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Direct and Indirect Spillovers from Content Providers' Switching: Evidence from Online Livestreaming

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Abstract. Content providers in online social media platforms, particularly livestreaming, often switch content categories. Despite its uniqueness and importance, there is a dearth of academic research examining the unintended effects of providers' content switching. We study the direct and indirect spillover effects of content switching for livestreamers—individuals who broadcast content through livestreaming platforms. We propose a framework based on theories related to viewer flow and network effects to conceptualize the direct and indirect spillover effects of entrant streamers' content switching on the incumbent streamers. Contrary to conventional wisdom, which concerns the negative effects on the incumbent's viewership, we propose two positive spillover effects that are unique to the social media platform setting: (a) the entrant streamers do not just increase competition among streamers, but they also bring their own viewers to the new category, which benefits the incumbent streamers because of a streaming flow effect (direct spillover), and (b) the entrant streamers influence incumbent streamers' viewer size by boosting category visibility through indirect network effects (indirect spillover). We also propose that the two spillover effects are contingent on the size of the entrant streamers' follower base. Based on a unique observational data set from the leading livestreaming platform (Twitch.tv), particularly with viewer flow data at the streamer–session level, we first estimate that average content switching is associated with a 1.3% net increase in direct net viewer flow from the entrant to an incumbent. And this direct spillover effect is attenuated by the size of the entrant streamers' follower base. We also estimate that average content switching is associated with a 2.6% net increase in (indirect) net viewer flow from outside categories to an incumbent streamer. And this indirect spillover effect is reinforced by the entrant streamers' follower base size. This study contributes to the emerging literature on the dynamics of content creation on social media platforms in the emerging context of livestreaming. We discuss the managerial implications of this study for streaming strategies and platform management.

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Keywords: livestreaming • content switching • viewer behavior • spillover effects • network effects

1. Introduction

Livestreaming refers to an emerging type of online social media service wherein streamers live-broadcast media, such as audio and video, to viewers in real time. Livestreaming has become one of the most popular social media services in recent years. It has experienced a significant expansion of its market scope and rapid growth in its number of users—as of 2016, it was already a $30.29 billion industry[1] and is expected to reach $60 billion by 2026 (MarketWatch 2020). Livestreaming platforms provide engaging video content and allow real-time interaction between streamers (individuals who broadcast their own activities through livestreaming platforms) and their viewers. Among livestreaming platforms, Twitch.tv is cited as the number one social video platform with 37.5 million viewers by February 2020 (Stephen 2020). With the stay-at-home order during the COVID-19 epidemic, Twitch witnessed a growth of 45% year over year with 24 billion hours watched in 2021 (StreamElements 2021). Given the popularity of livestreaming, an increasing number of brands, both gaming brands and nongaming brands, such as Hershey, are now advertising on *livestreaming channels* (a streamer's web page wherein the streamer broadcasts the streamer's content) to promote their brands and products.

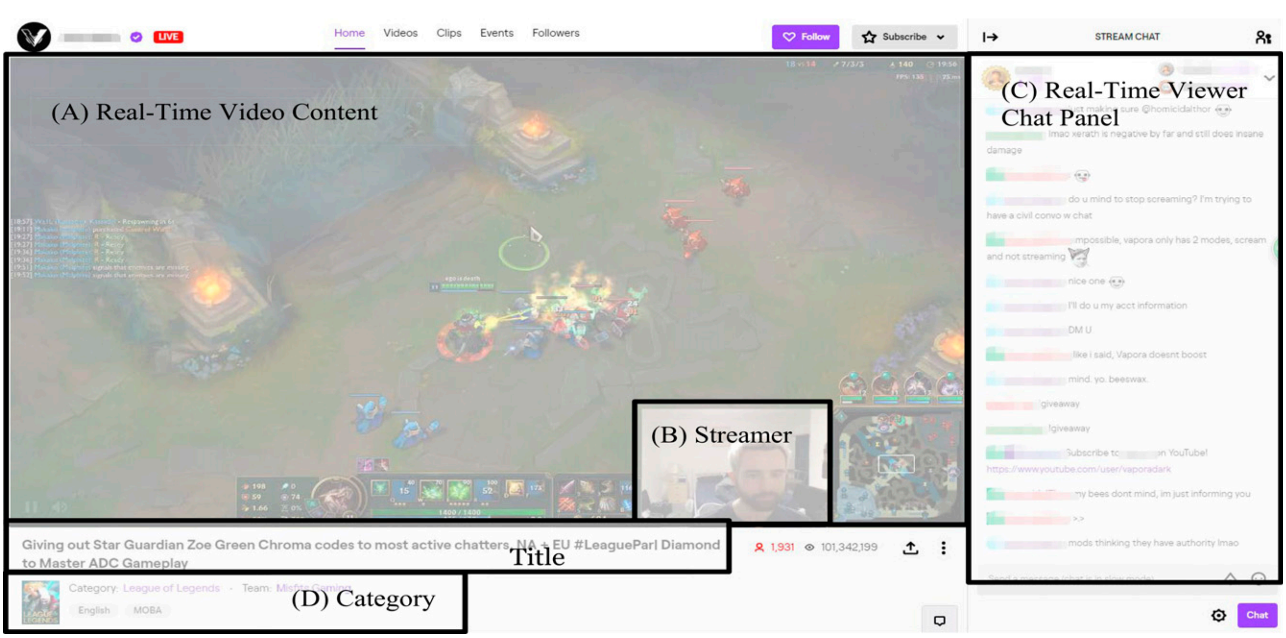
As with other social media platforms, such as Twitter and YouTube, streaming platforms rely heavily on user-generated content (UGC). Streamers (e.g., Figure

1(B)) who generate content (e.g., Figure 1(A)) on livestreaming platforms can be anyone interested in sharing an experience, such as gaming and outdoor activities, with viewers. Viewers can also freely communicate with streamers and other viewers by posting comments on the live chatting panel of the streaming room (e.g., Figure 1(C)). Notably, streamers perform livestreaming in specified categories (e.g., Figure 1(D)), allowing individuals to search for streamers within a specific category[2] based on their interests.

One notable phenomenon commonly observed in UGC platforms, particularly in livestreaming, is *content switching*. Content switching in livestreaming happens when streamers switch their streaming content from one category to another category during their entire streaming session. There are several reasons why content switching is common in online streaming. First, streamers can switch the content categories to increase content diversity to cater to viewers looking for novel content, thus enhancing viewer retention. Second, by streaming content in different categories, content switching can further help streamers receive more exposure from viewers in multiple categories and attract new viewers to follow and subscribe to their channels. Research also finds that streamers switch content to show off their skills (Kaytoue et al. 2012) or attract viewers with similar interests (Zhao et al. 2018). Attracting viewers is particularly important for streamers. Unlike traditional advertising, in which advertisements are inserted into TV program content, promoting a sponsor's product on livestreaming platforms is more similar to showcasing a product, for example, streaming a sponsor's game. In this case, streamers receive payment based on the amount of time they spend streaming the sponsor's games as well as their viewer amount (Hale 2018). Content switching in the middle of a streaming session can also help reduce the loss of ad-averse viewers and maximize reviewer retention (Brechman et al. 2016). Consequently, content switching is widely observed on livestreaming platforms. The data in our research suggests that 26.9% of streamers switch their content category during a typical livestream session.

Notably, content switching is also generally a prevalent phenomenon on UGC platforms when content creators switch their content category for product endorsement (Chung and Cho 2017, Munnukka et al. 2019). For example, on YouTube, a professional swimmer who uploads swimmer training videos daily may start uploading videos about swimming glasses recommendations on the swimmer's YouTube channel. However, most UGC platforms do not provide explicit boundaries between different content categories, which makes it challenging for researchers to identify content switching of a content creator. Fortunately, a streamer on livestreaming platforms, such as Twitch, has to claim the streaming channel in only one category that best describes the streaming product at a certain time. This unique feature allows us to clearly identify the time stamp of content switching as content switching can be projected to the change of streaming category, that is, switching the streaming

Figure 1. (Color online) A Live Streaming Channel on Twitch.tv



content from category A to category B (e.g., different games, cooking, or even coding) during a livestreaming session. In addition, streamers' content switch from category A to B to some extent can be viewed as an exogenous entry for viewers and streamers in category B. Therefore, livestreaming platforms, such as Twitch, provide researchers with an ideal context to study the effects of content switching. For notation purposes, we refer to streamers who switch to category B as *entrant streamers* and streamers who were already streaming in category B before entrant streamers switch content as *incumbent streamers*. Category B is denoted as an incumbent category.

Understanding the impact of content switching on viewership is critical as streamers' profit largely depends on their viewership. Theoretically, it is not readily clear how entrant streamers' content switching affects incumbent streamers' viewership. If we consider the platform as a large two-sided network, each category is a local network. One common concern for the incumbent streamers is about their own viewers being cannibalized (Sabnis and Grewal 2015) because of increased competition and network congestion. However, our online streaming context is unique in that each streamer also has its own viewer base, which is brought into the new category. Therefore, when the entrant streamers switch to a new category, they may create a positive (direct) spillover effect by bringing their own viewers as additional viewers to be potential viewers for the incumbent streamers. In addition, we may even observe a further downstream indirect spillover effect such that the increase in the total viewer size of the incumbent category can increase category visibility as well as enhance the value for viewers outside of the incumbent categories because of the positive network effects. Given the countervailing theoretical effects, it is important to examine each of these effects. Examining the impact of content switching on incumbent streamers' viewership is also important for livestreaming platforms. If incumbent streamers benefit from content switching, they are encouraged to generate more content, and more new streamers may be incentivized to join the incumbent category. This leads to a higher number of content generators for livestreaming platforms. However, if incumbent streamers face fiercer competition after content switching, they may be discouraged from content contribution or even drop out of the platform. Thus, livestreaming platforms may suffer because of the declining number of streamers. Thus, we separately identify the direct and indirect spillover effects and propose the following research questions: (1) Direct spillover: How does entrant streamers' content switching affect incumbent streamers' viewership through viewer flow between the entrant and the incumbent? (2) Indirect spillover: How does entrant streamers' content switching affect incumbent streamers' viewership through viewer flow between the other outside category streamers and the incumbent?

