The Impact of Network Neutrality Violation on the Streaming Platform Ecosystem : Evidence from Twitch TV

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Abstract

The widespread use of media streaming services has resulted in a surge in network traffic, triggering debates on network usage fees between Internet service providers (ISPs) and content providers (CPs). As a response to network usage fees imposed by ISPs, CPs have opted to provide discriminatory service quality as a means of mitigating costs associated with high traffic volume. In 2022, a leading Korean ISP charged discriminatory network usage fees to Twitch TV, the media streaming platform, due to its excessive network traffic. In response, Twitch implemented a discriminatory service quality reduction policy. Our study examines the impact of this policy on the streaming platform ecosystem. Our results indicate that the implementation of the service quality reduction led to a remarkable decline in the number of viewers, which then resulted in adverse effects for streamers. This study contributes to the literature on network neutrality violation by offering empirical evidence.

Keywords: Network neutrality violation, network usage fee, traffic discrimination, live-streaming service

Introduction

The network neutrality has been a subject of debate between Internet Service Providers (ISPs) and Content Providers (CPs) who share an interest in the costs and payments associated with network traffic. As Internet traffic has increased globally, the debate over network neutrality between the two parties has intensified. In particular, online video streaming applications have recently generated the highest amount of global network traffic and have been occupied for the largest share of the traffic congestion especially during Covid-19 pandemic (Triviño et al., 2021). Due to the exponential development of Internet technologies and corresponding network traffic congestion, questions have arisen about whether network neutrality must be upheld.

As network traffic congestion intensifies, ISPs have attempted to share the costs of network infrastructure investment for traffic growth by imposing network usage fees on CPs. CPs may implement data traffic restriction policies that violate network neutrality to reduce the network costs imposed by ISPs. According to the principle of network neutrality, all data traffic on the Internet should be treated equally. It can be argued that providing restricted traffic to particular user groups for content services violates this principle. With the evolution of CPs into two-sided platforms, end-users within the platform are divided into two parties: service providers and consumers. Therefore, data traffic restriction policies can have various impacts those two parties of the end-users within CP platforms.

However, extant literature on network neutrality has primarily focused on the relationship between ISPs and CPs, but not on end-users using Internet services, especially on live streaming platforms that generate a significant amount of global traffic. Streaming content that generates large amounts of data traffic congests ISPs' network broadband. With advancements in technology, video streaming content is not only available in 4k UHD, but also in virtual technologies such as VR/AR. Since these streaming contents generate huge amount of data traffic, it is critical for the future of streaming platforms to investigate how data traffic restrictions impact end-users offering such content. Moreover, there is still a paucity of empirical research exploring the impact of network neutrality violations on platform end-users.

To fill this research gap, our research aims to comprehend the impact on end-users of live streaming platforms when network neutrality is violated. One of the largest live streaming platforms, Twitch TV, attempted to reduce costs by adjusting the maximum bitrate - the amount of data transferred in one second - from 6000 kbps to 4500 kbps for its streaming service in response to increasing network usage fees and service costs in South Korea. Therefore, end-users within the platform in South Korea experienced reduced streaming service quality due to the data traffic restriction policy compared to users in other countries. Since all end-users within the platform are providing or receiving services at unequal bitrates, this observed phenomenon can be considered as a violation of network neutrality.

Thus, given where network neutrality is violated, our study has several research questions. First, if CP platforms implement data traffic restriction policies in response to network usage fees imposed by ISPs, what impacts would the policies have on end-users and the ecosystem within CP platforms? Second, how would the impact of the data traffic restriction policies vary depending on the heterogeneity of service providers on the platform?

To investigate the effects of the network neutrality violation on end-users and ecosystem of CP platforms, we adopt a quasi-experimental approach using the difference-in-differences (DID) method. We collected datasets from Twitch TV before and after the implementation of the data traffic restriction policy. The empirical results indicate that the violation of network neutrality has adverse effects on the demand side of the live streaming platform ecosystem. In addition, the findings reveal that the effects of the network neutrality violation differ among both the demand and supply sides, depending on the heterogeneity of content providers.

Our research makes theoretical contributions to the IS research on network neutrality. First, our research examined the impact of the network neutrality violations on end-users within CP platforms. Second, our study offers empirical evidence by analyzing the situation where the network neutrality principle is not upheld. Finally, we find the adverse effects of network neutrality violations on participants in the livestreaming platform ecosystem.

Literature Reviews

Network Neutrality

The fundamental principle of network neutrality asserts that Internet service operators should treat all Internet communications equally without discriminating toward specific applications or services (Wu, 2003). Internet Service Providers (ISPs) provide access to the Internet, while Content Providers (CPs) create and provide content, including music, games, information, and entertainment services. Any network management practice discriminating against different types of Internet traffic data is considered a violation of network neutrality (Guo et al., 2013). The ongoing debate surrounding network neutrality violations arises from concerns that ISPs may exploit the principle of network management to discriminate against CPs.

With the significant increase in global Internet traffic, however, the debate regarding network neutrality between ISPs and CPs has escalated. Especially during the pandemic period, the Internet traffic has surged ever before (Triviño et al., 2021) and ISPs have faced challenges in accommodating the increasing network traffic, thereby resulting in imposition of network usage fees on CPs. In this context, the mainstream of research on network neutrality has been extensively studied about the discriminatory pricing of the two-sided market between ISPs and CPs (Economedies & Tåg, 2012; Guo et al., 2013; Guo & Easley, 2016; Guo et al., 2017; Somogyi, 2017; Li & Hou, 2020). Guo et al. (2013) found that network management options maximize social welfare under specific market conditions and the options are categorized as "reasonable network management". According to Economedies and Tåg (2012), even in the existence of some competition, the regulation of network neutrality will increase the total surplus. Based on econometrics model for network neutrality with two-sided markets suggested by Economides and Hermalin (2012), Network neutrality would be welfare superior to any implementable price-discrimination scheme for prioritization. Guo et al. (2017) analyzed discriminatory pricing incentives of ISPs under competitive conditions of ISPs and CPs. Li and Hou (2020) argued that the introduction of non-neutral network pricing can lead carrier platforms (i.e., ISPs) to lower the traffic price, due to the presence of cross-network externality. Somogyi (2017) contended that zero-rating by a monopolistic ISP could benefit consumers if content provided by CPs is attractive, whereas it may decrease social welfare. Altman et al. (2013) claimed that implementing side payment along with usage-based pricing leads to significant degradation of performance for all players in markets. Although price discrimination policies by ISPs may sometimes enhance social welfare (Bandyopadhyay & Cheng, 2006; Edell & Varaiya, 1999; Hermalin & Katz, 2007), most of the policies discussed by the authors of those studies are based on traffic speed rather than based on usage.

