The Effects of Platform Superstars on Content Production: Evidence from Ninja

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Abstract: A characteristic of multi-sided platforms is the existence of a few "superstar" complementors who attract most demand. We investigate the effects that superstars exert on supply-side content production. Our empirical context is the online live-video streaming platform Twitch.tv. We report the results of two studies concerning the Fortnite superstar streamer Richard Tyler "Ninja" Blevins over 2018-2020. In Study 1, we investigate how the presence of a superstar on a platform affects content production. For inference, we exploit Ninja's temporary and unexpected absences from his streaming schedule. We find that a superstar's presence encourages differentiation: channels cast 9.8% (16.4 minutes) less Fortnite on days of Ninja's presence, and are 3.4% more likely to stream different content (as opposed to when he is exogenously absent). In Study 2, we assess how a superstar's switch to a rival platform affects content production. We exploit Ninja's 2019 announcement to leave Twitch for the rival Microsoft Mixer platform in a difference-in-differences design. We find that platforms suffer a reverberating loss in content production when they lose a superstar: affected Twitch channels stream 13.2% (24.8 minutes) less Fortnite after his switch, compared to before and compared to unaffected channels. Our findings have implications for the management of platforms, as well as for our understanding of the role of superstar complementors in content production.

1. INTRODUCTION

The business model of many multi-sided platforms, such as Twitch, YouTube or Apple iOS, is based on third-party content (Bhargava 2020; Parker and Van Alstyne 2018; Tiwana et al. 2010). A characteristic of such platforms is the existence of supply-side "superstars": contributors who create the most demand. For example, the Twitch channel Ninja has 15 Mn followers compared with a median of 20; the YouTube channel PewDiePie has more than 100 Mn followers compared with a median of 300; the mobile game Clash of Clans has a total daily revenue of USD 1.5 Mn compared with a median of USD 0.

It is well understood that superstars play a critical role in attracting demand for a platform. Stars are a primary reason for consumers to adopt a platform, they drive platform sales, and they serve as differentiators from competing platforms (e.g., Binken and Stremersch 2009; Corts and Lederman 2009; Rochet and Tirole 2003). It has become routine for platform owners to cultivate stars, or to hire stars in expensive deals.

By contrast, it is less well understood how stars impact the supply-side of the platform, in terms of complementors' content production. Given that platform firms are in charge of a micro-economy, it is crucial for them to take into account the effects on all sides of their market (e.g., Boudreau 2012; Parker and Van Alstyne 2018; Ransbotham et al. 2012; Sharma and Mehra 2020). In particular, as outlined in Bhargava (2020), complementors are not always competitors in a zero-sum logic. Therefore, without systematic evidence, the decision-making of platform firms relies on incomplete information.

In this paper, we investigate the effects that superstars exert on complementors' content production. We are particularly interested in two questions: (1) How does the presence of a superstar affect content production? (2) How does the switch of a superstar to a rival platform impact content production?

We empirically assess these questions using a novel dataset that we assembled from the online game streaming platform Twitch.tv (hereafter Twitch). On Twitch, third-party content takes the form of live video broadcasts, mostly about gaming. Anyone can sign up as a "channel" and then start live-streaming content, as with television channels. The platform has become significant. As of 2020, the platform has approximately 40 Mn concurrent registered viewers, and it represents the fourth-largest generator of Internet traffic in the United States. Thousands of channels compete on a daily basis for viewers, while only a handful of star channels garner most of the viewership.

To investigate the research questions, our paper conducts two distinct empirical studies that exploit unique identification-related opportunities in the history of the Twitch superstar streamer Richard Tyler "Ninja" Blevins. Ninja became a superstar in early 2018, earning a following of more than 15 million people and becoming the top channel for the game *Fortnite*.

In Study 1, we investigate how Ninja's presence affects complementors' supply of content. The basic empirical design is to compare the content supply of channels on the days on which Ninja was expected to stream and did actually stream with that of the days on which Ninja was expected to stream but did not stream. The primary empirical challenge in this regard is that superstars may deliberately decide to broadcast on a given day, causing other channels to stream less or avoid streaming altogether on the same days as the star. To overcome this simultaneity, we exploit the fact that Ninja had committed in 2018 and 2019 to stream every day for at least 12 hours, without any planned absence or vacation. Ninja is therefore expected to stream every day, which mitigates selection on the star-side. Despite his promise to stream every day, however, Ninja was unexpectedly absent on some days. For example, he cancelled streams due to illness, technical issues or family duties. These absences were plausibly beyond Ninja's direct control, and were not expected by other channels or by viewers. They provide a counterfactual for content supply on days of his presence on his platform.

The primary finding of Study 1 is that superstars force other complementors to differentiate.

Channels stream less Fortnite on days when Ninja is present than on the days on which he is exogenously absent. These effects are economically significant, and they mean that between 9.8% and 12.5% (16.4 and 20.9 minutes) less Fortnite content is provided. These results are robust to various definitions of the dependent variable and stricter definitions of Ninja's absences, and they take into account variations due to day-of-week, month, and year effects. Further analyses suggest that parts of this effect may occur because the production of Fortnite content is uneconomic on days of Ninja's presence. Channels have 6.9% fewer viewers and 6.1% fewer followers on days of Ninja's presence (versus his exogenous absence).

In Study 2, we investigate how the switch of a star affects channels' content supply. We exploit the fact that, in 2019, Ninja unexpectedly announced that he would leave Twitch and join the rival platform Microsoft Mixer. We construct a quasi-experiment in which we compare the outcomes of Fortnite channels on Twitch — who now no longer faced competition with Ninja — with those of an unaffected group of channels. We use German Fortnite channels as the unaffected control channels. Those channels are homogenous because they stream similar content but are not affected by Ninja's switch.

The primary finding of Study 2 is that Ninja's switch to Mixer had a large negative effect on the channels' production of Fortnite content. Channels streamed between 13.2% and 18.7% (24.8 and 34.9 minutes) less Fortnite than before and by comparison with unaffected German Fortnite channels. The result is robust to different windows around the switch, matching, and alternative control groups. Overall, Ninja's switch cut the number of active Fortnite channels almost by half throughout the post-event period. Further exploration of the causes of this decline suggests that Ninja's switch caused a substantial portion of viewers to abandon Twitch and follow him to Mixer. Consequently, streaming Fortnite on Twitch became uneconomic, forcing channels to seek different content.

Taken together, both studies yield a coherent picture. From the supply-side perspective, stars are crucial for platform owners for two reasons. First, their presence encourages differentiation, and therefore heterogeneous content. Second, losing a star to rival platform has strong negative effects on the original platform's content production.

These results contribute to several streams of literature. First, they add to our understanding of platform governance by revealing the effects of superstars on other complementors (Parker and Van Alstyne 2018; Wareham et al. 2014). Second, we contribute to the understanding of complementor heterogeneity (Binken and Stremersch 2009; Corts and Lederman 2009). Finally, the findings add to research on the economics of superstars by providing empirical evidence regarding the effects of superstars in two-sided markets (Azoulay et al. 2010; Rosen 1981).

This paper proceeds as follows. Section 2 provides definitions of the theoretical concepts and outlines related literature. Section 3 describes the empirical context and the dataset. Section 4 reports the design and results of Study 1, which assesses the direct effects of superstar presence on complementors. Section 5 summarizes Study 2, in which we assess the consequences of a star switch. In Section 6, we discuss our findings, and Section 7 concludes our work.