We examine these two research questions largely through the theories of network effects. When more streamers generate content in the category in which an outside viewer is interested, the viewer has more options to choose from in this category, increasing the value the viewer can obtain from this category. In addition, viewers can derive utility from their communications with other viewers through chat, and this utility increases if more viewers participate in this channel (Zhang et al. 2012a). From this network effect perspective, entrant streamers with different popularity levels naturally exert different influences on incumbent streamers. As such, we further propose the moderating effects of entrant streamer popularity (measured by their number of followers) on the direct and indirect spillover effects of the content switch. Specifically, on the one hand, we expect that popular entrant streamers could have a larger direct spillover effect to attract more viewers from incumbent streamers. On the other hand, a popular entrant streamer can better increase the incumbent category's value to other outside category viewers on the platform, boost the incumbent category's visibility, and attract more viewers from outside the incumbent category. Understanding the moderating effect of entrant streamer popularity is essential for the platform as platforms can better manage content switching of streamers with different popularity levels to facilitate viewer flow to categories that are strategically important for the platform. As such, we propose a third research question: (3) How does entrant streamers' popularity moderate the direct and indirect spillover effects of their content switching on the viewer flow to the incumbent streamers?

To address the research questions, we obtain a unique data set from Twitch.tv, which allows us to accurately capture the viewer list of each streamer channel over time for each streaming session. We collect panel data from streamers in the top 20 categories on Twitch.tv, including their streaming category, profile, viewer size, and viewer lists. This allows us to document detailed viewer flow information among different channels, thus exploring direct and indirect spillover effects of content switching. Accordingly, we conduct our empirical analyses at the streamer–session level to explore the sources of viewer flow among streamers (entrant, incumbent, and outside streamers) and distinguish the direct and indirect spillover effects.

Our empirical results demonstrate that the entrant streamer's content switching creates both a direct and positive spillover effect on the incumbent streamers' viewer size such that we observe a net surplus for the incumbent streamers in the viewer flow from the entrant streamer to incumbent streamers. Specifically, we estimate that average content switching is associated with a 1.3% net increase in direct net viewer flow from the entrant to an incumbent. And this direct spillover effect is attenuated by the size of entrant streamers' viewer base. We also estimate that average content switching is associated with a 2.6% net increase in net viewer flow from an outside category streamer to an incumbent streamer, and this indirect spillover effect is reinforced by the entrant streamers' viewer base size.

Our research makes the following contributions. First, using a unique data set from a live streaming platform, our study evaluates two types of spillover effects from content switching through the lens of the network effect. To the best of our knowledge, this is the first study that tracks individual-level viewing decisions for video content that has been previously unavailable for television viewership research. Second, we contribute to the network effect literature as our unique data set allows us to simultaneously track the sources of a negative direct network effect and a positive indirect network effect. This is one of the first few studies that examine various sources of network effects on viewer diffusion among media programs, channels, and platforms. Third, our research is among the first to empirically examine viewer choice in livestreaming platforms that are increasingly important in everyday life. And the results from this study provide valuable managerial insights regarding how platforms can better cultivate streamers of different sizes and offer actionable implications for streamers to optimize their streaming strategies. Finally, we discuss how and when some of our results can be generalized to content switching in other contexts, such as YouTube, blogs, and the like. This is because these UGC platforms share a similar structure with livestreaming platforms in which direct and indirect networks play an important role in consumer content consumption.

2. Related Literature

In this section, we discuss related literature, which lays the foundation for our research hypotheses. The specific literature we survey includes online livestreaming, spillover effects, network effects, and program viewing choice in the television industry.

2.1. Online Livestreaming

Despite the rapid growth of livestreaming platforms, there is limited academic literature on understanding livestreamers' behaviors. Existing literature on livestreaming mainly focuses on investigating viewers' needs and the motivations driving their preferences. In the livestreaming community, viewers frequently switch among channels based on their distinct motivations, for example, escaping from reality, gaining knowledge, curiosity, the novelty of streaming, and streamers' aggressiveness (Nam and Kwon 2015, Sjöblom and Hamari 2017). During this process, viewers reveal unique behavior patterns, such as staying during a stream's peak period and leaving at the end (Li et al. 2016). Meanwhile, researchers have also discovered that many viewers enjoy learning by watching livestreams, concluding that livestreaming can potentially be used for education purposes (Cheung and Huang 2011). However, there is scarce literature examining content switching on livestreaming platforms and the consequences thereof.

2.2. Spillover Effects

Based on the definition from Rutherford (2013), the spillover effect refers to the unintended impact of events in one setting on other individuals in a different, indirectly related setting. Our research is particularly related to spillover effects on online platforms. For example, Krijestorac et al. (2020) study content cross-posting to different platforms to find that posting a video onto a lag platform increases its view growth in a lead platform. In addition, researchers utilize aggregate measures to examine the spillover effect of online product reviews on purchases and product recalls on rival brands (Borah and Tellis 2016). Moreover, the switch of vlog (video blog) content on YouTube is found to be an effective way to increase brand credibility perception through switching of vlog content (Munnukka et al. 2019). There is also literature regarding the spillover in an off-line context or those occurring between an online and off-line context (Parker and Gatignon 1994, Libai et al. 2009).

The spillover effect can be either direct or indirect, depending on the type of interactions between the subject (e.g., an event or behavior) and affected individuals (Fershtman and Gandal 2011). Direct spillover refers to scenarios in which the subject exerts effects through a direct interaction channel. Examples of such direct interaction include brand competition (Wu et al. 2021), seller competition on the platform (Haviv et al. 2020), competition as a result of market entry (Gallant et al. 2017), and direct collaboration among individuals (Fershtman and Gandal 2011). Indirect spillover is the effect exerted through an intermediate channel of interaction or by-product. This intermediate channel can have different formats depending on the research context. For example, Joe and Oh (2018) study the indirect spillover of credit rating announcements on other firms within the same group through the channel of market reaction. Indirect spillover occurs when a developer takes what the developer learned from one project to a different project and shares it with developers in the latter project (Fershtman and Gandal 2011). Lee (2005) examines indirect knowledge spillover, and the intermediate channel in this context is goods imported.

It is notable that previous literature on spillover in an online context generally does not distinguish between direct and indirect spillover. The main reason is that detailed digital trace, such as viewing history data, is generally extremely difficult to obtain at the viewer level. For example, in a recent study examining the spillover effect of online product reviews on product purchases (Kwark et al. 2021), the authors do not distinguish direct (e.g., the impact of the review on corresponding products) and indirect (e.g., impact through word of mouth) spillover involved in the procedure. Similarly, Lu and Yang (2017) study the spillover effect of keyword market entry in sponsored search advertising. However, their research captures the spillover effect of direct competition but not the indirect spillover through the change in market size after keyword market entry.

Thus, one of the contributions of this paper is to simultaneously separate direct and indirect spillover effects from content switching. On one side, viewers choose streamers by browsing the streamer list within the same category, thus creating a direct interaction channel among those streamers. This competition is further intensified because of the network effect as viewers derive higher utility from interacting with more, other viewers in the same streamer session. The resulting viewer flow allows us to measure the direct spillover effect. On the other side, viewers also choose a category by browsing the category list at the category level. Because a content switch affects the visibility of the category by changing the aggregated number of viewers of this category, this change in visibility of categories serves as an indirect channel of the spillover effect. Note that category ranking is a novel channel for indirect spillover that is not explored in previous literature. We describe in more detail the direct and indirect spillover effects, particularly through the lens of network effect, in Sections 2.3 and 3.

Finally, we want to note that existing literature on market entry extensively examines the spillover effects under the assumption of the fixed market size (Gallant et al. 2017, Llanes et al. 2019, Haviv et al. 2020). However, a unique characteristic of our livestreaming context is that content switching increases the incumbent category's number of viewers as entrant streamers bring their existing viewers into an incumbent category. This unique feature highlights the theoretical challenge of spillover research with a flexible market size. This research gap is also observed by Susarla et al. (2012) in the context of information diffusion on YouTube. Thus, this is a research gap we intend to fill in this study.

2.3. Network Effects

One key element driving viewers' decisions is the network effects (i.e., externality) on livestreaming platforms. The network effect is defined as a type of externality in which an individual's decision is affected by the actions or status of peers (Katz and Shapiro 1985, Tucker 2008). In the traditional media context, when people make viewing decisions among TV programs, they generally derive higher utility if their friends and family also watch the same program (Kim et al. 2020). Similar network effects are also widely studied in the online platform context, particularly because of the intensive interactions among users online. Findings generally suggest a positive network effect in various online contexts, such as online auction platforms (Aggarwal and Yu 2012), video games (Cennamo and Santalo 2013, McIntyre and Srinivasan 2017), social media (Rochet and Tirole 2003), and internet companies (Eisenmann 2006).