In related studies, there is also ongoing discussion about the impact of network neutrality violation not only on the social welfare but also on the innovation of ISPs and CPs. Some negative views exist that regulating network neutrality could lead to lower content innovation of CPs and network investments from ISPs (Hermalin & Katz, 2007; Bourreau et al., 2015). However, Bourreau et al. (2015) questioned that ISPs may have incentives to sabotage the non-priority lane to earn more revenues from CPs. There also exist studies that have opposing views on network investments and content innovation. Cheng et al. (2011) analyzed social welfare and incentives to expand the capacity of the existing network infrastructure using game theoretical model when network neutrality is abolished. They argued that ISPs always invest in broadband at the socially optimal level under network neutrality. According to Economides (2008), growing prices through two-sided pricing will not contribute to network growth and the abolition of network neutrality could have substantial adverse effects on innovation on the Internet. Guo and Easley (2016) demonstrated that under network neutrality, content innovation increases through the pro bono innovation zone effect and the cross-side congestion effect. Choi and Kim (2010) suggested that a positive relationship between network neutrality regulation and investment incentives for network managers.

The challenge in regulating network neutrality is to establish a framework that can determine how reasonable network management practices in a complex and evolving markets (Stocker et al., 2020). As CPs have transformed into two-sided platforms with service providers and consumers, the ecosystems between CPs and ISPs, as well as within CP platforms have undergone significant changes from the past. Because CPs have transformed into platforms and end-users within CP platforms have become heterogeneous, the issue of network neutrality violation and discriminatory pricing have become even more complex. However, there has been little research on network neutrality within these platforms.

Furthermore, most of the research on network neutrality has been conducted through analytical modeling, hence there is a lack of empirical studies. Layton (2017) empirically studied the impacts of network neutrality policies of EU countries on mobile application ecosystem and found that content innovation decreased in countries that enforced regulations with hard network neutrality rules. Briglauer et al. (2022) estimated the impacts of implementation of network neutrality regulation on fiber investments using the share of the population voting for left-wing parties as an instrumental variable. Lee and Kim (2014) conducted an empirical analysis through survey in South Korea to examine incentives of ISPs to discriminate against CPs. While these studies provide empirical evidence on the effects of network neutrality on ISP's discriminatory incentives and CPs' content innovation, there are few studies that investigate the end-user within platforms and the ecosystem of those platforms.

Online Live Streaming

Online live streaming platforms are considered as two-sided platforms with streamers and viewers. These platforms allow streamers to broadcast themselves playing video games, eating food, singing, painting or whatever they want and viewers to communicate in real-time (Hilvert-Bruce et al., 2018), but the most popular categories are usually video gaming content and electronic sports (i.e., E-sports) (Smith et al., 2013). One of the main characteristics of live streaming is that it enables to facilitate a two-way connection between streamers and viewers. Streamers can directly respond to viewers' engagements, and viewers can actively engage in the live stream (Sjöblom & Hamari, 2017). Due to this trait, live streaming stands as one of the largest traffic generators for online content. Over the past few years, live streaming systems have been generating a significant amount of Internet traffic (Pires & Simon, 2015).

The primary focus of studies on online live streaming has been about viewer motivation and engagement. Zhao et al. (2021) studied the effects of viewership group size on viewer engagement. Simonov et al. (2023) examined viewers' utility preferences depending on entertaining information using E-sports tournaments data on live streaming platforms. Kunigita et al. (2023) analyzed subscription-gifting behavior of viewers on live streaming platforms. Contrary to the research from the viewer perspective, studies from the streamer perspective have also been conducted on the streaming behavior (Wollborn et al., 2023), spillover effects by switching streaming contents (Zhao et al., 2022), In-consumption information cues of video on demand (VoD) from live streaming videos (Sim et al., 2021), and communication interactivity by heterogeneity across streamer characteristics (Choi et al., 2022). In addition, Larkey (2015) studied the problem of copyright infringement on live streaming platforms.

Sjöblom and Hamari (2017) and Zhao et al. (2019) investigated viewers' motivations for consuming online live video gaming content using the Uses and Gratification Theory (UGT). They suggest that individuals choose certain streaming content rather than others, depending on the satisfaction or gratification it provides. UGT categorizes needs into five categories: Cognitive, Affective, Personal Integrative, Social Integrative and Tension Release. Data traffic restrictions may lead to a reduction in video quality. This can hinder the delivery of information, which can reduce viewers' cognitive motivation. Furthermore, video dynamics may be hindered as fewer bits are transmitted per second, decreasing the entertainment value of streaming content. This, in turn, can reduce the viewer's affective motivation. However, data traffic restrictions may not affect social integrative motivation. One of the major features of live streaming is real-time interaction between streamers and viewers, and thus video quality reduction may not directly affect the interaction itself.

However, there is still a lack of research on network neutrality related to online live streaming. Botta et al. (2016) argued that CPs may violate network neutrality to provide a better service compared to other CPs on video streaming services. In fact, some live streaming platforms have been implementing traffic prioritization services that violates the principle of network neutrality to avoid traffic congestion. Tudon (2022) studied the impact of prioritization on congestion, content provision, and consumer welfare with congestion models and empirical analysis using Xbox shocks on Twitch. Based on the findings, network neutrality may lead to a reduction in the variety of content provision and harm consumer welfare, but it can also promote the entry of smaller providers and prevent discriminatory prioritization. On the other hand, the increase in data traffic caused by network neutrality generates congestion externalities. This means that network managers can avoid congestion and improve the quality of high-bandwidth services by prioritization. While this study focuses on traffic prioritization, our study investigates the impact on the online live streaming platform ecosystem where network neutrality is violated due to the traffic restriction policy, providing lower service quality to specific end-users by CP platforms.

Institutional Background

Federal Communications Commission (FCC) in the U.S. introduced Open Internet Rules to prohibit ISPs from blocking or discriminating consumers' Internet access and preserve the network neutrality in 2010. However, ISPs have attempted to impose network usage fees on CPs to share the increased network costs. A well-known example is disputes between Netflix and Verizon. The dispute arose when Verizon demanded additional network usage fees to Netflix that provided streaming services through Verizon's network. Verizon argued that Netflix's streaming services were using high network bandwidth and it was congesting Verizon's network[1]. Additionally, the existing literature related to network neutrality have discussed various disputes between ISPs and CPs such as the conflict between Netflix and Verizon (Crocioni, 2011; Byun & Lee, 2013; Faris et al., 2015). As discussed in past studies, the conflicts between ISPs and CPs are a global issue that remains as a challenge to be solved.

Byun and Lee (2013) studied on controversial issues related to network neutrality regulations in South Korea. According to Cloudflare, a global content delivery network company, South Korea is the only country where the bandwidth costs are increasing and the costs are 15 times higher compared to Europe or North

[1] T.C. Sottek 2014, March 21. "Netflix blasts Comcast and Verizon on net neutrality: 'some big ISPs are extracting a toll'," *The Verge*. https://www.theverge.com/2014/3/20/5530898/netflix-blasts-comcast-and-verizon-on-net-neutrality-some-big-isps

America.[2] Due to the expensive network usage fees in Korea, there have been several disputes between giant global CPs and Korean ISPs. Representative examples include the lawsuit between Netflix and SK Broadband[3], a leading Korean broadband service provider.

Expensive network usage fees charged by ISPs may lead CPs to restrict data traffic, resulting in low-quality service for end-users. One example is the network usage fee dispute between Facebook and Korea Telecom, a tier 1 ISP in South Korea[4]. Due to the change of Korea's network-sharing regulations in 2016, the cost burden of KT, which was receiving data traffic from Facebook, increased. KT requested additional fees from Facebook, and Facebook diverted its existing connection to Hongkong to reduce data traffic to South Korea. By rerouting data traffic overseas, end-users' internet access was slowed down, and this case eventually led to investigation by the South Korean government into Facebook's discriminatory service offerings, invoking the principle of network neutrality.