2. THEORETICAL BACKGROUND AND RELATED WORK

2.1. Theoretical Background

Platform businesses are widespread across industries, and have attracted significant attention through research into information systems, management, and economics (Parker and Van Alstyne 2018; Tiwana et al. 2010). We refer to a "platform" as a business model that enables transactions and innovation by bringing together different types of market actors in the presence of network effects. Based on Brandenburger and Nalebuff's (1996) definition, we use the term "complementor" to refer to firms or individuals on the supply side of the platform, i.e., those actors that contribute content to a platform.

We follow the notion of superstar competition as a systematic pattern in markets, wherein the majority of consumer attention concentrates on a few actors, although a considerable number of substitutes are available (Rosen 1981). More specifically, in such a market demand concentrates "on a group of best sellers, although there exists a large number of very good and highly substitutive alternatives" (Rosen 1981, p. 845). This pattern is widespread in platform markets. Clements and Ohashi (2005), for example, find that the top 5% of video games account for over 50% of video game sales. Garg and Telang (2013) observe that the top-ranked app for the Android mobile platform generates 184 times more downloads than the app ranked at 200.

There is no definition of what represents a star in the case of two-sided markets, and similarly there is little agreement on the properties or outcomes that define a star in other markets. For example, in the case of star scientists, Hess and Rothaermel (2011) define star scientists based on the deviation of their publication and citation counts from the mean, whereas Azoulay et al. (2010) classify star scientists based on a seven-criteria catalogue, including measures such as research funding, citations, and patenting. Another example concerns star executives, where Malmendier and Tate (2009) infer stardom from the receipt of a prestigious award, and Groysberg et al. (2008) infer stardom from a position in a ranking.

We acknowledge the variety of definitions of stardom. For the purpose of this paper, we offer the working definition that superstar complementors are those complementors who are in the top percentile of the demand distribution. Extant work refers to star complementors also as "outliers" or "marquees".

2.2. Related Work

Our research primarily relates to extant work on platform governance (Tiwana et al. 2010; Wareham et al. 2014). This stream of research is based on the notion that platform owners' activities go beyond platform development and marketing. A platform firm is in charge of a micro-economy (Parker and van Alstyne 2018). In the foreground of investigation is the design of interventions to improve the quantity, quality, and novelty of content supply.

Previous studies have researched various governance decisions, including pricing (Hagiu 2006), resourcing (Ghazawneh and Henfridsson 2013), matching (Bhargava et al. 2020), awards (Burtch et al. 2020), regulating the number of participants (Boudreau 2012; Casadesus-Masanell and Halaburda 2014; Ransbotham et al. 2012), rule-setting (Claussen et al. 2013), intellectual property rights (Ceccagnoli et al. 2012; Huang et al. 2013), value capture (Bhargava and Choudhary 2001; Foerderer et al. 2018; Li and Agarwal 2017; Sharma and Mehra 2020; Zhu and Liu 2018), seeding (Huang et al. 2018; Nagaraj 2020), endorsements (Li and Zhu 2020; Rietveld et al. 2019), social comparison (Burtch et al. 2017; Chen et al. 2010), collaboration (Kane and Ransbotham 2016; Ransbotham and Kane 2011), and signaling (Hukal et al. 2020).

There exists comparably little work on decisions related to stars (or marquees). Several models of multi-sided markets assume that participants are homogenous on both sides of the market (Caillaud and Jullien 2003; Evans and Schmalensee 2010; Parker and Van Alstyne 2005). Others incorporate heterogeneity in terms of different utility obtained from participation (Armstrong 2006), from cross-side interactions (Ambrus and Argenziano 2009; Bhargava 2020; Rochet and Tirole 2003), or from both cross-side interactions and participation (Rochet and Tirole 2006; Weyl 2010). Heterogeneous attractiveness of certain users is of particular interest to Rochet and Tirole (2003), who argue that the existence of marquee participants increases desirability to the other market side.

Empirical work considers the impact of stars on the demand side, in terms of user adoption of the platform (Binken and Stremersch 2009; Corts and Lederman 2009; Landsman and Stremersch 2011). The findings consistently indicate that stars are a primary driver of platform adoption by users. So far, however, only few studies have investigated decisions regarding star complementors, and to the best of our knowledge, none has so far studied the effects of stars on content production on the platform.

There is a broader stream of research on stars in a number of fields adjacent to information systems, including management, economics, and finance (e.g., Adler 1985; Lazear and Rosen 1981; Rosen 1981). A related review summarizing existing research in sociology, psychology, economics, and management is found in Call et al. (2015). The majority of research in this stream has documented that stars can increase demand, such as product ratings or sales (Hausman and Leonard 1997; Krueger 2005). There is also a stream of work investigating the emergence of stars (e.g., Autor et al. 2020). Other work studied the effects of superstars on their peers or organizations. Azoulay et al. (2010) and Malmendier and Tate (2005) investigate the effects of stars on their peers and the organizations they work for, respectively.

Much less work has focused on the effects of superstars on their competitors (e.g., Ammann et al. 2016; Brown 2011). These studies are concerned with the effects of superstars on their competitors' efforts and risk-taking. However, these studies are primarily investigating the behaviors of sports champions and CEOs, not the behavior of actors in the presence of network effects that have repercussions for competitors on the demand side.

3. EMPIRICAL SETTING AND DATA

3.1. Twitch.tv

Twitch.tv is an online live streaming platform. Complementors ("channels") broadcast audio and video to viewers in real time. In the majority of cases, channels are individuals. Anyone can open a channel, alone or together with other individuals, and become a streamer. The vast majority of channels are focused on gaming. These include the personal streams of individual players, tournaments or gaming-related chats or talk shows. Viewers can follow channels in such a way that the channels are displayed in their feed on the platform, and they are notified when the channel is on air.

Figure 1 provides a screenshot of a live cast. A live cast is usually focused on a specific type of content, typically a game that is played by the streamer and displayed prominently on the screen (Panel A). Viewers can see the gamer through a webcam (Panel B). Viewers can also see how many others are currently viewing or following the channel (Panel C).

[Figure 1]

Figure 2, Panel A shows that Twitch has been growing steadily over the years. Twitch is the largest live-streaming platform with approximately 40 Mn concurrent viewers, and is the fourth-largest generator of Internet traffic in the United States. As of 2020, Twitch is available in more than 200 countries, with its main viewership residing in the U.S. (24%) and Germany (7%). Panel B corroborates that a key feature of Twitch is the concentration of viewership on few star channels. The vast majority of channels have a small followership and the distribution is heavily skewed toward a few stars. When those stars streamed, there was a high probability that they reached a large audience. Those stars are also making significant returns from their streaming activity. For example, the superstar Ninja earns approximately half a million USD per month (Paumgarten 2018).

[Figure 2]

For most streamers the choice of what game to cast on their channels is determined by their previous experience and skills in that game and their membership of a group of top players of that game. Playing a new game is risky for a streamer, because viewers may be disappointed if the streamer consistently loses or does not display expertise. This can lead to lower numbers of viewers, followers, and subscribers, all of which are detrimental to the returns of a channel.