We consider online livestreaming platforms as a multisided market in which the business value is derived from the network effect through interaction among content providers and consumers (Kaytoue et al. 2012, Zhang et al. 2012a, Zhao et al. 2021). The network effect can be both direct and indirect as the utility that users derive is affected by peers (Katz and Shapiro 1985). Users subject to direct network effects tend to make decisions based on the number of users in the same group (De Reuver et al. 2018). For example, the use of Twitter becomes more valuable if more people own Twitter accounts or post more Tweets. Compared with the direct network effect, the indirect network effect's value depends on the number of users in different groups (Katz and Shapiro 1985, Evans 2003, Wilbur 2008). For instance, the installed base of brands (product sellers) can help increase the number of consumers on e-commerce platforms (Chu and Manchanda 2016). Such a direct network effect is generally measured using the number of peers on the same side of the market (Shankar and Bayus 2003, Park 2004). An indirect network effect also exists in UGC platforms as the number of content creators increases the variety of generated content on the platform, which, in turn, attracts more content consumers (Zhang et al. 2012a).

We argue that livestreaming channels are subject to a more significant network effect than traditional media channels, thus enhancing the direct and indirect spillover effects. First, one unique characteristic of livestreaming platforms is that viewers can interact with other viewers participating in the same stream in real time (Doughty et al. 2011). Unlike traditional television channels, livestreaming has a social aspect that likely amplifies the network effect because individuals generally derive higher utility when communicating with more users in the same streaming channel. Second, livestreaming platforms implement a ranking scheme so that more popular streamers (i.e., streamers who have a lot of followers and viewers) are placed higher on the page of available streamers, which increases their visibility for individuals browsing for new streaming channels. Finally, interactions between content consumers (i.e., viewers) and content creators (i.e., streamers) happens more often on livestreaming platforms than on traditional UGC platforms because a large amount of information is communicated between streamers and viewers using both audio and video in real time (Nam and Kwon 2015, Sjöblom and Hamari 2017). These factors all contribute to a strong network effect in the livestreaming community, wherein the rich get richer (Merton 1968, Kaytoue et al. 2012).

The unique feature of livestreaming, which a viewer needs to watch in real time, can further enhance the network effect on livestreaming platforms (Kingma 1989) compared with traditional social media platforms. Whereas content consumers on traditional social media platforms can sequentially view content generated from different content creators, a consumer watching one streamer forfeits the opportunity of watching other streamers who livestream at the same time. Given the network effect among viewers, livestreaming platforms get inadvertently biased toward popular streamers, and new or unpopular streamers may find it more challenging to build connections with viewers and are more easily crowded out (Choudary 2014). In addition, streamers on livestreaming platforms are ranked by their viewership; thus, unpopular streamers in a category with thousands of streamers become more difficult to be accessed by viewers. As such, the network effect further intensifies the competition, thus imposing a negative effect on streamers. This, in turn, may also hurt platforms by discouraging streamers with low viewership from contributing content on the platform. Given the potential intensified competition among streamers, platforms need to be cautious when considering policies on content switching (Merton 1968, Schilling 2002). We want to highlight that, despite the handful of research examining how content creators compete for viewership on social media platforms (i.e., Luo and Zhang 2013, Huang et al. 2015, Luo et al. 2017, Yoo et al. 2019), there is no research examining the impact of content switching on social media platforms.

One subset of network effect theory lies in user popularity. The popularity effect (also called the Matthew effect) refers to the biased accumulated advantage or inequality acquired from individuals' "high status" (Merton 1968), also described as power-law distribution (Adamic et al. 2000). Because individuals with high status can easily accrue resources (i.e., in our context, the viewer's attention), popular streamers are expected to enjoy competitive advantages in our context. In the management and marketing literature, research on Matthew effect theory finds that the popularity of products has a significant and positive impact on product consumption. For example, with the increase in popularity of fiction books (Sorensen 2007), music (Salganik et al. 2006), crowdfunding projects (Van De Rijt et al. 2014), and YouTube videos (Susarla et al. 2012), such products tend to be able to attract more customers. In addition, television viewers' viewing choices are also observed to be affected by channel popularity (Webster and Ksiazek 2012). Similarly, Kaytoue et al. (2012) find that skewness of the streamer popularity distribution is higher than that in other social media services as nearly 88% of viewers are attracted by the top 10% of streamers. This also provides evidence suggesting a significant popularity effect for livestreaming platforms.

In this study, we follow existing literature and use the number of followers of a streamer to measure streamer popularity. For example, Bakshy et al. (2011) investigate the attributes of popularity and claim that followers of social network users can appropriately measure popularity. Following this research, the number of followers is widely used to measure popularity (Zhang et al. 2012b) and rank users (Reilly et al. 2014).

2.4. Program Viewing Choice in the Television Industry

The characteristics of real-time content consumption in livestreaming share many similarities with the program viewing choice for television programs. Accordingly, our research is related to the literature on viewing choices in the traditional TV industry. Webster and Wakshlag (1983) propose the first comprehensive model of factors that influence TV program viewing choices. In this model, program availability and viewing preference are found to be two crucial factors that directly influence program viewing choice. This model is also based on the rational choice assumption that viewers rationally locate the best match between the available programs and their preferences (Wonneberger et al. 2009). Based on this model, research further demonstrates that program availability, channel preference, and program preference largely influence viewer viewing choice (Cohen 2002). More recently, Wonneberger et al. (2009) extend the Webster and Wakshlag (1983) model and propose a content-oriented program viewing choice model, indicating that program viewing choice should be influenced by the perception and evaluation of TV program content. In our context, content switching is extremely similar to the change of program availability for TV channels (for example, after channel A switches to broadcast football games, the availability of football content increases) when program availability increases for the incumbent channel after content switching of entrant streamers. Although all studies in this stream realize or demonstrate that viewers' program viewing choice heavily depends on the program's availability, its impact on consumer viewing choice still remains unclear for streaming platforms because of the unique characteristics of streaming platforms we mention in previous paragraphs.

Because we explore content switching by examining viewer flow among streamers, our research is also related to viewer flow among TV programs. Specifically, viewer flow is defined as *viewer duplication* (or lead-in) in the communications literature (Goodhardt 1966; Headen et al. 1979; Webster 1985). Duplication refers to the level of media viewer overlap when current channels change their broadcasting content (i.e., viewer duplication between channels A and B refers to the number of viewers watching channel A at time t and channel B at time $t + 1$). More recently, a network analysis approach has been proposed to model viewer flow and examine how individuals consume content on social media platforms (Ksiazek 2011). In addition, Webster and Ksiazek (2012) examine how viewer groups fragment in terms of content platform, channels, and content. McDowell and Sutherland (2000) identify a positive relationship between brand equity and viewer retention as well as between brand equity and the influx of viewers from other sources. However, there is a lack of research distinguishing direct and indirect spillover effects in this research stream.

We want to mention that our research makes contributions for both social media research and research in program viewing choices on TV channels. To our best knowledge, we are the first research that examines content switching in the context of livestreaming platforms. In fact, whereas content switching widely exists on various social media platforms, such as YouTube, blogs, TikTok, and the like, there is no academic research examining content switching on broader social media platforms. One potential reason is that there is no clear boundary marking the switch from one type of content to another. In addition, although difficult to capture, the detailed time-variant viewer flow data in livestreaming platforms allows us to examine the direct and indirect spillover effect of content switching on viewer choice decisions. This is in comparison with research on traditional TV channels in which viewing data are mainly collected through surveys. As a result, most of the prior data are cross-sectional and often lack detailed viewer flows.

3. Research Hypotheses

In this section, we elaborate on the impact of direct and indirect spillover effects in content switching on livestreaming platforms to propose several hypotheses related to the research questions in this study. We disentangle several effects by proposing two hypotheses on the main effects (two spillover effects Hypotheses 1a and 2a), and two hypotheses on the moderating effects of entrant streamer popularity (Hypotheses 1b and 2b).

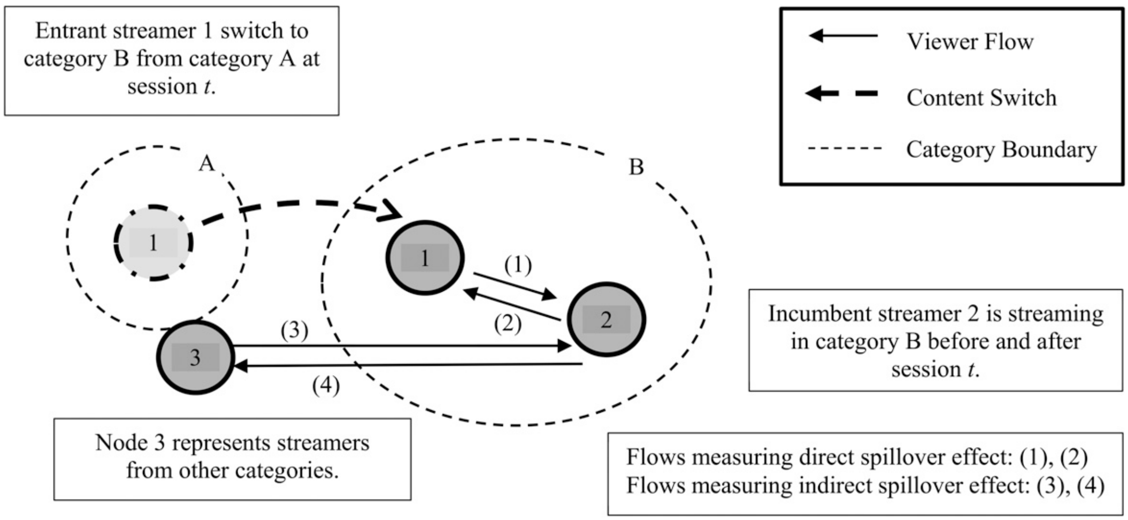
Program availability is identified as a critical factor that directly influences program viewing choice in the TV industry (Webster and Wakshlag 1983, Wonneberger et al. 2009). The findings on program viewing choice in the television industry suggest that, when new programs become available, the viewers' choice set becomes larger; therefore, viewers become inevitably distracted by new programs, particularly in the context of multiple programs with similar content. This is consistent with previous research in which market entry increases product availability and negatively impacts the incumbent through intensifying competition (Carpenter and Nakamoto 1990, Bowman and Gatignon 1996, Libai et al. 2009). Therefore, in the context of livestreaming, this stream of theory suggests a possible negative spillover effect from content switching.