The high cost of maintaining servers also led some CPs to control data traffic by reducing the quality of service. Dorama Korea, a small and medium-sized OTT streaming platform in South Korea, has adjusted the quality of its content from 1080p to 540p due to a huge increase in usage. While this case may not have been linked to discriminatory network charges by ISPs, it shows that high network costs can force streaming platforms to adjust the quality of their services. ISPs charging discriminatory network usage fees to certain CPs, which violates network neutrality, compel CPs to adjust their traffic. Consequently, CPs restrict data traffic to end-users, which also violates network neutrality.

Amazon's live streaming platform, Twitch, has also struggled with high network costs in South Korea. Moreover, in South Korea, a regulation was proposed to allow Korean ISPs to charge discriminatory network usage fees to CPs that use excessive network traffic including global CPs such as Amazon, YouTube, and Google[5]. In response to excessive network fees, Twitch implemented a policy that adjusts the maximum bitrate from 6000 kbps to 4500 kbps, decreasing the streaming quality for Korean viewers from 1080p to 720p resolution. The quality of video on live streaming has significant effects on user engagement (Dobrian et al., 2011). Especially for gaming content, video quality such as video resolution is even more critical than non-gaming content because video game is high-motion content (Shang et al., 2021). On the other hand, Kara et al. (2019) found no significant difference in viewers' subjective scores for UHD (4k) and HD (1080p) when experimenting with no labels for video quality. Van Wallendael et al. (2016) argued that the perceived video quality depends on the video content, as it is difficult to detect high resolution in a smoothing background, low light environment. The impact of bitrate reduction on viewership remains an empirical puzzle.

Therefore, we empirically analyze the impact of network neutrality violations on end-users of the live streaming platforms, utilizing Twitch's case of implementing the discriminatory policy that reduces video quality due to network usage fees.

Empirical Methods and Results

Data

Twitch is the world's largest online live streaming platform. The number of average concurrent views on Twitch had 2.58 million and the number of streamers reached 7.6 million in 2022. Twitch currently holds the largest market share in terms of either total hours watched, or total hours streamed among live streaming platforms (i.e., YouTube Gaming Live, Facebook).[6] In this research, we utilize the event of Twitch's data traffic restriction policy as the treatment event (i.e., exogenous shock). This treatment was

[2] Rao, N. 2016, August 18. "Bandwidth Costs Around the World," *CloudFlare*. https://blog.cloudflare.com/bandwidth-costs-around-the-world

[3] Ryoo, K. H., Park, J. E., and Kim, D. I. 2021, July 5. "Korean court ruling over a network usage fee dispute between Netflix and SK Broadband," *Chambers and Partners*. https://chambers.com/articles/korean-court-ruling-over-a-network-usage-fee-dispute-between-netflix-and-sk-broadband

[4] Kim, J. H. 2019, October 1. "Facebook inks network usage deal with KT," *Korea JoongAng Daily*. https://koreajoongangdaily.joins.com/2019/10/01/industry/Facebook-inks-network-usage-deal-with-KT/3068565.html

[5] Yoon, S. Y. 2022, November 1. "Tumultuous network usage fee debate is clear as mud as public sentiment turns," *Korea JoongAng Daily*. https://koreajoongangdaily.joins.com/2022/11/01/business/tech/Korea-network-usage-fee-Google/20221101172720310.html

[6] May, E. 2021. "Streamlabs and Stream Hatchet Q4 Live Streaming Industry Report," *Streamlabs Blog*. https://blog.streamlabs.com/streamlabs-and-stream-hatchet-q4-live-streaming-industry-report-a898c98e73f1

implemented on September 30, 2022, and Twitch notified this only two days before the event on September 28, 2022, without any prior notice. Due to this sudden notification, we assume that there was no anticipation of the event for users on the platform. To investigate the effects of this treatment, we collected streaming session-level data for Twitch streamers ranked within the top 2,500 in each of the top 10 languages used on the platform, including Korean which was ranked seventh, using Twitch's API and a third-party website, twitchtracker.com (https://twitchtracker.com/). The data covered the period from June 2022 to October 2022[7], and was aggregate into weekly data, resulting in a balanced panel dataset comprising a total of 5,643 unique streamers over 22 weeks. Table 1 shows the descriptive statistics and definitions of key research variables.

VARIABLE (N= 124,146)	**Mean (Std. Dev.)**	**Min. (Max.)**	**Description**
Dependent Variables			
Concurrent_View$_{it}$	538.727 (1,672.530)	6 (110,366)	Average concurrent views of sessions by a streamer *i* in week *t*
Stream_Duration$_{it}$	327.222 (211.087)	11 (3306.667)	Average streaming time of sessions by a streamer *i* in week *t* (in minutes)
Independent Variables			
Treat$_{i}$	0.176 (0.381)	0 (1)	1 if streamer *i* belongs to the treatment group (i.e., Korean streamers) 0 otherwise
Post$_{t}$	0.227 (0.419)	0 (1)	1 if week *t* is after September 30, 2022 0 otherwise
Control Variables			
Channel_Age$_{it}$	1,958.398 (1,063.308)	12 (5,560)	Number of elapsed days (at week *t*) since streamer *i* launched the first streaming
Session_Game&Chat$_{it}$	0.941 (0.200)	0.0 (1.0)	A ratio of games and just chatting genre that streamer *i* streamed at week *t*
Session_Game$_{it}$	0.656 (0.426)	0.0 (1.0)	A ratio of games genre that streamer *i* streamed at week *t*
Session_Chat$_{it}$	0.113 (0.271)	0.0 (1.0)	A ratio of just chatting genre that streamer *i* streamed at week *t*
Session_Game_Popular$_{it}$	0.227 (0.382)	0.0 (1.0)	A ratio of popular games in Korea that streamer *i* streamed at week *t*
Streamer_Game$_{i}$	0.856 (0.351)	0 (1)	1 if streamer *i* is game-oriented, 0 otherwise
Streamer_Chat$_{i}$	0.102 (0.303)	0 (1)	1 if streamer *i* is talk/chat-oriented, 0 otherwise
Streamer_Other$_{i}$	0.041 (0.199)	0 (1)	1 if streamer *i* is oriented to other genres (i.e., Music, Food, Painting), 0 otherwise
Streamer_Top10$_{i}$	0.122 (0.327)	0 (1)	1 if streamer *i* belongs to streamers in the top 10 percent of views, 0 otherwise
Streamer_Virtual$_{i}$	0.119 (0.324)	0 (1)	1 if streamer *i* streams using a virtual avatar, 0 otherwise
Streamer_Partner$_{i}$	0.673 (0.469)	0 (1)	1 if streamer *i* is a streamer who signs "Partner" contract with Twitch 0, otherwise
Streame_ Affiliate$_{i}$	0.308 (0.462)	0 (1)	1 if streamer *i* is a streamer who signs "Affiliate" contract with Twitch 0, otherwise

Table 1. Descriptive Statistics of Research Variables

To measure the effects of the treatment, we utilized the average number of concurrent views (*Concurrent_View*$_{it}$) and the duration of each streaming session (*Stream_Duration*$_{it}$) as the dependent variables. These variables represent the demand-side and supply-side of the live streaming platform, respectively. By leveraging these variables, we investigate how the ecosystem of the platform is affected by the implementation of discriminatory traffic policies.