Channels monetize their activity in different ways, the primary ones being advertisement, subscribers, and donations. They typically show advertisements, with many channels opting for approximately three ads per hour, each typically lasting 10-30 seconds, and in full display, as on TV. Channels can also earn money from having users subscribe to their channel. Subscribers pay 5 USD per month, and in exchange they gain access to special perks such as exclusive chats, access to recorded broadcasts, and special emoticons. Finally, channels can earn money from donations by viewers. Many channels have a donation counter displayed during the broadcast, and donors may also receive special perks.

Twitch offers an ideal real-world laboratory in which to investigate superstar effects, for two further reasons. First, the channels — at least, the majority of them — are run by professional streamers making real decisions that affect their financial success and career on the platform. The competitive stakes are substantial, given that there are many thousands of channels competing for attention. In contrast to other social media platforms in which users consume content after it has been generated, streaming audiences consume video content in real time. Furthermore, since live stream audiences can watch only one stream at any time (as switching back and forth between streams would lead to much loss of content), there is intense competition among channels which stream at the same time of day, particularly channels which stream similar types of content. Indeed, Twitch, as the largest live streaming platform, has recently been criticized because small channels are struggling in its fiercely competitive environment (Hernandez 2018; Perez 2019). Second, the context is attractive for empirical reasons. We can observe in detail the content provision of channels, and the context provides a unique opportunity for identifying superstar effects, as we outline in what follows. Online streaming also provides a unique opportunity to examine channel competition, in that it records detailed audience flows among different channels. While stars attract hundreds of thousands of viewers to their channels, the majority of live streaming content is nonetheless produced by small channels. Furthermore, the status of streamers changes constantly on live streaming platforms, and channels can quickly rise to the top.

3.2. Superstar Richard Tyler ‘Ninja’ Blevins

Both studies investigate events surrounding the Twitch superstar Richard Tyler “Ninja” Blevins. Ninja, a 29-year-old from Illinois, has the most-followed channel on Twitch, with over 15 million followers. Over 50,000 of those are paying subscribers with a support of USD 5 or more. He had sponsorships from a number of companies, including Red Bull, Samsung, and Uber.

Remarkably, he is one of the few streamers to have broken through into mainstream fame. He has been a guest on the Jimmy Fallon and Ellen DeGeneres shows, has appeared on the cover of ESPN magazine and in a Super Bowl commercial, and has released his own toy line sold at Target. His sponsor

Adidas sells shoes and clothing with his branding (Montag and Huddleston 2019). Forbes estimated his earnings in 2019 at $17 million.

Figure 3 illustrates Ninja's rise in popularity. Panel A plots the monthly increase in followers of his channel; Panel B displays the concurrent viewers of his channel by month. He joined Twitch in 2011, but his rise to stardom took until 2017. Ninja's rise is considered to be closely tied to the success of the game *Fortnite*, which appeared in July 2017. Ninja was one of the first to adopt the game, shortly became one of the best players, and one of its most active streamers. His followership began to grow in late 2017 along with the outstanding success of the game. Between July 2017 and March 2018 his followership increased from 100,000 to more than 2,000,000.

Several reasons make an investigation of Ninja empirically attractive. Ninja's direct competitors can be identified in a relatively straightforward way. Competition on Twitch can be defined by three forms of differentiation: game played, language, and time. Viewers tend to be interested in watching streams of a particular game, mostly related to their own interest in the game. Ninja has almost exclusively streamed Fortnite and has primarily been known for this particular game. In 2018, for example, of the total of 2,982 hours which Ninja streamed, he was casting Fortnite for 2,767 hours. Given that Ninja has committed to streaming every day throughout the main hours of interest, there is little room for any competitor to differentiate by streaming at another time.

[Figure 3]

3.3. Data Sources and Variables

Our primary data sources are the Twitch analytics providers Twitchtracker and Sullygnome.[1] These websites track various data on Twitch channels, including their daily viewers, followers, and content provision. They provide access to full historical daily data for each channel.

Both studies investigate the effects of superstars on channels' supply of content. We infer channel i's content supply from the total number of minutes of video stream it contributes to the platform on day t. In particular, we create the variable $MINUTES\ STREAMED\ FORTNITE$ which is the total count of minutes for which channel i streamed Fortnite on day t. We log-transformed the variable to account for its skewed distribution. We create the variable $MINUTES\ STREAMED$ which is the total number of minutes for which channel i casted on day t. We log-transformed the variable to account for its skewed distribution.

[1] See www.twitchtracker.com and www.sullygnome.com, respectively. The data collection procedure complies with the fair use policy of Management Science.

Both studies also investigate channels' demand-side outcomes. The variable $VIEWERS$ gives the number of viewers per hour of channel i on day t. $FOLLOWERS$ gives the number of followers gained by channel i on day t. We logged both variables to account for skewness.

Table 1 presents the summary statistics of the datasets of Studies 1 and 2.

[Table 1]

3.4. Study Overview

Both research questions are addressed in the same empirical setting and leveraging the same base data. We address each question in an individual study. Figure 4 provides an overview of the studies which we describe in the following. In study 1, we investigate the direct effects exerted by Ninja on other Twitch channels. In study 2, we investigate channels' content supply after the switch of Ninja to the rival platform Microsoft Mixer. Both studies are complementary.

[Figure 4]

4. STUDY 1: EFFECTS OF SUPERSTAR PRESENCE

4.1. Research Design: Ninja's Temporary Absences 2018-2019

The goal of Study 1 is to investigate the direct effects of platform superstars on complementors' content production.

Econometrically, the simplest approach would be to compare channel i's content supply on days t on which a superstar streamed with the days on which a superstar did not stream. Such an approach would lead to inconsistent estimates in many cases, because a superstar may only stream on days with the highest expected demand (i.e., Friday to Sunday). In addition, channels may decide to stream on days when a superstar is absent, to avoid direct competition. If one of these reasons were the case, the results would be biased: any observed difference may be an artifact of stars' or channels' endogenous selection rather than being indicative of a true superstar effect.

These concerns are less problematic in the case of Ninja, for several reasons. First, beginning in 2017, Ninja had committed to stream every day by default, with no planned absences. Ninja argued that he had to stream every day in order to maintain his strong followership. Thus, Ninja's commitment to stream every day, and also to stream for most parts of the day, made any absence from Twitch unexpected for other channels and viewers.

Second, Ninja committed to stream during the prime hours of each day. His morning session ran from approximately 9.30 to15:00, his evening session from 19:00 to 02:00. On average, he streamed 12 hours per day. His intense streaming schedule stands out among channels, and has been subject to some debate in the press. Importantly, his streaming schedule makes him an important competitor for any other

English-speaking channels of Fortnite, which can do little to avoid him except by streaming at different days or times.

Finally, any absence from streaming is likely to be caused by an important or exogenously forced event rather than Ninja's unforced choice. Anecdotal evidence from interviews support this claim. For example, in an interview with the New York Times, he said that he might lose 200-300 followers by not streaming during the time of the interview. In 2018, he attended a four-day computer games conference and said "It's stressful. […] it was worth it, 100 percent, but I lost 100,000 subscribers." In addition, Ninja refrains from taking vacations: "[…] the longest vacation I've ever taken was my honeymoon, and that was like six days. And that was devastating. It was a calculated risk." (Draper and Bromwich 2018). Later in that year he tweeted: "Wanna know the struggles of streaming over other jobs? I left for less than 48 hours and lost 40,000 subscribers on twitch. I'll be back today (Wednesday) grinding again." In the light of these statements, one may expect that any absence on the part of Ninja is relatively exogenous. On the days of Ninja's absence, channels and viewers expected him to stream but faced a different environment.