However, despite existing research on content switching in traditional TV channels, the social media platform provides a unique context, which affords researchers with the lens of direct and indirect spillover effects to reexamine the role of content switching on viewing choices. To conceptualize the framework, we specify the sources of change in the viewership and investigate two types of viewer flow directions resulting from content switching: (1) the direct spillover effect, that is, the net viewer flow between the entrant streamer and the incumbent streamer, and (2) the indirect spillover effect, that is, the net viewer flow between an incumbent streamer and streamers from other categories resulting from increasing content providers after content switching. This is in comparison with most existing studies on viewer flow, which mainly focus on viewer flow from the entrant to the incumbent, whereas we are able to evaluate both effects as we observe the viewer lists for each streaming channel at the session level. Figure 2 shows the conceptual model of the framework, in which we use one session before and after one streamer's content switching as an example. We also use Figure 3 at the end of this section to summarize the two sources of viewership change we evaluate in this paper.

3.1. Direct Spillover Effect

We measure the direct spillover effect using the net viewer outflow from the entrant streamer to the incumbent streamer, that is, the number of viewers joining the incumbent streamer from the entrant minus the number of viewers flowing from incumbent streamers to the entrant (Figure 2, viewer flow (2) − viewer flow (3)). A positive (negative) net viewer outflow indicates a positive (negative) direct spillover from the entrant to the incumbent streamer. In other words, we measure the extent to which incumbent streamers attract viewers from or lose viewers to the entrant (i.e., surplus or deficit).

Figure 2. Viewer Flow Before and After an Entrant's Content Switching

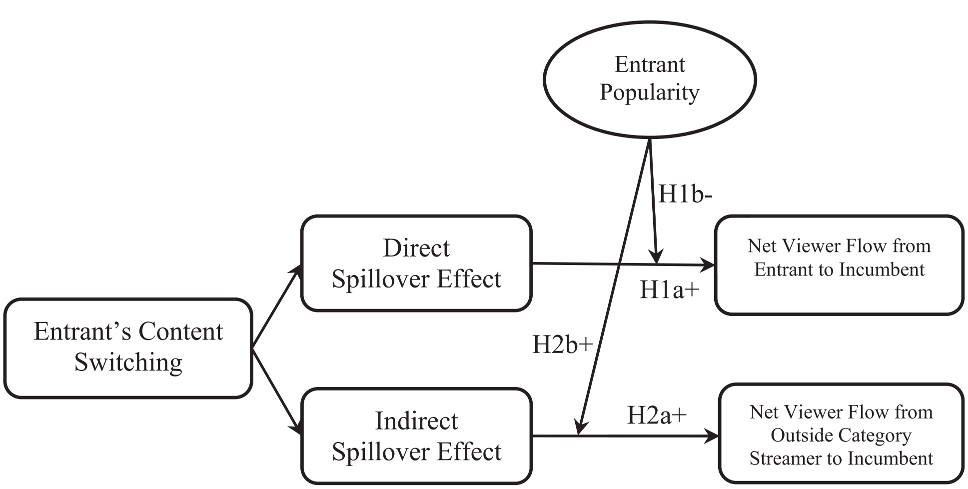


As an entrant streamer switches content from one category to another, a portion of the entrant streamers' viewers are brought to the new category, and viewers may be aware (through browsing or sidebar channel recommendations) of other currently live streams in this incumbent category. Therefore, the entrant streamer can bring new viewers to the incumbent streamers. At the same time, the incumbent streamers' viewers can also be attracted to the entrant streamers. We argue that, for the incumbent streamers, the positive spillover from the entrants is stronger than the negative spillover. When the content switching happens, it creates a content discontinuity in the entrant streamer's streaming flow. With the interruption in the streaming flow, users' cognitive engagement with the entrant streamer is disrupted, and they feel less enjoyment from the current stream (Agarwal and Karahanna 2000). However, for the incumbent stream viewers, the viewers do not experience similar disruptions in the same channel. Viewers in incumbent streamer need to voluntarily discontinue viewing the current streaming content to switch to a different category. Therefore, when some viewers switch channels to the entrant streamers, the viewer outflow from the entrant to the incumbent streamer is significantly larger than the outflow from the incumbent to the entrant viewer streamer. Whereas viewers flow bidirectionally, this argument provides a clear advantage for the incumbent in attracting viewers from the entrants than the other way around. Thus, we propose the following hypothesis.

Hypothesis 1a. *The entrant streamer's content switching creates a direct positive spillover of net viewer flow from entrant streamers to incumbent streamers.*

As we mention earlier, entrant streamers' popularity can potentially moderate the direct spillover effect. Specifically, we expect the popularity of entrant streamers to attenuate the positive spillover effect of the entrant

Figure 3. Conceptual Framework



streamers' content switching on the net viewer flow from the entrant to the incumbent such that the positive spillover effect is weaker when the entrant streamer has a larger size viewer base. We argue that this is primarily because of a direct network effect in the livestreaming context in which viewers derive utility based on the size of the entrant streamers' viewer base. When a popular streamer with a large viewer base (compared with a less popular streamer with a smaller viewer base) switches to a new category, that stream presents a more attractive option for incumbent streamer viewers because the interactive nature of livestreams creates a high value for the viewers who join a channel that has a large size of viewer base (Doughty et al. 2011, Van De Rijt et al. 2014). Previous literature documents that, because viewer attention is a scarce resource, one content creator attracting a higher level of attention leads to less attention drawn by other content creators (Webster and Ksiazek 2012). For example, Huang et al. (2015) suggest that blogs compete for users' attention in an enterprise blogging platform. Similarly, Zhang and Zubcsek (2011) demonstrate that competition among content providers increases the amount of effort content providers must spend in order to maintain their viewership. Given the strong direct network effect on livestreaming platforms compared with less popular entrant streamers, entrant streamers with higher popularity levels are, therefore, able to poach more current viewers from the incumbent streamers. Thus, we expect that the popularity of entrant streamers moderates the direct spillover effect of content switching on the viewership flow from entrant to incumbent streamers such that the entrant streamers with higher popularity are more competitive in poaching viewership from incumbent streamers.

Hypothesis 1b. *The popularity of entrant streamers attenuates the positive direct spillover effect of their content switching on the net viewer flow from the entrant streamer to the incumbent streamer.*

3.2. Indirect Spillover Effect

We herein also examine whether the entrant streamers' content switching can cause a viewer loss or gain for the incumbent streamer generated from sources outside the incumbent category (Figure 2, viewer flow (4) − viewer flow (5)) based on an indirect network effect (Susarla et al. 2012).

Different from the direct spillover effect in which entrant and incumbent streamers compete for a fixed number of viewers (the total number of viewers of incumbent and entrant streamers), the indirect spillover effect mainly examines how viewers from outside categories can be attracted to the incumbent category because of the entrant streamers' content switching. To conceptualize this effect, we leverage the indirect network effect in which viewers derive higher value from having more streamers in a category. The indirect network effect is observed in previous literature on the rich-get-richer scenario in various industry contexts, including fiction books (Sorensen 2007), music (Salganik et al. 2006), crowdfunding projects (Van De Rijt et al. 2014), and YouTube videos (Susarla et al. 2012). In our setting, the entrant streamers' content switching to the incumbent category has two important influences on the incumbent category related to network size. First, the number of viewers in the incumbent category increases with the entry brought in by the entrant streamer. A large number of viewers create a network effect that makes the category more attractive to the viewers outside categories as those viewers derive a higher value from potential interactions. Second, new streamers in the incumbent category lead to a higher amount of content and possibly more diverse content in the category, which further increases the value for viewers from outside categories who search for content in which they might be interested. Unlike the traditional TV industry in which viewers do not know the number of viewers for each TV program, one unique characteristic of the livestreaming platform is that the indirect network effect is further amplified by category ranking algorithms that are common in social media platforms as the total number of viewers in each category can push the incumbent categories to a more prominent position on the website, such as the front page. And this further enhances the visibility and attractiveness of these categories for viewers from other categories to join (Shocker et al. 2004). Thus, we propose the following hypothesis.