We collected date on when individual streamers' channel was created and calculate the number of elapsed days (*Channel_Age*$_{it}$) to control for streamer maturity. The key determinant of success in live streaming is the content being broadcasted. Thus, we tracked and recorded the genre of each streaming session broadcasted by individual streamers on a daily basis. As Twitch primarily specializes in gaming content, we collected the titles of each game from IGDB (https://www.igdb.com/), a Twitch-owned website providing

[7] These ranking were determined by third-part websites. Regardless of the reliability of the ranking criteria, we assume that almost all active streamers during the treatment period were include within the top 2,500.

game-related information. Twitch categorizes the content of streaming sessions by genres. While the majority of genres is games, there are also talk/chat-oriented steaming sessions categorized as "Just Chatting", music streaming sessions categorized as "Music" and so on. Accordingly, we used those categories to distinguish each session by genres. From our initial observation, we found that most streamers alternated between streaming "Games" and "Just Chatting". Thus, we separated sessions where the streamer only streamed game ($Session\_Game_{it}$), just chatting ($Session\_Chat_{it}$), or both ($Session\_Game\&Chat_{it}$). In addition, we classified the most popular games during the given period in Korean Twitch ($Session\_Game\_Popular_{it}$). Using these variables, we further created variables that indicate whether the streamer broadcasts their sessions based on games ($Streamer\_Game_i$), just chatting ($Streamer\_Chat_i$), or other genres ($Streamer\_Other_i$).

The dataset includes different types of Twitch streamers including "Partner", "Affiliate", and "Normal". These three types vary depending on the monetary contract between Twitch and the streamers. Partner type streamers ($Streamer\_Partner_i$) are the most beneficial regarding advertising revenue and membership fees, while affiliate type streamers ($Streamer\_\ Affiliate_i$) have no benefit for commissions from Twitch and normal type streamers do not receive any revenue at all. Finally, to measure the heterogeneity of streamers, we created a variable to distinguish virtual streamers from regular streamers. "Virtual streamers" refer to streamers who use a digital avatar or an animated character to broadcast without revealing their real appearance. This is a growing online entertainment trend especially on live streaming platforms. We measured whether specific words related to "virtual streamer" ($Streamer\_Virtual_i$) were included in the streamers' channel tags.

Empirical Analysis

Our main model utilizes the DID design to examine the impact of network neutrality violation on users' viewership and streamers' activities. Specifically, our treatment event is the beginning of Twitch's service quality reduction policy on September 30, 2022. As the treatment treated on viewers only in South Korea and viewers in the other countries were not treated, we assume that most untreated viewers do not speak Korean and thus, streamers whose language is Korean broadcast mostly to the viewers who are treated by the policy. Following these assumptions, the treatment affects not only viewers in Korea but also streamers whose language is Korean. Accordingly, we chose Korean streamers as the treatment group and the other streamers using foreign languages as the control group. Since official E-sports streaming channels are broadcasted in Korean but may have international viewers, we excluded E-sports broadcasters to separate the actual treatment group.

Model Specification

Since the DID design requires the parallel trend assumption, we checked whether the trends of the treatment and the control groups in the pre-treatment period are parallel.

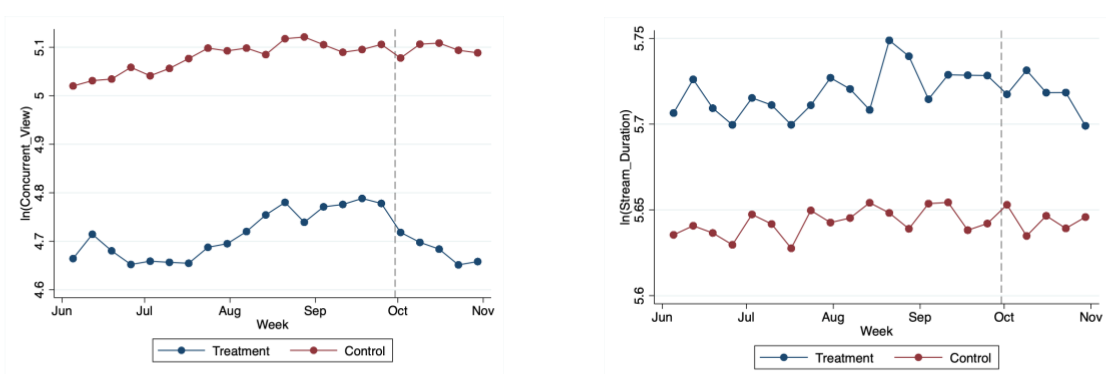

Figure 1. Trend Graph Before Matching

As presented in Figure 1, we failed to find clear parallel trends in the pre-treatment period. This may be due to the different popularity of streaming content across countries. Therefore, we utilized propensity score matching (PSM) to match the treatment group with the control group based on average viewership, streaming time, channel age, and content of streaming sessions during the pre-treatment period. Figure 2 presents the parallel trend between the treatment and control groups in the pre-treatment period. Next, we analyze differences between the two groups by comparing mean of each covariate in the pre-treatment period. From Table 2, there were significant differences for all covariates between two groups in the pre-treatment period. However, we find that there are no differences in the mean of covariates between the two groups after PSM. We assume that our treatment and control groups are balanced well during the pre-treatment period and therefore, follow the parallel trend assumption.