In addition, we exploit the fact that Ninja has been absent on some days for stricter exogenous reasons. Some of the absences could have plausibly been predicted by other channels, especially various offline events (e.g., Electronic Entertainment Expo E9, Super Bowl, Twitch Convention, Gaming Community Expo Charity Event). However, many other absences were comparatively unexpected, and also reasonably exogenous to Ninja. For example, at various days in the observation period, Ninja had explained that he was not streaming due to technical issues, sickness, exhaustion or family obligations.

To identify Ninja's absences, we started with a list of all days between January 1, 2018 (i.e., the beginning of the study period) and July 31, 2019 (the end of the observation period) on which Ninja had not streamed. Ninja maintains a relatively active Twitter feed, where he tweets about various topics. We manually collected all Tweets of Ninja during this period and inspected their content, keeping those in which he gave information about his absence. Ninja openly discusses his absences either on the day of absence or shortly afterwards, explaining the reason for his absence.

We create two variables. $PRESENT$ is 1 on days t on which Ninja has streamed and 0 otherwise. $PRESENT\ STRICT$ is 1 on days t on which Ninja has streamed, 0 on days t on which Ninja was exogenously absent, and coded as missing on days t on which Ninja was endogenously absent. We consider an absence as exogenous if the following conditions hold: (1) Ninja announced his absence less than 24 hours in advance on his Twitter feed; (2) the absence was due to family, sickness, technical issues, or business travel. Appendix A provides empirical examples of the Tweets and their coding.

Table 2 tabulates the absences. Of the overall 577 days in the sample, Ninja is absent on only 115 days, of which 80 are coded as strictly exogenous absences. The main reasons for the exogenous absences, by frequency of occurrence, are: family obligations, business travels, exhaustion, and sickness.

[Table 2]

Figure 5 provides descriptive plots of the absences by month from January 2018 to July 2019. Black bars indicate absent days and gray bars indicate how many of these absences are plausibly exogenous. It is evident that Ninja has been active almost every day. Still, there is variation in Ninja's absences over the observation period. Eyeballing indicates no systematic pattern in the absences. One exception may represent the higher number of absences in Mid-2019, that is, the time shortly before Ninja's switch to Microsoft Mixer. The robustness section confirms that the results hold when excluding this period from the sample as well as when controlling for a trend in the absences.

[Figure 5]

4.2. Data Collection

The starting point of the dataset construction was an index of all Twitch channels that fulfilled the following conditions: streamed Fortnite for at least one hour in the first week of 2018; streamed exclusively in English; had at least five average viewers during their stream; had affiliate or partner status on the platform. We restricted the index to those channels with affiliate or partner status to avoid inflating the sample with newcomers or occasional streaming channels. Partner channels are considered professional channels.[2] For each remaining channel, we collected daily data on the streams broadcast, their viewership, followers, games played, and various further information for the period January 1, 2018 to July 31, 2019. We convert streaming times to Eastern Standard Time to adjust for Ninja's time zone, and account for daylight savings time. The resulting dataset is on the channel-day level.

4.3. Econometric Framework

We estimate the impact of star absence on the dependent variables (Y) using the model:

$$Y_{i,t} = \beta_0 + \beta_1 PRESENT_t + \Gamma_t + v_i + \epsilon_{i,t} \quad (1)$$

where our main interest is in the parameter β_1, which describes the difference in content production by channels in the presence (strict) versus absence of Ninja on day t. We include the vector Γ_t, which contains time controls in terms of dummies for the hour-of-day when the cast started, day-of-week and month-of-year. These controls ensure that the observed effects are not due to correlates of time, such as

[2] As of 2020, to receive partner status, a channel must be individually approved by the platform team, must at least have streamed for a total of 25 hours within 30 days and for 12 unique days in the past 30 days, and must have reached an average of 75 concurrent viewers.

the general tendency to stream more during a holiday season. In addition, they account for time-specific shocks that affect all channels and that may be correlated with their casting outcomes, such as events in the general media. The vector v_i contains channel fixed-effects. We estimate the variables using ordinary least squares with a robust variance estimator that is clustered by channel-day.

4.4. Main Results

To foreshadow the results reported below, we document that channels supply less content on the days of Ninja's presence (compared with the days of his endogenous and exogenous absences).

Figure 6 presents the model-free evidence. Panels A plots the mean $MINUTES\ STREAMED\ FORTNITE$ along with 95% confidence intervals when Ninja is present as opposed to absent. Panel B proceeds similarly but with Ninja's strict absences as comparison benchmark. Evident in both plots is a marked difference: on days of Ninja's presence, channels supply less Fortnite content to the platform compared with when he is absent. In Panel A, the difference is 10.1 minutes and strongly significant ($p<0.001$). In Panel B, the difference is 8.6 minutes and strongly significant ($p<0.001$).

Panels C and D plot the same data, this time distinguishing between days of the week. Demand for Twitch differs strongly across weekdays, with substantially more viewers on the platform at weekends. Thus, the observed differences may represent an artifact of weekday-specific differences that correlate with Ninja's absence. Panels C and D document that this is not the case. In both plots the differences among the weekdays are marked. Taken together, and considering the descriptive evidence, it may be concluded that channels supply less Fortnite content on days of Ninja's presence than on the days of his absence.

[Figure 6]

Table 3 reports the analytical evidence. Column (1) provides the main evidence. It reports the base estimation of equation (1) with the daily minutes of Fortnite casted as dependent variable, including channel fixed effects as well as start hour-of-day, day-of-week, and month fixed effects. The estimates suggest that channels supply approximately 9.8% less content on the days of Ninja's presence than on the days of his absence. Given a mean stream length of 164 minutes, the difference amounts to approximately 16 minutes on average. Column (2) documents that the results differ only marginally when restricting the data to strictly unexpected absences. In particular, we estimate a difference of 9.5% (15.5 minutes) on average.

Columns (3) to (6) report immediate sensitivity checks for the independent variables, subsamples, and alternative dependent variables. Column (3) corroborates the results when using Ninja's total stream duration on day t as predictor. The coefficient indicates that a 1% longer stream from Ninja translates into

0.016% shorter Fortnite streams by other channels. Column (4) reports the estimates when adding a time trend to the model. One may be concerned that Ninja's absences increased over time, for example, because Ninja may have been more likely to be hired for offline events. The results remain qualitatively similar, but the estimate is lower at 4.9%. Column (5) excludes July 2019 from the analysis. As evident in Figure 5, there is a bunching of absences in July 2019, which also shortly precedes his switch to Mixer. In this case, the estimated effect is much more pronounced, indicating that channels supply 12.5% less Fortnite content during his presence than during his absence. Column (6) documents that the results hold when adding a lagged dependent variable capturing channels' average cast duration in the preceding month.