Hypothesis 2a. *Entrant streamers' content switching creates an indirect positive spillover of net viewer flow from viewers in outside categories to incumbent streamers.*

We expect that entrant streamer popularity moderates the indirect spillover effect of the entrants' content switching. Compared with content switching from a less popular entrant streamer, entrant streamers with higher popularity bring a larger viewer base and possibly higher quality content to the incumbent category. Therefore, the aggregate viewership of all streamers in the incumbent category (incumbent plus the newly entered entrant streamers) increases by a larger margin. Having more viewers in a category also suggests that viewers can derive higher expected utility if they join channels in the incumbent category. Thus, coupled with a typical social media page rank algorithm, the incumbent category receives higher visibility and becomes more attractive to viewers from outside categories. As such, we expect that the positive indirect spillover effect of content switching on viewer flow from outside categories to the incumbent category becomes stronger when the entrant streamer is more popular.

Hypothesis 2b. *The popularity of entrant streamers reinforces the positive indirect spillover effect of their content switching on the net viewer flow from the viewers in outside categories to the incumbent streamer.*

To sum up, as shown in Figure 3, we seek to further perform empirical analyses at the streamer–session level to analyze both the direct (Hypothesis 1a) and indirect (Hypothesis 2a) spillover effects from entrant streamers' content switching. And we further evaluate the differential moderating roles of entrant streamer popularity on the direct (Hypothesis 1b, an attenuation effect) and indirect (Hypothesis 2b, a reinforcing effect) spillover effects.

4. Research Methodology

4.1. Data set

We collected data from the largest livestreaming platform, Twitch.tv, from May 19, 2020, to June 3, 2020, through a distributed system consisting of 10 Google Cloud and Microsoft Azure virtual machines. The data set contains streamer information, category status, individual viewership, and the viewer list for each streamer in the top 20 categories[3] on Twitch.tv. One key feature of this data set is that we are able to measure viewer flows at the session levels by mapping viewer lists of the streamers.

We created a panel data set by tracking the category information and each streaming channel's information in the top 20 categories over time. We defined every 30 minutes as one session for the following reasons: (a) Entrant streamers almost always spend more than 30 minutes in the new category after the content switch. Thus, 30-minute sessions are appropriate in capturing the effects of content switching. (b) Thirty minutes is a reasonable amount of time to allow a viewer to react to content switching. (c) For the practical purposes of data collection, the viewership in top categories on Twitch generally hovers above 100,000 viewers; thus, it becomes technically difficult to collect viewer list data for every streamer when we use a smaller time window for sessions.

To construct the panel data set, we first create a list containing streamer names of the top 20 categories on Twitch at the beginning of each session. By comparing viewer lists in the top 20 categories with total Twitch viewer data, our data suggests that the top 20 categories cover about 77.03% of viewers on Twitch during our observational period. By incorporating the majority of viewers' activity on Twitch, we believe our estimation results broadly capture the impact of content switching on viewership. At each session, we collected category information (e.g., number of streamers and number of viewers in the category) and acquired the streamer list (i.e., a list of streamers' IDs) in the top 20 categories. Then, we tracked each streamer and documented the streamer's viewer list (a set of unique viewers' IDs) for each streamer during each session. Meanwhile, we recorded streamer information, such as follower number, streaming category, and channel description as well as category information, such as the number of streamers and number of viewers in the category. We later exclude streamers whose accounts have been suspended. Overall, the data collection resulted in 437,768,210 observations of viewers and 967,844 observations of streamers. We then distinguish entrant and incumbent streamers by comparing the active streamer list in each session with that in the last session. Remember, a streamer is an entrant if the streamer streams in category A at session $t-1$ and category B at session t. A streamer is an incumbent if the streamer streams in category A at both session $t-1$ and session t. As for the length of the time window, we include two sessions (i.e., 60 minutes) before and after the switch when possible. The (incumbent) streamer–session level data consists of 2,418,488 observations for 269,983 incumbent streamers across 728 sessions. We also set an alternative time window length for the robustness check. The data collection process is illustrated in Figure 4.

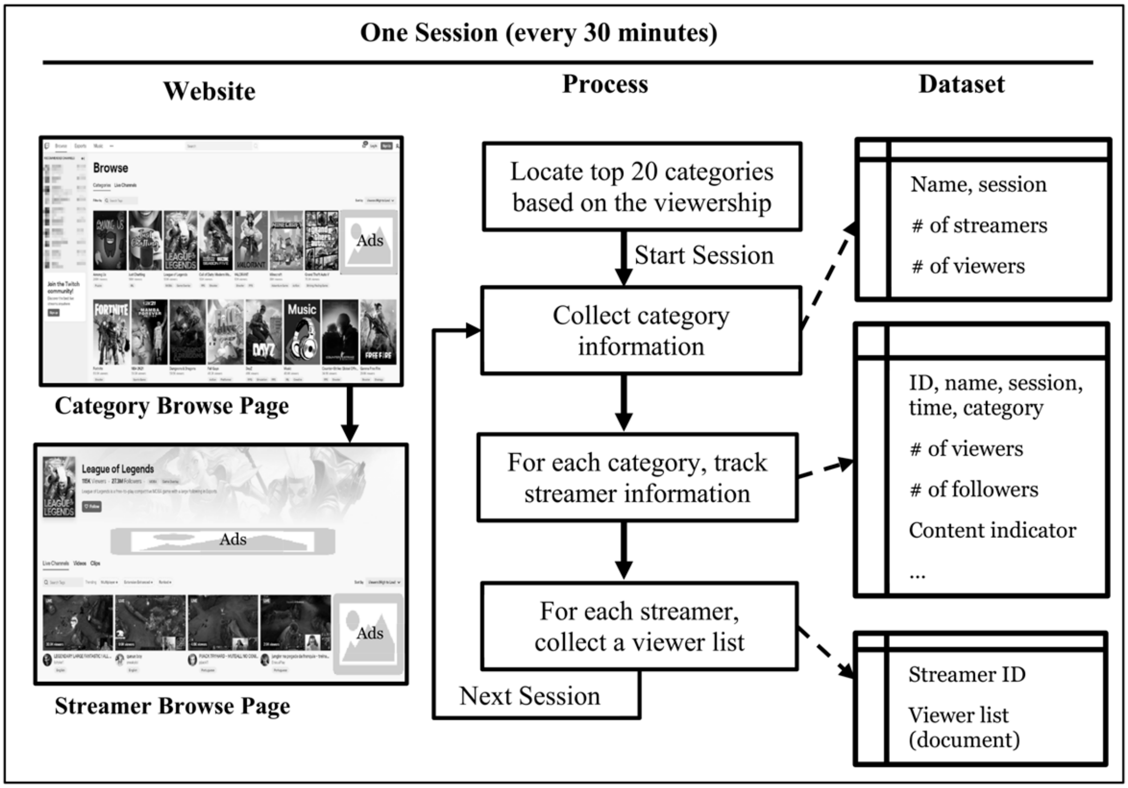
We further calculate the cosine similarity between the textual description of before- and after-switch categories as entrant streamers from similar categories may have a different impact on viewer flow compared with ones from drastically different categories. To be more specific, we first collect the category description using internet game database (IGDB) API,[4] which includes genre, theme, and mode of games.[5] We then compute the cosine similarity based on the word overlap between description texts of each pair of games. Table 1 shows an example of a similarity calculation with two categories in our data set.

Meanwhile, we categorize streaming time into four periods (morning, afternoon, night, and midnight), according to the viewer periodicity described by Kaytoue et al. (2012), and include these periods as a fixed effect in our estimation model. Table 2 presents the descriptive statistics of the key variables.

4.2. Direct and Indirect Spillover Effect of Content Switching

To test Hypotheses 1a and 2a, we focus on examining how direct and indirect spillover effects can impact viewer flow. Specifically, we estimate the effects of entrant streamers (other streamers' entry from outside of the incumbent category) on the viewer flow between

Figure 4. Data Collection Process



incumbent and entrant streamers and between incumbent streamers and streamers from outside the incumbent category.

By mapping viewer lists, we calculate two types of viewer flow corresponding to our conceptual model discussed in the previous section. For each session t, we first concatenate viewer lists of all streamers in a category. Second, we map each incumbent streamer's viewer list at session t with (a) the entrant streamer(s)'s viewer list at session $t-1$ to calculate the viewer inflow from entrant streamers (Figure 2, flow (1)) and (b) the category viewer list at session $t-1$ to calculate the viewer inflow from outside of the category (Figure 2, flow(3)). At the same time, we map each incumbent streamer's viewer list at session $t-1$ with (a) the entrant's viewer list at session t to calculate the viewer outflow to the entrant streamer (Figure 2, flow (2)) and (b) the category viewer list at session t to calculate the outflow to the outside of the category (Figure 2, flow (4)). Third, following our conceptual model, we create direct and indirect spillover measures based on the mapping results. The resulting data set contains 2,418,488 observations. Following the Iverson bracket notation (Blum and Iverson 2006) for count-based measurements, the directional viewer flow can be mathematically expressed as

$$\text{Direct Spillover}\left(\text{Viewer flow (1)–(2) in Figure 2}\right):$$

$$Direct_{j,t} = \sum_{i=1}^{n}[v_i \in \{Viewer_{j,t}\} \text{ and } v_i \in \{Viewer_{E,t-1}\} \text{ and } v_i \notin \{Viewer_{j,t-1}\}] - \sum_{i=1}^{n}[v_i \in \{Viewer_{j,t-1}\} \text{ and } v_i \in \{Viewer_{E,t}\} \text{ and } v_i \notin \{Viewer_{j,t}\}], \quad (1)$$