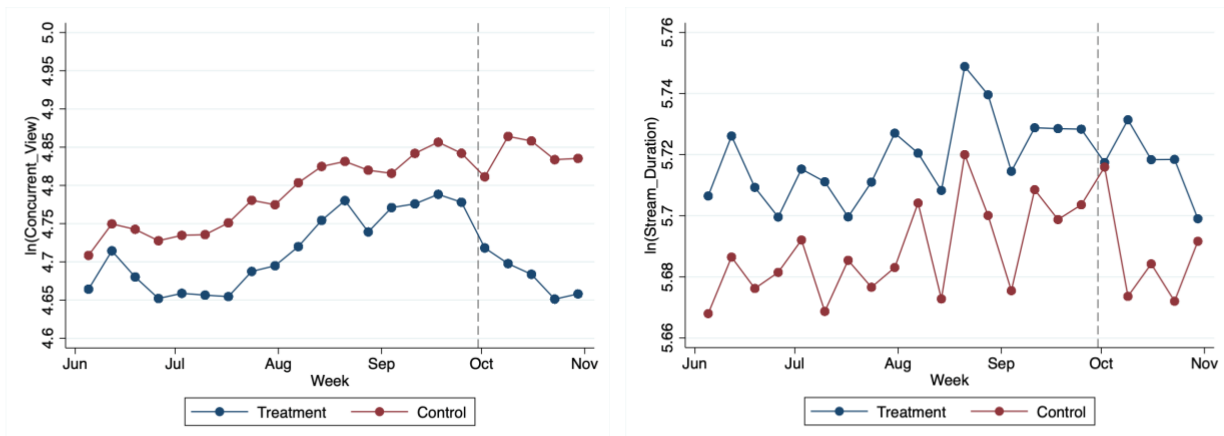

Figure 2. Trend Graph After Matching

		Before Matching		After Matching	
Variables	**Treatment Mean (Std. Dev.)**	**Control Mean (Std. Dev.)**	**Difference (t-value)**	**Control Mean (Std. Dev.)**	**Difference (t-value)**
Observations	995	4,648		705	
ln(Concurrent_View$_{it}$)	4.72 (.042)	5.09 (.021)	0.36*** (7.32)	4.78 (.055)	0.06 (1.0)
ln(Stream_Duration$_{it}$)	5.72 (.012)	5.64 (.006)	-0.08*** (-5.11)	5.68 (.017)	-0.04 (-1.49)
Channel_Age$_{it}$	1,524 (25)	2,030 (16)	506*** (13.86)	1,584 (39)	60 (1.34)
Session_Game&Chatt$_{it}$	0.91 (.006)	0.95 (.002)	0.04*** (5.52)	0.92 (.008)	0.01 (.49)
Session_Chat$_{it}$	0.17 (.009)	0.10 (.003)	-0.07*** (-8.61)	0.16 (.011)	-0.01 (-.17)
Session_Game$_{it}$	0.49 (.014)	0.69 (.006)	0.20*** (14.75)	0.53 (.015)	0.04 (1.88)
Session_Game_Popular$_{it}$	0.29 (.012)	0.20 (.005)	-0.09*** (-7.52)	0.27 (.014)	-0.02 (-.84)
Streamer_Game$_{i}$	0.76 (.014)	0.88 (.005)	0.12*** (9.97)	0.77 (.015)	0.01 (.085)
Streamer_Other$_{i}$	0.06 (.008)	0.04 (.003)	-0.02*** (-3.99)	0.05 (.008)	-0.01 (-.64)
Streamer_Virtual$_{i}$	0.22 (.013)	0.10 (.004)	-0.12*** (-11.4)	0.19 (.014)	-0.03 (1.63)
Streamer_Partner$_{i}$	0.49 (.016)	0.71 (.007)	0.22*** (13.47)	0.52 (.018)	0.03 (1.29)
Streame_ Affiliate$_{i}$	0.45 (.016)	0.28 (.007)	-0.17*** (-11.16)	0.43 (.018)	-0.02 (-.71)
Note : *** p<0.001, ** p<0.01, * p<0.05					

Table 2. Balance of Covariates in the pre-treatment period

Then, we employed the DID specification to identify the treatment effects:

$$Y_{it} = \alpha + \beta_1 Post_t + \beta_2 Post_t \times Treat_i + \beta_3 Control_{it} + \delta_t + \gamma_i + \varepsilon_{it} \quad (1)$$

where Y_{it} represents the dependent variable, which is either the log of the average concurrent views of a session (i.e., ln($Concurrent\_View_{it}$)) and the log of the average streaming time of a session (i.e., ln($Stream\_Time_{it}$)) made by streamer i at week t. $Treat_i$ is an indicator that takes a value of one if a streamer belongs to the treatment group. $Post_t$ is an indicator that takes a value of one if the observation week is after the treatment event. $Treat_i$ * $Post_t$ is a standard DID term indicating whether a streamer belongs to the treatment group and streamed after the treatment event. γ_i and δ_t are streamer- and week-specific fixed effects, respectively. $Control_{it}$ is a vector of control variables including session genres and $Channel\_Age_{it}$. Finally, ε_{it} is an unobserved error term.

To examine the dynamic treatment effect over time, we extend the DID model to a relative time model. Furthermore, the relative time model estimates the treatment effect over both the period before and after the treatment, allowing us to check the parallel trend assumption. If there is no significant difference between the treatment group and the control group before Twitch's traffic discrimination policy, we can assume that the two groups follow a parallel trend in the pre-treatment period. Therefore, we used the relative time model specification as follows:

$$Y_{it} = \alpha + \Sigma Rel\_Time_t \times Treat_i + \beta_3 Control_{it} + \delta_t + \gamma_i + \varepsilon_{it} \quad (2)$$

This model uses Rel_time_t as a vector of time dummy variables instead of $Post_t$. We set the baseline a week prior to the treatment ($Rel\_Time(t\text{-}1)_t$) and create time dummies for every five period before and after the baseline. The time dummy, $Rel\_Time(t\text{-}5+)_t$, indicates the time period from t = 1 to t - 5. Thus, the dynamic treatment effects are represented by ΣRel_Time_t, which is a vector of coefficients for each time dummy.

Estimation Results

	(1) **ln(Concurrent_View$_{it}$)**	(2) **ln(Stream_Duration$_{it}$)**
Post$_t$	-0.674 (0.429)	-1.094** (0.376)
*Treat$_i$ * Post$_t$*	-0.089*** (0.018)	0.011 (0.010)
ln(Stream_Duration$_{it}$)	0.240*** (0.012)	
ln(Concurrent_View$_{tt}$)		0.159*** (0.010)
Session_Game&Chatting$_{it}$	-0.061* (0.026)	0.143*** (0.027)
Session_Game$_{it}$	0.084*** (0.019)	-0.160*** (0.015)
Session_Chat$_{it}$	0.065** (0.021)	-0.412*** (0.019)
Session_Game_Popular$_{it}$	-0.151*** (0.020)	0.089*** (0.015)
Channel_Age$_{it}$	0.005 (0.003)	0.007** (0.003)
Constant	-4.586 (4.396)	-6.218 (3.867)
Individual Streamer FE	Yes	Yes
Time(Week) FE	Yes	Yes
Robust SE	Yes	Yes
Number of Clusters	1700	1700
R^2	0.062	0.092
Observations	37,400	37,400
Note: Clustered standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.		

Table 3. Estimation Results of Main Effects

We estimated the DID model and the estimation outcomes are presented in Table 3. Column (1) presents the causal effects of the network neutrality violation on the average concurrent views. This shows that when the CP (i.e., Twitch TV) implemented the traffic-discriminatory policy to reduce network usage fees, the average concurrent views of streaming sessions decreased by approximately 8.5%. Despite our findings on the average concurrent views, we do not observe significant effects on the streaming duration of streaming sessions.

To further evaluate how the effects change according to the heterogeneity of streamers, we re-estimate the main model using different types of streamers. We grouped streamers into four categories, namely streamers (1) offering game-related content, (2) listed in the top 10% charts, (3) using virtual characters or avatars streamers, and (4) partnered with Twitch. Column (1) in Table 4 indicates that the platform's discriminatory degradation of video quality resulted in a 10.1% decrease in average concurrent views for game-focused streamers, while non-game streamers did not have a significant effect (see Column (2)). The top 10 percent of streamers do not show a statistically significant effect of the discriminatory policy (see Column (3)). However, we find that the policy significantly reduced the average concurrent views of the remaining 90% streamers by 8.4% (see Column (4)). Interestingly, streamers using virtual characters are not affected by the discriminatory policy, but the average concurrent views of non-virtual streamers are significantly reduced by 9.9% (see Column (5)). Finally, partner streamers, who earn economic profits from Twitch, experienced a 7.6% decrease in average concurrent views due to the policy (see Column (7)), while non-partner streamers, who receive relatively fewer economic benefits, experienced a 9.8% decrease in average concurrent views (see Column (8)).