Finally, the results are also consistent when considered in the light of two alternative measures of channel content supply. Column (7) regresses channels' overall content supply (i.e., total minutes cast). We find that in Ninja's presence, channels not only cast less Fortnite content but cast less content overall compared with when he is absent. Our estimate suggests that Ninja presence reduces the overall streaming time of competitors by 3.4%. In Column (8), we estimate the likelihood of streaming a game other than Fortnite. Consistent with the above results, we find that channels have a 1.7% smaller likelihood of streaming Fortnite when Ninja is present than when he is absent.

Taken together, the results consistently support that channels supply less (similar) content on the days of Ninja's presence.

[Table 3]

4.5. Mechanism

What explains the lower content supply from channels on the days of Ninja's presence? Isolating the precise mechanisms that underlie any causal effect is very difficult with observational data alone, especially so when demand and supply are simultaneous. In what follows, we attempt to provide evidence that channels experience lower demand on days of Ninja's presence, therefore making content production less economic.

We conduct an indirect effects (i.e., mediation) analysis (Imai et al. 2011). With indirect effect evaluation, a variable X is assumed to have an effect on another variable, Y, yet part of the effect is allowed to operate through a third variable, M. The indirect effect is given by X influencing M which influences Y. The indirect effect is the portion of the X-Y effect that can be explained, whereas the direct effect is the unexplained portion. The aim of this analysis is to identify the mechanisms through which X influences Y. In our case, the demand for a channel acts as the third variable M for the relationship between Ninja's presence (X) and channels content supply (Y). We prefer the Imai et al. (2011) indirect effects approach, given the criticism that has emerged in recent years concerning the classic Baron and

Kenny (1986) approach to mediation analysis (see Zhao et al. 2010). Appendix B provides the estimated equations and more technical details on the approach.

Table 4 reports the results. Column (1) shows that channels experience 20.8% fewer viewers on days where Ninja is present. Please note that the variable $VIEWERS$ already accounts for the overall stream length. Column (2) represents the estimation of indirect effects. The mediation is strongly significant, and approximately 95% of the direct effect is explained by the mediator.

The remainder of the columns show that the results are consistent when using $FOLLOWERS$ as an alternative mediator variable for inferring demand. Column (3) shows that channels experience a 3.4% lower growth in followers during their cast. Column (4) presents estimates of the full indirect effects. The indirect effect of FOLLOWERS is strongly significant. Approximately 72% of the effect is explained.

Taken together, these analyses suggest that channels have lower viewership on the days of Ninja's presence than on the days of his absence, which makes it uneconomic for channels to produce more live content.

[Table 4]

4.6. Robustness

We conduct several checks to address concerns over spurious estimates. In the first check, we seek to assess whether the results represent a false positive that arises from the data structure or simply occur by chance (Bertrand et al. 2004). We restrict the data to days with Ninja's presence, and generate a calendar of random absence days. That is, we randomly set absences for the same number of days as Ninja's days of unexpected absence. Table 5, Panel A confirms this prediction. The coefficients are close to zero and insignificant. It is therefore unlikely that the results merely represent an artifact of the data structure.

In a second check, we seek to assess concerns over omitted variables that are both correlated with Ninja's absence and channels' content supply. Although star absences are plausibly exogenous to channels, one may be concerned with unobserved events taking place exactly at the same time as the absences, which might explain the differences in other channels' content supply. One simple counterfactual analysis would assess whether a reasonably unaffected group of channels also shows differences in their content supply on days of Ninja's absence. It would corroborate our results if we observed that a group of unrelated channels showed no significant change in content supply.

In Table 5, Panel B reports the results of this exercise. It repeats our main analyses, but this time with German Fortnite channels as the sample. German Fortnite channels should not be affected by Ninja's absence: differences in language prevent most German viewers from watching English channels. Fortnite is a game that targets children, who in German-speaking countries are unlikely to be highly conversant in

English. Thus, it is unlikely that Ninja has a substantial followership in German-speaking countries. Reassuringly, all the results of our robustness checks are in line with our expectations, and confirm the validity of our findings.

[Table 5]

5. STUDY 2: EFFECTS OF A SUPERSTAR'S SWITCH

5.1. Research Design: A Quasi-Experiment of Ninja's Switch to the Microsoft Mixer Platform

To assess how the switch of a superstar impacts content production, we rely on a quasi-experimental design. The quasi-experiment leverages the fact that on August 1, 2019 Ninja, in a statement unexpected by his fans or the media, announced that he would quit Twitch, and that he had signed a deal to stream exclusively on the Microsoft Mixer platform. Mixer is a platform rival to Twitch and had previously been lagging behind in followership. At the time of the switch, Twitch had the largest market share as measured by hours watched on the platform (75.6%), followed by YouTube Gaming (17.6%), Facebook Gaming (3.7%), and Microsoft Mixer (3.2%).

Several reasons make this empirical situation well-suited for studying the switch of a star. First, the announcement was unexpected. Ninja had not communicated the switch to his fans before the announcement. The move was considered surprising by various media outlets, including Forbes and the Wall Street Journal (Needleman 2019). The Verge described the announcement as "a tweet that blew up gaming's corner of the internet" (Stephen 2019). Second, the announcement was implemented immediately, enabling a clear cutoff date to be defined. Ninja started to stream on the day following his announcement, that is, on August 2, 2019. Finally, it seems unlikely that the move was correlated with the behavior or outcomes of other Fortnite channels on Twitch. In a later interview, Ninja's manager stated that one primary motive for the switch was that Twitch had hindered licensing and brand deals outside the platform.[3]

5.2. Quasi-Experimental Setup and Matching

In our quasi-experiment, the treatment group consists, just as before, of all English-language Fortnite channels on Twitch (i.e., all English-language channels that had streamed Fortnite for at least one hour at the beginning of 2019).

As a control group of unaffected channels, we use all German-language Fortnite channels. This group of channels is likely to represent a suitable control group for several reasons. First, the channels are reasonably unaffected by Ninja's move, due to language differences. Streaming content in English is

[3] Please note that Microsoft shut down Mixer in July 2020 citing a lack of growth. Mixer moved its streamers and viewers to Facebook Gaming and released Ninja from his contract. Ninja took a break and streamed occasionally on Facebook Gaming, until he announced on September 10, 2020 that he had signed a deal with Twitch to stream exclusively for their platform again.

unlikely to appeal to German viewers, and German channels may not have a substantial non-German audience. This language barrier is particularly marked because Ninja's primary audience is composed of children and young teenagers (Marchese 2021). With its comic style, Fortnite generally appeals primarily to children and young teenagers. Children and teenagers in German-speaking countries are unlikely to consume English-language streams because, despite learning English as a second language, they might not be capable of enjoying an English-only stream by Ninja. Thus, we expect that both groups have different audiences in terms of their language.[4]

Second, despite the language barrier, it is likely that both German channels and their audiences are similar enough to their English counterparts. Fortnite has enjoyed similar popularity in German-speaking countries. In addition, by comparing the effects only within Fortnite channels, we can account for game-specific effects that occur at the same time (e.g., the release of new levels or game items, and game updates).