Table 1. Example Illustrating the Similarity Between Categories

Category	*League of Legends* (before switching)	*Dota 2* (after switching)
Themes	Action, fantasy	Action, fantasy, warfare
Genre	Multiplayer online battle arena (MOBA)	MOBA
Modes	Cooperative, multiplayer, single player	Cooperative, multiplayer
Inputs (bold overlaps)	**Action, fantasy, MOBA, cooperative, multiplayer,** single player x: [1, 1, 1, 1, 1, 0]	**Action, fantasy,** warfare, **MOBA, cooperative, multiplayer** y: [1, 1, 0, 1, 1, 1]
Calculation	$Similarity(x, y) = \frac{x \cdot y}{\|x\|\|y\|}$	
Result	0.8	

Table 2. Descriptive Statistics of Key Variables

Variable	Description	Mean	Standard deviation	Minimum	Maximum
$After_{i,t}$	A dummy variable (0, 1) = 1 if there are entrants in i's category within the time window	0.5	0.5	0	1
$I\_Viewer_{i,t}$	Number of viewers for streamer i at session t	149	2,021.425	0	84,643
$In\_Follower_{i,t}$	Number of followers for incumbent streamer i at session t	1,435.29	133,272.5	0	14,442,649
$En\_Follower_{i,t}$	Popularity measure: number of followers for entrant streamers who enter the incumbent streamer i's category	12,765.21	232,116.52	5	701,028
$Similarity_{i,t}$	The text similarity between the description of the before- and after-switch categories	0.412	0.289	0	0.8
$Period_{t,t}$	Factor of streaming time period (0-3), 0: morning (6 a.m.–12 p.m.); 1: afternoon (12–6 p.m.); 2: night (6 p.m.–12 a.m.); 3: midnight (12–6 a.m.)	1.4	1.04	0	3
$Restricted_{i,t}$	A dummy variable (0,1) = 1 if streamer i claims that there might be adult content in the streaming at session t	0.26	0.439	0	1
Number of observations		2,418,488			

Indirect Spillover $\Big($Viewer flow (3)–(4) in Figure 2$\Big)$:

$$Indirect_{j,t} = \sum_{i=1}^{n}[v_i \in \{Viewer_{j,t}\} \text{ and } v_i \notin \{Viewer_{E,t-1}\} \text{ and } v_i \notin \{Category_{j,t-1}\}] - \sum_{i=1}^{n}[v_i \in \{Viewer_{j,t-1}\} \text{ and } v_i \notin \{Viewer_{j,t}\} \text{ and } v_i \notin \{Category_{j,t}\}], \quad (2)$$

where n denotes the number of viewer IDs in incumbent streamer j's channel at time t. Variable v_i denotes the individual viewer, and $\{Viewer_{j,t}\}$ denotes the list of viewer IDs. Subscript E in $\{Viewer_{E,t-1}\}$ represents the entrant streamer(s) in j's channel. We allow E to be either one or multiple streamers. In cases of the latter, the entrant streamers' viewer lists are concatenated. List variable $\{Category_{j,t}\}$ is the viewer list of all streamers in streamer j's category at time t. The descriptive statistics of these two types of viewer flow are listed in Table 3.

Given the high skewness in the distribution of $Direct_{j,t}$ and $Indirect_{j,t}$, a commonly adopted approach is to log-transform the variables (Webster and Ksiazek 2012). The other advantage of log transformation is that it also allows for percentage interpretation of the estimates. Meanwhile, because these two outcomes are count-based with negative values, we apply a normalization approach to account for the negative values (Osborne 2008). We define dependent variables $Direct\_log_{j,t}$ and $Indirect\_log_{j,t}$ as follows:

$$Direct\_log_{j,t} = log(Direct_{j,t} + 1 - \min(Direct_{j,t})), \quad (3)$$

$$Indirect\_log_{j,t} = log(Indirect_{j,t} + 1 - \min(Indirect_{j,t})). \quad (4)$$

A statistical challenge of this estimation is that the viewer flow is simultaneously influenced by the characteristics of individual streamers and category-specific factors; thus, different categories can have distinct viewer flow patterns. To address this challenge, we employ a multilevel model with mixed effects for both individual incumbents and categories to investigate the proposed viewer flows. The model also controls time-variant streamer-related factors, such as whether the incumbent stream session contains adult content and the incumbent streamer's number of followers. Specifically, there are two levels in our multilevel model with fixed effects. In the first level model, the units are the individual streamers in each category (Equation (5)). The focal independent variables at this level are the indicator of content switch *After*. At this level, we control for time-variant characteristics of streaming content, such as the number of followers, mature content indicator *Restricted*, and the streaming period. We also include lagged viewership $I\_Viewer_{j,t-1}$ to further control the time-variant characteristics of the individual incumbent. To account for time-invariant heterogeneity, we add fixed effects at individual incumbent and category levels, which account for the effect related to the streamers' historical experience (e.g., the duration of streaming). In addition, viewers may appreciate entrant streamers from categories that provide similar content. Therefore, we add the cosine similarity of before- and after-switch categories as a control variable. In this model, the slope and the intercept are allowed to vary across categories (random intercepts and random slope) because different categories can have different viewer flow patterns. Accordingly, we control for the possibility that content switch effects vary with content-related factors in before- and after-switch categories. We further introduce the

Table 3. Descriptive Statistics of Decomposed Viewer Flow

Direction	Variable	Description	Mean	Standard deviation	Minimum	Maximum
1. Direct Spillover	$Direct_{j,t}$	The difference between the number of viewers flowing to incumbent j from the entrant(s) and the number of viewers flowing from incumbent j to the entrant(s)	5.214	53.54	−182	5,065
2. Indirect Spillover	$Indirect_{j,t}$	The difference between the number of viewers flowing to incumbent j from the streamers in other categories and the number of viewers flowing to other streamers from incumbent j	−28.5	502.75	−70,671	412
Number of observations		2,418,488				

second level model of the multilevel model grouped at the category level, which we specify in Equation (6). In this equation, we include the total number of streamers and the total number of viewers in the incumbent category. This second level of estimation allows us to control for the time-variant observed heterogeneity in categories.

To sum up, we estimate the following multilevel model to examine the proposed direct and indirect spillover effect of streamer content switching:

$$\begin{aligned} DV_{j,t} = {} & \beta_{0j} + \beta_1 After_{j,t} + \beta_2 \log(I\_Viewer_{j,t-1}) \\ & + \beta_3 Similarity_{j,t} + \beta_4 \log(In\_Follower_{j,t}) \\ & + \beta_5 Restricted_{j,t} + \beta_6 Period_{j,t} + Individual_j \\ & + Category_{j,t} + Time_t + e_j, \end{aligned} \tag{5}$$

$$\beta_{0j} = \gamma_0 + \gamma_1 \log(C\_Streamer_{j,t}) + \gamma_1 \log(C\_Viewer_{j,t}) + \varepsilon_j, \tag{6}$$

where $DV_{j,t}$ denotes the dependent variables $Direct\_log_{j,t}$ and $Indirect\_log_{j,t}$ specified in Equations (3) and (4). Intercept β_{0j} captures the impact of the streaming category. $Individual_j$, $Category_{j,t}$, and e_j, respectively, represent the individual incumbent streamers' fixed effects, categorical fixed effects, and the error term. And $Time_t$ is the time fixed effect included as a dummy variable of each session. We present the description of other variables in Table 2.

To estimate the moderating effect of the entrant streamer's popularity, we consider the number of followers suggested by Bakshy et al. (2011) to measure the entrant streamer's popularity, denoted as $En\_Follower_{it}$ in the following models. In cases wherein multiple entrant streamers exist for a session, we concatenate their follower lists and add them up for the measure of $En\_Follower_{it}$. Specifically, we decompose the impact of content switching into two categories: direct and indirect spillover effect. The corresponding model for estimating each moderating effect is as follows:

$$\begin{aligned} DV_{j,t} = {} & \beta_{0j} + \beta_1 After_{j,t} + \beta_2 After_{j,t} \times \log(En\_follower_{j,t}) \\ & + \beta_3 \log(En\_follower_{j,t}) + \beta_4 \log(I\_Viewer_{j,t-1}) \\ & + \beta_5 Similarity_{j,t} + \beta_6 \log(In\_Follower_{j,t}) \\ & + \beta_7 Restricted_{j,t} + \beta_8 Period_{j,t} + Individual_j \\ & + Category_{j,t} + Time_t + e_j, \end{aligned} \tag{7}$$

$$\beta_{0j} = \gamma_0 + \gamma_1 \log(C\_Streamer_{j,t}) + \gamma_1 \log(C\_Viewer_{j,t}) + \varepsilon_j, \tag{8}$$

where notations remain the same as in Equations (5) and (6), and the additional coefficient β_2 refers to the moderating effect of the entrant streamer's popularity.

5. Results

5.1. Main Effects

Following the proposed models, Table 4 reports the results of the decomposed impacts of the entrant streamers' content switching. When we focus on results for Model 1, we find that the coefficient before $After_{j,t}$ is significant and positive (0.013, $p < 0.001$). Thus, content switching is associated with a 1.3% increase in the direct spillover, which indicates that content switching, on average, associates with more viewers flowing from the entrant to the incumbent streamer. This result supports Hypothesis 1a.