Contrary to the estimation results of main effects, we find that the discriminatory policy has a significant impact on streaming duration in a certain group. As shown in Column (8) of Table 4, non-partner streamers had a 3.9% longer streaming duration compared to partner streamers.

ln(Concurrent_View$_{it}$)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Post$_t$	-1.070* (0.454)	0.578 (1.045)	0.090 (2.005)	-0.814* (0.399)	0.079 (1.190)	-0.906* (0.443)	-0.582 (0.703)	-0.708 (0.488)
*Treat$_i$ * Post$_t$*	-0.106*** (0.021)	-0.040 (0.036)	-0.095 (0.060)	-0.088*** (0.018)	-0.047 (0.037)	-0.104*** (0.020)	-0.079** (0.026)	-0.103*** (0.024)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.069	0.056	0.026	0.074	0.089	0.063	0.046	0.095
ln(Stream_Duration$_{it}$)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Post$_t$	-1.247** (0.421)	-0.501 (0.814)	-2.783** (1.064)	-0.814* (0.398)	-0.215 (0.831)	-1.286** (0.421)	-1.632** (0.549)	-0.551 (0.508)
*Treat$_i$ * Post$_t$*	0.017 (0.011)	-0.003 (0.022)	-0.011 (0.025)	0.014 (0.011)	0.021 (0.022)	0.010 (0.011)	-0.012 (0.013)	0.038* (0.015)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.098	0.092	0.112	0.094	0.099	0.092	0.097	0.092
Subsample	Game	Non Game	Top10	Bottom90	Virtual	Non Virtual	Partner	Non Partner
Individual Streamer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time(Week) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Clusters	1,299	401	218	1,482	358	1,342	863	837
Observations	28,578	8,822	4,796	32,604	7,876	29,524	18,986	18,414
Note: Clustered standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.								

Table 4. Estimation Results of heterogeneous effects

Robustness Checks

For robustness checks, we conduct the relative time model presented in Equation (2). The estimation results are reported in Table 5. Based on the results presented in Column (1) of Table 5, we find that average concurrent views are not significantly different between the treatment and the control group at each time point prior to the platform's discriminatory video quality degradation policy, but that after the policy, the treatment group experienced a negative effect on average concurrent views compared to the control group. These results suggest that the traffic discrimination policy negatively affects average concurrent views by up to approximately 12%. We further find no significant effect of the policy on streaming duration. Although we discover that some streamers extend their streaming duration after the treatment during certain period, it still questions whether the result is consistent.

	(1) **$ln(Concurrent\_View_{it})$**	**(2)** **$ln(Stream\_Duration_{it})$**
$Treat_i * Rel\_Time(t\text{-}5\text{+})_t$	-0.012 (0.020)	-0.010 (0.016)
$Treat_i * Rel\_Time\ (t\text{-}4)_t$	0.017 (0.019)	0.013 (0.019)
$Treat_i * Rel\_Time\ (t\text{-}3)_t$	-0.001 (0.017)	0.002 (0.018)
$Treat_i * Rel\_Time\ (t\text{-}2)_t$	-0.006 (0.016)	0.009 (0.016)
$Treat_i * Rel\_Time\ (t\text{-}1)_t$	(Omitted as a baseline)	
$Treat_i * Rel\_Time\ (t)_t$	-0.025 (0.016)	-0.019 (0.017)
$Treat_i * Rel\_Time\ (t\text{+}1)_t$	-0.108*** (0.018)	0.045* (0.018)
$Treat_i * Rel\_Time\ (t\text{+}2)_t$	-0.114*** (0.020)	0.027 (0.018)
$Treat_i * Rel\_Time\ (t\text{+}3)_t$	-0.128*** (0.021)	0.043* (0.019)
$Treat_i * Rel\_Time\ (t\text{+}4)_t$	-0.111*** (0.022)	0.005 (0.020)
Control Variables	Yes	Yes
Individual Streamer FE	Yes	Yes
Time (Week) FE	Yes	Yes
Robust SE	Yes	Yes
Number of Clusters	1700	1700
R^2	0.063	0.092
Observations	37,400	37,400
Note: Clustered standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.		

Table 5. Estimation Results of Relative Time Model

The "Just Chatting" category may be more focused on auditory content than visual content, such as radio and podcasts. In these cases, video quality or bitrate may not have a significant impact on viewership. Therefore, we re-estimate our model by subsampling only those streamers who broadcast "Just Chatting" for less or more than half of their broadcast content. According to the results in Column (1) and (2) of Table 6, both "Just Chatting" oriented streamers and streamers who rarely streamed "Just Chatting" have significantly negative results. We find that the data traffic restriction policy has a significant impact, as visual aspects of streamers' appearance, emotions, and gestures have a substantial impact on viewership.

Depending on when a game was released, its motion and graphics quality are likely to be substantially lower than today's one. These characteristics of game quality can have a heterogeneous impact on the data traffic restriction policy. To control for these, we estimate our model by including a variable ($Released\_Date_{it}$) that represents the difference between the released date of games and the date of streaming sessions. From Column (3) of Table 6, despite adding a variable for the game's released date, our results are consistent.

Since our treatment effects may be due to temporary shocks, we extend our data period to conduct a long-term analysis. However, as Twitch implemented a policy to restrict VOD services for Korean users, we employ our model with data until 13 December, the date of the policy's implementation. From Column (4) of Table 7, the results of the long-term analysis are consistent with our main results.

	(1) "Just Chatting" streamers	(2) Non-"Just Chatting" streamers	(3) Control game's released date	(4) Long-term analysis	(5) Language-fixed effects
*$Treat_i$ * $Post_t$*	-0.060* (0.024)	-0.124*** (0.026)	-0.088*** (0.018)	-0.072*** (0.018)	-0.089** (0.023)
$Released\_date_{it}$			-0.000 (0.000)		
Control Variables	Yes	Yes	Yes	Yes	Yes
Individual Streamer FE	Yes	Yes	Yes	Yes	Yes
Time (Week) FE	Yes	Yes	Yes	Yes	Yes
Language FE	No	No	No	No	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes
Number of Clusters	928	771	1,699	1,699	1,700
R^2	0.048	0.086	0.0615	0.060	0.046
Observations	20,416	16,962	37,378	47,288	37,400

Note: Unobserved data were dropped during additional variable collection. Clustered standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.

Table 6. Robustness Check Tests

Country-specific variables inherently including numerous confounding factors may also make the treatment group and the control group heterogeneous. Countries with more advanced IT infrastructure may be more sensitive to the quality of video streaming than those without. To control this heterogeneity, we conduct language-fixed effects instead of country specific variables. With the exception of some languages, most languages, such as Italian, Chinese, and Japanese, make it possible to identify nationality by the language itself. Nonetheless, languages such as English, Spanish, and Portuguese are not inherently country-specific. To address this, we re-estimate our DID model with a new control group that excludes one of the languages in the control group. Table 7 shows that the results are consistent with our main results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Excluded	**English**	**Chinese**	**Japanese**	**Spanish**	**Portuguese**	**German**	**Russian**	**Italian**	**French**
*$Treat_i$ * $Post_t$*	-.090*** (0.019)	-.094*** (0.019)	-.077*** (0.020)	-.092*** (0.018)	-.086** (0.018)	-.095*** (0.018)	-.083*** (0.019)	-.100*** (0.018)	-.084*** (0.018)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Streamer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Week) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Clusters	1,649	1,572	1,564	1,617	1,617	1,626	1,642	1,647	1,661
R^2	0.061	0.061	0.059	0.064	0.062	0.063	0.060	0.063	0.061
Observations	36,278	34,584	34,408	35,574	35,574	35,772	36,124	36,234	36,542

Note: Clustered standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.