To further reduce pre-switch heterogeneity between groups, as well as to address the fact that there are many more English-language channels than German channels, we employ coarsened exact matching (CEM). It is suggested that CEM yields better matches than propensity score matching (PSM). Simulations suggest that PSM seldom produces matches of better quality than random matching, especially for smaller samples (see King and Nielsen 2019). It is argued that CEM improves matching quality because it classifies based on coarsening variables (Iacus et al. 2012). Units are placed into strata based on their values for the coarsened variables. Units within the same stratum are then weighted according to the number of treated units. Strata without at least one pair of a treated and control unit are pruned, which obviates the need for subjective calipers, as in PSM. We rely on the default coarsening algorithm "the Sturges rule" and enforce the same number of treated and control units.

Table 6 summarizes the key evidence that the matching procedure has effectively addressed the heterogeneity between groups. Within each block, the left column reports a simple t-test for differences in means. The right column reports a test for differences in trends, which is based on restricting the sample to the pre-switch period and estimating regressions that regress the dependent variable on the treatment indicator, a linear time trend, and their interaction. Importantly, even before matching there were no significant differences between groups regarding their supply of Fortnite content. However, groups differed with regard to their average number of viewers and followers, both in means and trends. After the matching, those differences have become close to zero and are statistically insignificant.

[4] In Appendix C, we also replicate the main analyses of Study 2 using channels with different European languages as control groups to assuage concerns over the choice of our control group. However, we opt for German channels as the control group in Study 2 because Scandinavian countries and the Netherlands have especially high English proficiency, which makes them relatively unsuitable for our purposes. Nevertheless, the results using the alternative control group are consistent.

[Table 6]

5.3. Data Collection

The starting point of the dataset construction was an index of all Twitch channels that fulfilled the following conditions: streamed Fortnite for at least one hour in the first week of 2019; streamed exclusively in English (German); at minimum of five average viewers during their stream; affiliate or partner status on the platform. We restricted the index to those channels with affiliate or partner status to avoid inflating the sample with newcomers or occasional streaming channels. Partnered channels are considered professional channels.[5] For each remaining channel, we collected daily data on the streams they broadcast: their viewership, followers, games played, and various other items of information for the period January 1, 2018 to October 31, 2019. The resulting dataset is balanced on the channel-day level.

5.4. Econometric Framework

Our primary approach is a standard difference-in-differences (DID) model given by:

$$Y_{i,t} = \beta_0 + \beta_1 AFFECTED_i \times NINJA\ ON\ MIXER_t + \Gamma_t + v_i + \epsilon_{i,t} \qquad (2)$$

where of main interest is the parameter β_1, which describes the difference in content production by affected channels before and after Ninja's absence compared to the control group of unaffected channels. As before, we include the vector Γt which contains time controls in terms of dummies for the hour when the cast started, calendar day, week-of-year, month-of-year, and year. The vector v_i contains channel fixed-effects. We estimate the variables using ordinary least squares with a robust variance estimator that is clustered by channel-day.

In addition, we estimate a relative-time DID (Angrist and Pischke 2009, equation 5.2.6). We interact dummies for each day relative to Ninja's switch with the treatment group indicator to allow for differences in each day:

$$Y_{i,j,t} = p[AFFECTED_i \times T_t] + \kappa_j + \phi_t + \epsilon_{i,j,t} \qquad (3)$$

where T is a dummy that reflects each observation's distance from the switch in days. The coefficient of interest is p', which can be interpreted as the difference between treated and control observations within each relative period.

One parameter of both models concerns the time windows around the switch. Generally, shorter time periods allow the more precise capture of the effects of an event, whereas larger windows bear the risk of capturing the effects of other events taking place during the post-event period. In our main

[5] As of 2020, to receive partner status a channel must be individually approved by the platform team, must have streamed for a minimum of 25 hours within 30 days and for 12 unique days in the past 30 days, and must have reached an average of 75 concurrent viewers.

specification, we rely on a time window of [-30, +30] days around the switch. We document that the results are robust to shorter and longer windows.

5.5. Results

To foreshadow the findings established below, we observe that Ninja's switch to Mixer caused a strongly negative and permanent decline in Fortnite content production on Twitch.

Figure 7 begins with descriptive evidence. The dashed line gives the total minutes of Fortnite streamed per day on Twitch around the switch. There is one larger peak end at July 2019, which coincides with the Fortnite World Championships, but otherwise the supply of Fortnite content has been relatively stable before the switch. After the switch, there is a marked decline in Fortnite content provision. In fact, content is almost halved by the end of the post-switch period. The solid line displays the total number of channels on Twitch that stream Fortnite. The line is almost identical. Before the switch, the number of Fortnite-streaming channels is relatively constant at about 8,000. After the switch, the number of channels declines sharply to about 4,000. Finally, the dotted line is the number of viewers of Fortnite channels. The number of viewers is also halved over the post-switch period. Taken together, the descriptive plots suggest that Twitch suffered from a steady decline in Fortnite content and viewers after Ninja's switch to the rival Mixer platform.

[Figure 7]

Table 7 reports the results from estimating the standard DID model in equation (2). Column (1) is the baseline, comparing the content supply of Twitch channels affected by Ninja's switch with that of unaffected and matched control channels. We observe a strongly negative and significant effect of the switch on the Twitch channels' content supply. In particular, Ninja's switch reduced the channels' supply of Fortnite content by $100(e^{-0.188} - 1) = -17.14\%$ or 32.07 minutes.

The subsequent columns evaluate the effect magnitude for different windows around the switch. Column (2) restricts the window to [-20, +20] days around the switch. The effect is marginally larger in absolute terms at -18.70%. Column (3) extends the window to [-60, +60]. The effect is smaller in absolute terms, amounting to -13.24%. This suggests that the negative effect slightly decreases over time.

The remainder of the columns show that the results also hold for two further sensitivity checks. Column (4) shows that the results are also plausible when controlling for an additional time trend. Column (5) uses an alternative dependent variable, namely $STREAMED\ FORTNITE$. Even though channels are less likely to stream Fortnite, this coefficient slightly misses statistical significance at the 5%-level.

Taken together, these results suggest that Ninja's switch to the Mixer platform negatively affected the supply of Fortnite-related content.

[Table 7]

We also estimate the effects in a relative DID framework, as of equation (3) and using a time window of [-30,+30]. For brevity, Figure 8 plots the p'-coefficients. We observe that none of the pre-switch indicators is significant. Thus, it is unlikely that the obtained effects originate in the pre-switch period. This evidence is also in line with the pre-switch balance and parallel trends documented above. In addition, several of the post-switch coefficients are negative and significant, especially those close to the switch date. This further corroborates what the above estimation has indicated: Ninja's switch to the rival Mixer platform negatively impacted the production of Fortnite content.

[Figure 8]

5.6. Mechanism

Why did Ninja's move to Mixer reduce the production of Fortnite content on Twitch? The descriptive evidence in Figure 7 indicates a potential explanation: Ninja's switch reduced the overall viewers interested in Fortnite content on Twitch.

For this reason, we would expect to find that the permanent switch of a superstar would decrease user demand on the platform for the superstar's content category. Therefore, we expect to find that Ninja's move to Mixer would lower the overall viewership for the affected English-speaking channels on Twitch. The model-free evidence presented in Figure 7 is already corroborating these expectations, as we observe a steady decline of viewership upon Ninja's switch. To formally test this explanation, we proceed parallel to the above and estimate an indirect effects model.