With respect to the indirect spillover effect, the content switching coefficient in Model 2 is significant and positive (0.026, $p < 0.001$). It indicates that there is a 2.6% increase in indirect spillover after content switching. In other words, content switching is associated with more viewers who join incumbent channels to watch the incumbent's stream from other

Table 4. Result of Main Effect

Model	(1)	(2)
Viewer Flow in Figure 2	(1) – (2)	(3) – (4)
Dependent variable	*Direct_log*	*Indirect_log*
$After_{j,t}$	0.013*** (0.002)	0.026*** (0.004)
Control variable		
$\log(I\_Viewer_{j,t-1})$	−0.001*** (0.0001)	−0.020*** (0.0003)
$Similarity_{j,t}$	0.038 (0.078)	−0.001 (0.001)
$log(In\_Follower_{j,t})$	0.009*** (0.0002)	−0.014*** (0.0003)
$Restricted_{j,t}$	−0.01*** (0.001)	0.019 (0.014)
Period (period = 1)	0.003* (0.001)	0.017*** (0.003)
Period (period = 2)	0.002 (0.001)	0.012** (0.004)
Period (period = 3)	0.0003 (0.001)	0.011*** (0.003)
Session dummy	Yes	Yes
Individual fixed effects	Yes	Yes
Categorical fixed effects	Yes	Yes
Number of observations	2,418,488	2,418,488
Number of categories	20	20
R^2	0.587	0.385

Note. Standard error is in parentheses.
Significance levels: $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

categories. Thus, Hypothesis 2a is supported by this result. Notably, our estimation results remain qualitatively the same with different combinations of control variables.

It's worth mentioning that, despite the statistical significance, our results are economically significant for the following reasons. First, given the construct of our dependent variable that inflow and outflow cancel out each other, the magnitude of the coefficients represents a net gain instead of the strength of viewer flows. Considering that there are multiple sources of viewer flows, we argue that incumbent streamers gain significant advantages from direct and indirect spillover. Second, as the spillover effect in this study is measured in a relatively short time period, the effect may be cumulated. Third, given the large viewer base of streamers, the percentage change can be easily turned into a large number of viewers. Thus, it may benefit incumbent streamers to a large extent.

5.2. Moderating Effects of Entrant Streamers' Popularity

We present the results for the moderating effects in Table 5. The results in Table 5 generally confirm our expectations regarding the moderating effects. First, the interaction coefficient in Model 1 is significant and

Table 5. Result of Moderating Effects

Model	(1)	(2)
Viewer flow in Figure 2	(1) – (2)	(3) – (4)
Dependent variable	*Direct_log*	*Indirect_log*
$\log(En\_follower_{j,t})$	0.001*** (0.0002)	0.0002 (0.0004)
$After_{j,t}$	0.028** (0.009)	0.013*** (0.003)
$After_{j,t} \times \log(En\_follower_{j,t})$	−0.004*** (0.001)	0.003* (0.002)
Control variable		
$\log(I\_Viewer_{j,t-1})$	−0.001*** (0.0001)	−0.019*** (0.0003)
$Similarity_{j,t}$	0.045 (0.008)	−0.001 (0.001)
$log(In\_Follower_{j,t})$	0.009*** (0.002)	−0.175*** (0.036)
$Restricted_{j,t}$	−0.010 (0.001)	0.015 (0.016)
Period (period = 1)	0.003* (0.001)	0.018*** (0.003)
Period (period = 2)	0.002+ (0.001)	0.012** (0.004)
Period (period = 3)	0.0004 (0.001)	0.009** (0.003)
Session dummy	Yes	Yes
Individual fixed effects	Yes	Yes
Categorical fixed effects	Yes	Yes
Number of observations	2,418,488	2,418,488
Number of categories	20	20
R^2	0.591	0.382

Note. Standard error is in parentheses.
Significance levels: $^+p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

negative (−0.004, $p < 0.001$), which is in the opposite direction of the main effect (0.028, $p < 0.01$). Thus, when the entrant streamer has a high popularity level, the direct spillover effect of content switching is weaker or even reversed. This result suggests that the higher popularity of the entrant is associated with less net incumbent inflow from the entrant. In other words, more incumbents' viewers flow to the entrant streamer's channel if the entrant is popular. This appears to support our argument that higher popularity leads to a stronger direct network effect, thus attenuating the direct spillover effect. As a result, Hypothesis 1b is supported by this result.

Second, in Model 2, the coefficient of the main effect is significant and positive (0.013, $p < 0.001$). Thus, the indirect spillover effect becomes stronger when the entrant streamer has more followers (0.003, $p < 0.05$). These coefficients suggest that the popularity of the entrant is positively associated with more net inflow from other categories to incumbent streamers, which is also consistent with the predictions from the indirect network effect. Hence, Hypothesis 2b is supported by this result.

By combining the moderating effects with results in Table 4, we can see that, when entrant streamers are more popular, the role of the indirect spillover effect becomes salient in content switching compared with the direct spillover effect.

To summarize, we find that content switching generally has a positive direct and indirect spillover effect on incumbent streamer viewership. Second, the entrance of popular streamers in a category not only leads to more intense competition with incumbent streamers, but also makes the entire incumbent category more attractive to viewers from other categories.

6. Robustness Checks

6.1. Generalized Method of Moments–Based Dynamic Panel Estimation

To further check the robustness of our results, we first reestimated both main and moderating effects using the Arellano–Bover/Blundell–Bond estimator (Arellano and Bond 1991, Blundell and Bond 1998). By leveraging lagged variables as an instrument, we can better exploit information available in the sample; thus, the estimates of the model can be more efficient. In this estimation, we use the second lags as instruments to replace the lagged control variable in our main estimation. We present the result in Table 6. The result shows an insignificant AR (2), indicating that the second lags are valid instruments for the current values. The result is stable and consistent with our main estimation. Moreover, the Hansen J statistics are all insignificant across all models, which indicates that we cannot reject the overidentification restrictions.

6.2. Different Time Window

Next, we perform the second robustness check by varying the time window. We change the time window to a shorter range (30 minutes before and after the content switch) with the same estimation setting. Although the result, as shown in Table 7, is consistent with our main estimation, the model fit generally becomes worse with respect to the significance of coefficients and the R^2 compared with our main analysis. It suggests that viewers in the incumbent channels may need a longer time to be aware of and react to content switching.

6.3. Content Switch Between Channels with Similar Content

To further rule out the potential bias introduced by content similarity, we reestimate our empirical model on two

Table 6. Arellano–Bover/Blundell–Bond Estimator

Dependent variable	*Direct_log*	*Direct_log*	*Indirect_log*	*Indirect_log*
$Direct\_log_{(t-1)}$	0.046***	0.033***		
	(0.009)	(0.009)		
$Indirect\_log_{(t-1)}$			0.086***	0.055***
			(0.01)	(0.007)
$\log(En\_follower_{j,t})$		0.003***		0.0001
		(0.0006)		(0.0003)
$After_{j,t}$	0.013***	0.019***	0.005**	0.003***
	(0.001)	(0.002)	(0.002)	(0.001)
$After_{j,t} \times \log(En\_follower_{j,t})$		−0.002*		0.0004**
		(0.0008)		(0.0001)
Control variable	Yes	Yes	Yes	Yes
Number of observations	1,813,866	1,813,866	1,813,866	1,813,866
AR(2)	0.31	0.30	0.41	0.40
Hansen J	Insignificant	Insignificant	Insignificant	Insignificant
Period dummy	Yes	Yes	Yes	Yes

Note. Standard error is in parentheses.
Significance levels: $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 7. Estimation Results with Different Observational Time Window

Dependent variable	*Direct_log*	*Direct_log*	*Indirect_log*	*Indirect_log*
$\log(En\_follower_{j,t})$		0.001***		0.0001
		(0.0001)		(0.0002)
$After_{j,t}$	0.009*	0.016*	0.028***	0.022***
	(0.004)	(0.008)	(0.003)	(0.003)
$After_{j,t} \times \log(En\_follower_{j,t})$		−0.003**		0.001**
		(0.001)		(0.0004)
Control variable	Yes	Yes	Yes	Yes
Session dummy	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Categorical fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,211,344	1,211,344	1,211,344	1,211,344
Number of categories	20	20	20	20
R^2	0.520	0.523	0.346	0.348

Note. Standard error is in parentheses.
Significance levels: $^+p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

selected categories: *League of Legends* and *Dota 2*. These two games are usually considered exchangeable (high similarity) because they are in the same game genre. In this estimation, we exclude the similarity, which previously controls the type of content switch. Again, we found the results to be highly consistent, as shown in Table 8.

6.4. Estimation on Dependent Variables Without Standardization

As one may be concerned that our dependent variables are constructed by adding a constant to the log transformation, which may introduce bias into the estimation, we conduct an additional robustness check by removing the log transformation of our dependent variables. Specifically, we run

$$\begin{aligned} DV2_{j,t} = {} & \beta_{0j} + \beta_1 After_{j,t} + \beta_2 \log(I\_Viewer_{j,t-1}) \\ & + \beta_3 Similarity_{j,t} + \beta_4 \log(In\_Follower_{j,t}) \\ & + \beta_5 Restricted_{j,t} + \beta_6 Period_{j,t} + Individual_j \\ & + Category_{j,t} + Time_t + e_j, \end{aligned} \tag{9}$$

$$\beta_{0j} = \gamma_0 + \gamma_1 \log(C\_Streamer_{j,t}) + \gamma_1 \log(C\_Viewer_{j,t}) + \varepsilon_j, \tag{10}$$

where $DV2_{j,t}$ is the count measure of $Direct_{j,t}$ and $Indirect_{j,t}$ calculated in Equations (1) and (2). Other notations remain the same as shown in Models (5) and (6). As shown in Table 9, the result is highly consistent with our main analysis.