Table 7. Robustness Check Excluding Control Groups

Conclusion

Discussion

This study examines the impact of the data traffic restriction policy on live streaming platforms and finds that the policy has negative effects on viewership, which vary depending on the type of streamers. Specifically, we find that the reduction in streaming quality resulting from data traffic restriction has a significant impact on the decrease in viewership of game streamers. As games are high-motion content, we found that such a data traffic restriction policy on live streaming platforms is more detrimental to streamers offering gaming content. On the other hand, virtual streamers, who use virtual avatars instead of showing their real-life appearance during streaming sessions, were not affected by the policy. Our results also indicate that the top 10% of streamers are not affected by the restriction policy, whereas the remaining 90% of streamers experience a significant decrease in viewership. Moreover, partner streamers experience a smaller decline in viewership compared to non-partner streamers. All of the top 10% of Twitch streamers consist of partner streamers, and most partner streamers have more viewers than non-partner streamers. Considering this, these results seem quite reasonable and consistent. According to superstar effects, a small number of individuals dominate and obtain the most portion of the rewards in the media industry. As our research has shown, if data traffic restriction policies have no impact on the top 10% of superstars but only have negative effects on the long tail of service providers within the platform, it may decrease the content diversity on the platform. Similarly, some of the service providers who receive less economic profits from the platform are new entrants to the platform. If data traffic restriction policies have a greater impact on these new entrants, the platform may create entry barriers and generate negative network effects.

From the perspective of streamers, the impact on streaming behavior seems minimal, although we identified some positive in particular streamer groups. The data traffic restriction policy allowed non-partner streamers to broadcast more, but they experienced a greater decrease in their viewership compared to partner streamers. As they have fewer ways to earn revenue than partner streamers, increasing streaming duration may be considered the only viable option for them.

This study makes several contributions to the literature. First, previous studies have intensively focused on homogenous CPs, but in our study, we expanded the scope of CPs to two-sided platforms and examined the impact on two-sided users within the CPs. Second, we provided empirical evidence of the impact on end-users when the principle of network neutrality was violated. Lastly, we examined the differential effects of the network neutrality violation on users of live streaming platforms depending on their heterogeneous characteristics.

This study suggests managerial implications. First, our findings suggest that, when implementing data traffic restriction policies to reduce network usage fees, CPs should mitigate policies to alleviate the negative impact on unprivileged service providers within the platform regarding the corresponding sustainability of their role in upholding digital inclusion. Policies violating network neutrality harm new, financially unstable, and less popular streamers in the live streaming platform. This, in turn, can lead to a reduction in the diversity of the live streaming platform and the absence of platform diversity may ultimately threaten the platform ecosystem by decreasing the overall network size.

Second, a decrease in one side's users leads to a decrease in the other side's user due to network effects in live streaming platforms. This can ultimately threaten the platform ecosystem by resulting in a decrease in the overall network size. This problem is not limited to live streaming platforms only. Johnson and Woodcock (2019) examined the impact of live streaming platforms on the gaming industry and found that live streaming affects the success of independent games in niche markets. Huang and Morozov (2022) discovered that games broadcasted through live streaming platforms are purchased and played more by people who watched the streaming session. Thus, the growth of live streaming platforms has positive spillover effects on other connected industries. However, if data traffic restriction policies are implemented by CPs in response to excessive network usage fees that violate network neutrality, it may lead to a negative impact not only on end-users of CP platforms but also on the related Internet industry. Even from the perspective of ISPs, a decrease in the internet industry may lead to a loss of consumers in the long run, making a decrease in network size unfavorable for them. Finally, this study provides insights to service providers on the online platform. Service providers with diverse content or unique characteristics are likely to avoid the negative effects of discriminatory policies. Therefore, platform service providers should focus on diversifying or highlighting their unique characteristics.

Limitations

This research is not without the limitations. First, while viewers may intuitively feel the change in the platform's video quality reduction policy, streamers may not immediately feel a significant difference. In this study, the post-treatment period was limited to one month after the policy change, which may not have been long enough for streamers to demonstrate their reactions to the policy. Future research could examine a longer period to identify streamers' reactions to the policy more accurately. Second, generalization issues may arise as this study only investigated one lives streaming platform. As network usage fees have been a subject of dispute over time, some live streaming platforms are attempting to practice traffic discrimination through various pricing or premium membership options. As such, future research could investigate different types of discrimination on end-users of live streaming platforms. Third, due to the limitation of the data collected, detailed information about the content during each streaming session was not available for analysis. If such data were available, however, it would allow researchers to evaluate the results more accurately by incorporating information on games streamed or chat and donation records during streaming sessions. Additionally, whether streamers are multi-homing or not can affect the impact of net neutrality violation on viewership and streaming time. Future research could explore this further to gain a better understanding of the impact of network neutrality violations on live streaming platforms.

References

Altman, E., Bernhard, P., Caron, S., Kesidis, G., Rojas-Mora, J., & Wong, S. (2013). A model of network neutrality with usage-based prices. *Telecommunication Systems*, *52*, 601-609.

Bandyopadhyay, S., & Cheng, H. K. (2006). Liquid pricing for digital infrastructure services. *International Journal of Electronic Commerce*, *10*(4), 47-72.

Bourreau, M., Kourandi, F., & Valletti, T. (2015). Net neutrality with competing internet platforms. *The Journal of Industrial Economics*, *63*(1), 30-73.

Botta, A., Avallone, A., Garofalo, M., & Ventre, G. (2016, January). Internet Streaming and Network Neutrality: Comparing the Performance of Video Hosting Services. In *ICISSP* (pp. 514-521).

Briglauer, W., Cambini, C., Gugler, K., & Stocker, V. (2023). Net neutrality and high-speed broadband networks: evidence from OECD countries. *European Journal of Law and Economics*, *55*(3), 533-571.

Byun, J. E., & Lee, S. (2013). Study on controversial issues related to network neutrality in leading countries, focusing on economic efficiency and user protection. *2013 Proceedings of PICMET'13: Technology Management in the IT-Driven Services (PICMET)*, 2784-2794.

Cheng, H. K., Bandyopadhyay, S., & Guo, H. (2011). The debate on net neutrality: A policy perspective. *Information systems research*, *22*(1), 60-82.

Choi, H. S., Sim, J., Cho, C., & Cho, D. (2022). Beyond Viewership: How Streamer-Viewer Interactivity Shapes Gendered Economy of Live-Streamed Media. *Available at SSRN 4092684*.

Crocioni, P. (2011). Net neutrality in Europe: Desperately seeking a market failure. *Telecommunications Policy*, *35*(1), 1-11.

Dobrian, F., Sekar, V., Awan, A., Stoica, I., Joseph, D., Ganjam, A., ... & Zhang, H. (2011). Understanding the impact of video quality on user engagement. *ACM SIGCOMM computer communication review*, *41*(4), 362-373.