Table 8 presents our results. Column (1) shows that Ninja's switch has a negative effect on the affected channels' daily viewership. Column (2) represents the indirect effects estimation. The indirect effect is strongly significant. Approximately 95% of the direct effect is explained by the mediator.

The remainder of the columns show that the results are consistent when using $FOLLOWERS$ as alternative mediator variable for inferring demand. Column (3) shows that Ninja's switch caused a reduction in affected channels' daily follower growth by 3.4%. Column (4) presents the full indirect effects estimates. The indirect effect of $FOLLOWERS$ is strongly significant. Approximately 72% of the effect is explained.

In summary, the results underscore that Ninja's permanent absence decreases the demand for affected channels, which makes it less economic for them to stream, hence the lower production of Fortnite content.

[Table 8]

5.7. Robustness

5.7.1. Difference-in-Differences Diagnostics

Table 9 reports various robustness checks that follow the recommendations in Bertrand et al.

(2004) and Angrist and Pischke (2009) for DID estimations.

First, we conduct a placebo test to assess the plausibility of our results. We restrict the sample to the control group and then randomly assign a placebo treatment indicator to channels. Estimating equation (1) with a randomly assigned placebo variable should not indicate any significant effect. Column (1) reports the results. The effects are insignificant, as expected. In addition, similarly, we generate a placebo event. In particular, we restrict the sample to the pre-exit period and then set a placebo $AFTER$ variable. Column (2) shows the resulting coefficient, which is insignificant, as expected. Second, to address concerns of autocorrelation we follow Bertrand et al. (2004) and aggregate the panel into two periods, such that each channel is observed once before the switch and once after it. Column (3) reports the result, which is consistent. Finally, following Angrist and Pischke (2009, p. 238, equation 5.2.7) we estimate the main model with a channel-specific time trend included. Column (4) displays the estimate, which is also consistent.

[Table 9]

5.7.2. Alternative Control Group

One may be concerned over the use of German channels as control group. Despite their observational similarity and the employed matching, German channels may differ from the treated channels on unobservable characteristics. In addition, there may be much less German channels in terms of viewership that could serve as matches for the English channels.

To address, we conducted the entire set of analysis using an alternative control group. In particular, we consider all German, French, Swedish, Norwegian, Italian, Greek, Finnish, Dutch, and Danish channels as a base for constructing the control group. Appendix C provides further details and reports the results. Overall, we find results consistent with our main findings. The effects are consistently negative and significant, yet smaller than in our primary specification. These results further corroborate the analysis.

6. DISCUSSION

6.1. Summary of Findings

To investigate superstar complementors' supply-side effects, we conducted two empirical studies. In Study 1, we find that stars encourage the differentiation of content production. Channels stream between 9.8% and 12.5% (16.4 and 20.9 minutes) less Fortnite on days when Ninja is present than when he is exogenously absent. As for the mechanism, we document that the production of Fortnite content is uneconomic on days of Ninja's presence, as channels have between 4.8% to 5.2% fewer viewers on those days (in contrast with the days of his exogenous absence).

In Study 2, we find that the switch of a star to a rival platform negatively affects content production. The effect we observed was large and persistent, indicating a decline of between 13.24% to 18.7% (24.8 to 34.9 minutes) of Fortnite content. One likely explanation is that, after Ninja left Twitch, fewer viewers used Twitch to watch Fortnite, making the production of Fortnite content on Twitch less economic for English-speaking channels.

Taking these findings together, we conclude that stars are crucial for supply-side content production for two reasons. First, their presence encourages differentiation, and therefore greater heterogeneity in content. Second, losing a star to rival platform has strongly negative effects on the content production on the platform, such that it suffers a reverberating loss in that type of content.

6.2. Theoretical Contributions and Implications

Our study makes three contributions. First, we contribute to the research on platform governance, which has primarily investigated star complementors' ability to attract demand (Binken and Stremersch 2009; Parker and Van Alstyne 2018). Our study incorporates the supply-side point of view.

Second, we contribute to the literature on multi-sided markets, particularly the work that studies the heterogeneous cross-side and same-side effects of participants (Ambrus and Argenziano 2009; Armstrong 2006; Rochet and Tirole 2003). Those studies are predominantly theoretical, whereas our study contributes empirical evidence on the effects of one particular type of heterogeneous participant, namely a star complementor.

Finally, we add to the broader interdisciplinary research on stars (Azoulay et al. 2010; Call et al. 2015; Rosen 1981). Those studies have investigated the effects of stars on their organizations, peers, and demand. Our study contributes by investigating the effects of stars on their competitors in an environment that is characterized by network effects.

6.3. Managerial Implications

The results we observe have important implications for platform firms. In particular, platform owners should take into account the effects that superstars have for other supply-side participants. The findings matter because it remains a pressing question for platform firms whether or not they should hire stars. Platforms actively seek to contract stars to stimulate competitive differentiation by other platforms. Video game console manufacturers such as Sony or Nintendo typically highlight titles that will be released jointly with the console. Media platforms such as Netflix or Apple TV+ have begun to produce their own content. Mobile operating system platforms act similarly: Apple recently contracted Super Mario as a temporally exclusive title.

Our findings suggest that star presence is not only crucial for increasing the attractiveness of a platform to users. It is also crucial because it encourages other complementors to differentiate, which can act as a precursor to innovation.

To mitigate the decrease in content supply, platform management could devise countermeasures to encourage content production by complementors even when stars are present. Possible approaches could include recommender systems for new channels or free subscriptions to competitors to encourage channel discoveries. In the grand scheme of things, these actions depend on whether the platform desires more concentrated demand for one star supplier or more fragmented demand for multiple suppliers.

7. CONCLUSION

We have conducted two empirical studies on the live-video-streaming platform Twitch. From Study 1, we conclude that superstars encourage differentiation. From Study 2, we conclude that platforms suffer a reverberating loss in content production when they lose a superstar. Overall, stars appear to have a substantial impact on content production on the platform by enforcing differentiation and enabling content creation. Our findings have implications for the management of platforms, as well as our understanding of the role of superstar complementors for content production.

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TABLES AND FIGURES

Table 1: Summary Statistics

		Description		Mean	SD	Min.	Median	Max.
1	Minutes streamed Fortnite	Minutes that channel i broadcasted Fortnite on day t	Study 1	167.45	205.90	0.00	105.00	4020.00
			Study 2	187.12	205.45	0.00	149.00	7009.00
2	Minutes streamed	Total minutes that channel i broadcasted on day t	Study 1	263.35	205.17	0.00	225.00	4020.00
			Study 2	285.18	217.42	5.00	241.00	10179.00
3	Streamed Fortnite	1 if channel i broadcasted Fortnite on day t, else 0	Study 1	0.63	0.48	0.00	1.00	1.00
			Study 2	0.69	0.46	0.00	1.00	1.00
4	Viewers	Average number of viewers of channel i on day t	Study 1	89.43	1099.31	0.00	3.67	38603.00
			Study 2	46.67	243.54	3.00	20.00	30008.00
5	Followers	Average number of followers gained by channel i on day t	Study 1	26.56	280.25	-592.00	1.00	19026.00
			Study 2	14.64	251.13	-765.00	3.00	88949.00

Note: The table summarizes the key variables in both studies. Please note that the summary statistics of the variables differ across studies, which is primarily because the studies rely on a different selection of channels.