In addition, this result shows that, after the content switch, incumbent streamers, on average, gained 1.772 viewers ($p < 0.001$) from the entrant streamer and 3.876 ($p < 0.01$) viewers from other categories. We note that using highly skewed dependent variables without log transformation may be risky as the model may violate the normality assumption. Hence, we check the distribution of residual and find it acceptable for the assumption.

7. Implication and Conclusion

In this study, we document the existence of content switching on the emerging livestreaming platform and explore the direct and indirect spillover effects of

Table 8. Estimation Results for Subsamples

Dependent variable	*Direct_log*	*Direct_log*	*Indirect_log*	*Indirect_log*
$\log(En\_follower_{j,t})$		0.001***		−0.002
		(0.0002)		(0.004)
$After_{j,t}$	0.008**	0.008*	0.014***	0.020***
	(0.004)	(0.004)	(0.003)	(0.005)
$After_{j,t} \times \log(En\_follower_{j,t})$		−0.001***		0.001***
		(0.0003)		(0.0002)
Control variable	Yes	Yes	Yes	Yes
Session dummy	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Categorical fixed effects	Yes	Yes	Yes	Yes
Number of observations	272,548	272,548	272,548	272,548
Number of categories	2	2	2	2
R^2	0.696	0.701	0.478	0.479

Note. Standard error is in parentheses.
Significance levels: $^+p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 9. Estimation Results for Unstandardized Dependent Variables

Viewer flow in Figure 2 Dependent variable	(1) − (2) *Direct*	(3) − (4) *Indirect*
$After_{j,t}$	1.772*** (0.371)	3.876** (1.478)
Control variable		
$\log(I\_Viewer_{j,t-1})$	−0.158** (0.065)	−1.250*** (0.604)
$Similarity_{j,t}$	−49.46 (10.96)	168.324 (123.2)
$\log(In\_Follower_{j,t})$	3.052*** (0.008)	−15.87*** (0.735)
$Restricted_{j,t}$	−3.327*** (0.398)	19.59*** (3.591)
Period (period = 1)	1.345*** (0.315)	−13.32*** (2.904)
Period (period = 2)	0.550 (0.355)	−14.07*** (3.275)
Period (period = 3)	−4.946 (1.096)	−6.623* (3.198)
Session dummy	Yes	Yes
Individual fixed effects	Yes	Yes
Categorical fixed effects	Yes	Yes
Number of observations	2,418,488	2,418,488
Number of categories	20	20
R^2	0.368	0.337

Note. Standard error is in parentheses.

content switching on incumbent streamer viewership through the lens of network effects. Relying on a large-scale data set captured from Twitch.tv, we investigated how exogenous entry can affect the viewers' flow among streamers and demonstrate the moderating effect of entrant streamer popularity. Our estimation results offer the following conclusions: (1) Content switching generally benefits incumbent streamers and the incumbent category because of the positive direct spillover effects. However, when the entrant streamer becomes more popular, it may bring more challenges to incumbent streamers because of the negative moderating effect on direct spillover. (2) The incumbent streamers could benefit from the content switch by attracting more viewers from other categories or offline. The effect becomes stronger when the entrant is popular.

Our results provide important managerial implications for livestreaming platforms regarding managing the streaming content and helping incumbents flourish. First, incumbent streamers benefit from content switching because they can acquire viewers from entrant streamers as well as outside of the category. However, they may lose viewers if the entrant streamer is relatively popular. Thus, to help incumbent streamers retain their existing viewers and engage new viewers from outside the category, a platform reminder of popular streamer content switching could potentially help incumbent streamers adapt and adjust their strategies. For example, when incumbent streamers were sent reminders of the content switch of popular entrants, incumbent streamers could employ a campaign (e.g., an announcement of free gifts sent 20 minutes later) to improve viewer engagement and further prevent viewer outflows. Alternatively, given the higher number of viewers from other categories after content switching, streamers may choose to provide more background information for these viewers to reduce the learning cost of these new viewers.

Second, as the largest livestreaming platform, Twitch has recently been criticized because most streamers are dominated by top streamers (Hernandez 2018, Perez 2019). Given a large number of small streamers and the content they generate on the platform, the loss of less popular streamers may severely hurt the platform ecosystem and viewer base in the incumbent category (Zhang et al. 2012a, Reiss 2016). Our results demonstrate that encouraging popular streamers to switch to a category with many promising small streamers can be viable for streaming platforms as it attracts viewers from outside the incumbent category. However, this strategy should be implemented with extra cautiousness as it could also lead to a negative direct spillover effect. This also suggests that livestreaming platforms may consider incentivizing streamers to switch content for categories that need promotion.

Our results also shed managerial implications for sponsoring companies, brands, and advertisers. As a powerful tool to introduce video games and electronic devices to viewers, livestreaming has drawn considerable attention from sponsoring companies (e.g., Ubisoft and EA Sports) and electronics manufacturers (e.g., Sennheiser and Nvidia) who sponsor streamers to play their games or promote their product. Whereas some practitioners are concerned that incentivizing streamers, particularly popular streamers promoting their games, may intensify competition and discourage existing streamers, our results suggest that this strategy can benefit existing streamers by exposing their game to more viewers from other categories.

More importantly, having streamers with high levels of popularity switching to play their game also helps other incumbent streamers (those who already start streaming their games) expose their channels to more viewers (e.g., stronger indirect spillover effect). This improves the entire ecosystem among streamers of their game.

Our results can also easily be generalized to other types of social media services, such as YouTube, blogs, etc., and help unpopular users attract additional viewers to their generated content. Similar to our finding in the context of livestreaming, popular bloggers and YouTubers can also drive traffic to a category by switching to this category. This, then, generates positive indirect spillover effects for incumbent content creators in this category. Note that our context is a social media platform in which category boundaries are clearly defined. However, we believe our results can also be generalized to other platforms without clear boundaries among content categories. This is because most social media platforms implement recommendation systems that recommend similar content based on previous content consumption. This allows viewers to be exposed to a new category of content after content generators switch content even with the absence of a clear category boundary.

This study makes important contributions to several streams of literature. First, as far as we know, this is the first study to decompose the viewer flow and specify the corresponding direct/indirect spillover effect in the context of digital platforms. This is in comparison with previous literature, which mostly investigates the spillover effect at the aggregate level. We collect a unique data set with detailed viewer flow information and propose a directional viewer flow model to better understand the different network effects around streamers' exogenous entry from other categories. Notice that our framework can be generalized to other fields, such as the study of the traditional TV market, social TV, and other UGC digital platforms. Second, compared with previous literature in information diffusion on social media platforms with an inexplicit content boundary (e.g., Susarla et al. 2012), our research explicitly defines the content boundary through the category setting, which contributes to the research stream exploring the role of content switching in user content choice on a UGC platform. Third, to our best knowledge, there are very few studies in the livestreaming community that use firsthand data to empirically examine user behavior, especially from a content-switching perspective. Finally, our research directly contributes to literature investigating the association between program availability and viewer viewing choice. Unlike other existing literature that mostly focuses on what factor influences the viewer's viewing choice, our study provides a theoretical framework on how program availability affects the viewer's choice based on the existing theoretical models (Webster and Wakshlag 1983, Wonneberger et al. 2009).

Our research has several limitations, which may open opportunities for future research. First, we were unable to directly observe the exact time of content switching. Although we observe the content switching within a session, whether the content switching happens during the first minute of a streaming session or the last minute is still unknown. Second, we mainly focus on the short-term network effect, and we leave how content switches influence viewership in the long term for future research. Finally, there are heterogeneities among livestreamers that were not captured in this study, particularly the characteristics of streamers, such as gender, race, and geolocation. These factors can be examined as additional moderators calling for future research with deep learning and text mining approaches.

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Endnotes

[1] See https://www.researchandmarkets.com/research/8xpzlb/video_streaming.

[2] The term "category" is defined by Twitch as a content folder consisting of livestreams about the same game product, such as *Dota 2* and *League of Legend*, or a set of nongame activities, such as Just Chatting and Music & Art. Twitch uses category to organize livestreams on the browse page.

[3] The list of the top 20 categories on Twitch as of the data collection includes the following: game categories: *Valorant*, *Grand Theft Auto V*, *Fortnite*, *League of Legends*, *Call of Duty: Modern Warfare*, *Counter-Strike: Global Offensive*, *Minecraft*, *FIFA 20*, *Escape from Tarkov*, *Dota 2*, *Hearthstone*, *Terraria*, *World of Warcraft*, *Apex Legends*, *Dead by Daylight*, *Those Who Remain*, *Player Unknown's Battlegrounds*, and *NBA 2K20* and nongame categories: *Just Chatting* and *Music & Performing Arts*.

[4] The IGDB is a game-related database maintained by Twitch.tv. The IGDB API provides a game developer's information, comments of users, usage, and game description such as genre, theme, platform, and versions. See https://www.igdb.com/api.

[5] The term "genre" is defined by the game industry to describe the type of game listed in https://en.wikipedia.org/wiki/List_of_types_of_games. The term "modes" and "themes" are defined by the game mechanics to describe how the game works and how the people play as listed in https://en.wikipedia.org/wiki/Game_mechanics. Generally, these three metrics are used to classify games.

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