Economides, N. (2008). Net neutrality, non-discrimination and digital distribution of content through the internet. *ISJLP*, *4*, 209.

Economides, N., & Tåg, J. (2012). Network neutrality on the Internet: A two-sided market analysis. *Information Economics and Policy*, *24*(2), 91-104.

Economides, N., & Hermalin, B. E. (2012). The economics of network neutrality. *The RAND Journal of Economics*, *43*(4), 602-629.

Edell, R., & Varaiya, P. (1999). Providing Internet access: What we learn from INDEX. *IEEE network*, *13*(5), 18-25.

Faris, R., Roberts, H., Etling, B., Othman, D., & Benkler, Y. (2015). Score another one for the Internet? The role of the networked public sphere in the US net neutrality policy debate. *The Role of the Networked Public Sphere in the US Net Neutrality Policy Debate (February 10, 2015). Berkman Center Research Publication*, (2015-4).

Guo, H., Bandyopadhyay, S., Lim, A., Yang, Y. C., & Cheng, H. K. (2017). Effects of competition among internet service providers and content providers on the net neutrality debate. *MIS Quarterly*, *41*(2), 353-370.

Guo, H., Cheng, H. K., & Bandyopadhyay, S. (2013). Broadband network management and the net neutrality debate. *Production and Operations Management*, *22*(5), 1287-1298.

Guo, H., & Easley, R. F. (2016). Network neutrality versus paid prioritization: Analyzing the impact on content innovation. *Production and Operations Management*, *25*(7), 1261-1273.

Hermalin, B. E., & Katz, M. L. (2007). The economics of product-line restrictions with an application to the network neutrality debate. *Information Economics and Policy*, *19*(2), 215-248.

Hilvert-Bruce, Z., Neill, J. T., Sjöblom, M., & Hamari, J. (2018). Social motivations of live-streaming viewer engagement on Twitch. *Computers in Human Behavior*, *84*, 58-67.

Huang, Y., & Morozov, I. (2022). Video Advertising by Twitch Influencers. *Available at SSRN 4065064*.

Johnson, M. R., & Woodcock, J. (2019). The impacts of live streaming and Twitch. tv on the video game industry. *Media, Culture & Society*, *41*(5), 670-688.

Kara, P. A., Robitza, W., Pinter, N., Martini, M. G., Raake, A., & Simon, A. (2019). Comparison of HD and UHD video quality with and without the influence of the labeling effect. *Quality and User Experience*, *4*, 1-29.

Kunigita, H., Javed, A., & Kohda, Y. (2023). Analysis of Subscription-Gifting Behavior As Pay-What-You-Want Donation Behavior Considering Community Characteristics As Collective Action in Virtual World. *Available at SSRN 4357952*.

Larkey, M. (2015). Cooperative play: anticipating the problem of copyright infringement in the new business of live video game webcasts. *Rutgers JL & Pub. Pol'y*, *13*, 52.

Layton, R. (2017). *Which Open Internet Framework is Best for Mobile App innovation? An empirical inquiry of net neutrality rules around the world.* Aalborg Universitetsforlag. Ph.d.-serien for Det Tekniske Fakultet for IT og Design, Aalborg Universitet https://doi.org/10.5278/vbn.phd.engsci.00181

Lee, D., & Kim, Y. H. (2014). Empirical evidence of network neutrality–The incentives for discrimination. *Information Economics and Policy*, *29*, 1-9.

Li, M., & Hou, L. (2020). Welfare effects of network neutrality in mobile Internet market. *Enterprise Information Systems*, *14*(3), 352-367.

Pil Choi, J., & Kim, B. C. (2010). Net neutrality and investment incentives. *The RAND Journal of Economics*, *41*(3), 446-471.

Pires, K., & Simon, G. (2015, March). YouTube live and Twitch: a tour of user-generated live streaming systems. In *Proceedings of the 6th ACM multimedia systems conference* (pp. 225-230).

Shang, Z., Ebenezer, J. P., Wu, Y., Wei, H., Sethuraman, S., & Bovik, A. C. (2021). Study of the subjective and objective quality of high motion live streaming videos. *IEEE Transactions on Image Processing*, *31*, 1027-1041.

Sim, J., Choi, K., Cho, D., & Han, S. P. (2021). In-Consumption Information Cues and Digital Content Demand: Evidence from a Live-Streaming Platform. *KAIST College of Business Working Paper Series*.

Simonov, A., Ursu, R. M., & Zheng, C. (2023). Suspense and surprise in media product design: Evidence from twitch. *Journal of Marketing Research*, *60*(1), 1-24.

Sjöblom, M., & Hamari, J. (2017). Why do people watch others play video games? An empirical study on the motivations of Twitch users. *Computers in human behavior*, *75*, 985-996.

Smith, T., Obrist, M., & Wright, P. (2013, June). Live-streaming changes the (video) game. In *Proceedings of the 11th european conference on Interactive TV and video* (pp. 131-138).

Somogyi, R. (2017). The economics of zero-rating and net neutrality. *Unpublished manuscript. Université catholique de Louvain, Center for Operations Research and Econometrics (CORE)*.

Stocker, V., Smaragdakis, G., & Lehr, W. (2020). The state of network neutrality regulation. *ACM SIGCOMM Computer Communication Review*, *50*(1), 45-59.

Tudon, J. (2022). Prioritization vs. congestion on platforms: evidence from Amazon's Twitch. tv. *The RAND Journal of Economics*, *53*(2), 328-355.

Triviño, R. D., Franco, A. A., & Ochoa, R. L. (2021, July). Internet and net neutrality in the time of covid-19: a global overview. In *2021 Eighth International Conference on eDemocracy & eGovernment (ICEDEG)* (pp. 133-138). IEEE.

Van Wallendael, G., Coppens, P., Paridaens, T., Van Kets, N., Van den Broeck, W., & Lambert, P. (2016, June). Perceptual quality of 4K-resolution video content compared to HD. In *2016 Eighth International Conference on Quality of Multimedia Experience (QoMEX)* (pp. 1-6). IEEE.

Wollborn, P., Dornekott, D., & Holder, U. (2023). Entrepreneurial efforts and opportunity costs: evidence from twitch streamers. *International Entrepreneurship and Management Journal*, 1-30.

Wu, T. (2003). Network neutrality, broadband discrimination. *J. on Telecomm. & High Tech. L.*, *2*, 141.

Wu, T., & Yoo, C. S. (2007). Keeping the internet neutral?: Tim Wu and Christopher Yoo debate. *Federal Communications Law Journal*, *59*(3), 06-27.

Zhao, K., Hong, Y., Ma, T., Lu, Y., & Hu, Y. (2021). Group Size, Content Moderators, and User Engagement in Online Synchronous Content Platforms. *Content Moderators, and User Engagement in Online Synchronous Content Platforms (December 1, 2021)*.

Zhao, K., Hu, Y., Hong, Y., & Westland, J. C. (2019). Understanding characteristics of popular streamers on live streaming platforms: Evidence from Twitch. tv. *Journal of the Association for Information Systems, Forthcoming*.

Zhao, K., Lu, Y., Hu, Y., & Hong, Y. (2022). Direct and indirect spillovers from content providers' switching: Evidence from online livestreaming. *Information Systems Research*.