction is to explore the heterogeneous effect among different devices. The effect of this quality limitation will vary depending on the device you are watching the stream on. Tablets and TVs with relatively large display sizes may be more affected by video quality limits, while mobile devices may be less affected. There is a lot of existing research on the effects of screen size, but none in the context of live streaming, so it would be interesting to see further research on the differences between devices based on screen size. From the perspective of net neutrality, it would be possible to calculate consumer/producer surplus based on the impact of CPs' policies on actual users and follow-up research on how much it would be reasonable to charge for network usage if net neutrality is abolished.

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