Table 2: Ninja's Reasons for Temporary Absences 2018-2019

	N	Expected	Unexpected
Events			
- Las Vegas Heat	3	✓	
- Super Bowl 2019	3	✓	
- Twitch Con 2018	3	✓	
- Gaming Community Expo 2018	2	✓	
- Other	24	✓	
Family (birthdays. weddings)	5		✓
Family (family time)	16		✓
Family (not specified)	12		✓
Sickness (cold, eye infection)	6		✓
Sickness (exhausted)	4		✓
Sickness (not specified)	4		✓
Recreation	1		✓
Technical issues	4		✓
Business travel	23		✓
No reason stated	5		✓

Note: This table tabulates the reasons for Ninja's absences and categorizes them into expected and unexpected absence reasons.

Table 3: Channels' Content Production in the Presence versus Absence of Ninja

	Log(Minutes streamed Fortnite)						Log(Minutes streamed)	Streamed Fortnite
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ninja present (vs absent)	-0.098*** (0.022)			-0.049** (0.018)	-0.125*** (0.023)	-0.059* (0.026)	-0.034*** (0.009)	-0.017*** (0.004)
Ninja present (vs absent) strict		-0.095*** (0.026)						
Ninja minutes streamed			-0.016*** (0.004)					
Controls								
Lagged DV$_{t-1,\ t-30}$)						0.137*** (0.013)		
Fixed Effects								
Channel	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour of day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97,317	91,337	97,317	97,317	91,768	67,305	97,317	97,317
Number of channels	936	936	936	936	935	906	936	936
Mean of DV	3.271	3.262	3.271	3.271	3.277	3.454	5.147	0.367
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
adj. R-sq	0.170	0.171	0.170	0.171	0.176	0.181	0.041	0.032

Note: N are channel-day observations. N differs across columns due to the use of alternative independent variables or lags. Standard errors are heteroscedasticity robust and in parentheses. *, **, *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

Table 4: Mechanism

	Log(Viewers)	Log(Minutes streamed Fortnite)	Log(Followers)	Log(Minutes streamed Fortnite)
	(1)	(2)	(3)	(4)
Ninja present (vs absent)	-0.208*** (0.011)	0.018 (0.020)	-0.034*** (0.008)	0.006 (0.020)
Log(Viewers)		0.190*** (0.006)		
Log(Followers)				0.431*** (0.010)
% of Total Effect Mediated	95.75%		72.59%	
Fixed effects	Yes	Yes	Yes	Yes
Observations	97,317	97,317	97,317	97,317
Number of channels	936	936	936	936
Estimator	OLS	OLS	OLS	OLS
adj. R-sq	0.038	0.0246	0.141	0.017

Note: N are channel-day observations. Fixed effects for hour-of-day, day-of-week, month included. Standard errors are heteroscedasticity robust and in parentheses. *, **, *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

Table 5: Robustness Checks for Study 1

Panel A: Placebo Times

	Log(Minutes streamed Fortnite)	Log(Minutes streamed)	Streamed Fortnite	Log(Average viewers)
	(1)	(2)	(3)	(4)
Ninja present	-0.021	-0.014	0.003	0.001
	(0.017)	(0.010)	(0.003)	(0.004)
Fixed effects	Yes	Yes	Yes	Yes
Observations	97,317	97,317	97,317	97,317
Number of channels	936	936	936	936
Mean of DV	3.271	5.147	0.367	1.867
Estimator	OLS	OLS	OLS	OLS
adj. R-sq	0.025	0.041	0.021	0.023

Panel B: Placebo Channels (German Fortnite Channels)

	Log(Minutes streamed Fortnite)	Log(Minutes streamed)	Streamed Fortnite	Log(Average viewers)
	(1)	(2)	(3)	(4)
Ninja present	-0.029	-0.006	0.006	-0.001
	(0.021)	(0.006)	(0.004)	(0.006)
Fixed effects	Yes	Yes	Yes	Yes
Observations	97,317	97,317	97,317	97,317
Number of channels	936	936	936	936
Mean of DV	3.271	5.147	0.367	1.867
Estimator	OLS	OLS	OLS	OLS
adj. R-sq	0.025	0.041	0.021	0.023

Note: N are channel-day observations. Fixed effects for channel, hour-of-day, day-of-week, month included. Standard errors are heteroscedasticity robust and in parentheses. *, **, *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

Table 6: Pre-Switch Comparison and Trends

	Before matching		After matching	
	Difference in means	Difference in trends	Difference in means	Difference in trends
Log(Minutes streamed Fortnite)	0.067	0.000 (0.000)	-0.051	-0.002 (0.003)
Log(Minutes streamed)	0.076	-0.000 (0.000)	-0.006	0.003 (0.003)
Log(Average viewers)	0.235***	-0.001*** (0.000)	-0.013	-0.002 (0.002)
Log(Followers)	0.462***	0.000*** (0.000)	0.015	-0.002 (0.001)
Streamed Fortnite	-0.006*	0.000* (0.000)	-0.004	-0.002 (0.001)
Log(Age)	0.012	0.000 (0.000)	0.002	-0.000 (0.000)
N	901,933	901,933	53,550	53,550
Number of channels	4,235	4,235	2,550	2,550

Note: N are channel-day observations. Sample restricted to the pre-switch period. Difference in trends gives the coefficient when regressing the comparison variable on the interaction between the group indicator and a linear time trend. Standard errors are heteroscedasticity robust and in parentheses. *, **, *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

Table 7: Effects of Ninja's Switch to Mixer on the Content Production of Twitch Channels

	Log(Minutes streamed Fortnite)				Streamed Fortnite
	(1)	(2)	(3)	(4)	(5)
Ninja left x Affected	-0.188**	-0.207**	-0.142*	-0.188**	-0.062***
	(0.065)	(0.069)	(0.060)	(0.065)	(0.015)
Controls: Fixed effects					
Channel	Yes	Yes	Yes	Yes	Yes
Day of week	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes
Window	[-30, +30]	[-20, +20]	[-60, +60]	[-20, +20]	[-30, +30]
Observations	31,720	21,320	62,920	62,920	31,720
Number of channels	520	520	520	520	520
Mean of DV	2.27	2.27	2.27	2.27	0.69
Estimator	OLS	OLS	OLS	OLS	OLS
adj. R-sq	0.003	0.003	0.009	0.004	0.003

Note: N are channel-day observations. Window reported in days. Standard errors are heteroscedasticity robust and in parentheses. *, **, *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

Table 8: Mechanism

	Log(Viewers)	Log(Minutes streamedFortnite)	Log(Followers)	Log(Minutes streamedFortnite)
	(1)	(2)	(3)	(4)
Ninja left x Affected	-0.069*	0.046	-0.061***	-0.0260
	(0.027)	(0.0709)	(0.012)	(0.0191)
Log(Viewers)		0.449***		
		(0.0177)		
Log(Followers)				1.289***
				(0.00526)
% of Total Effect Mediated	65.38%		67.70%	
Observations	21,919	21,919	94,120	94,120
Number of channels	394	394	520	520
Estimator	OLS	OLS	OLS	OLS
adj. R-sq	0.038	0.044	0.141	0.393

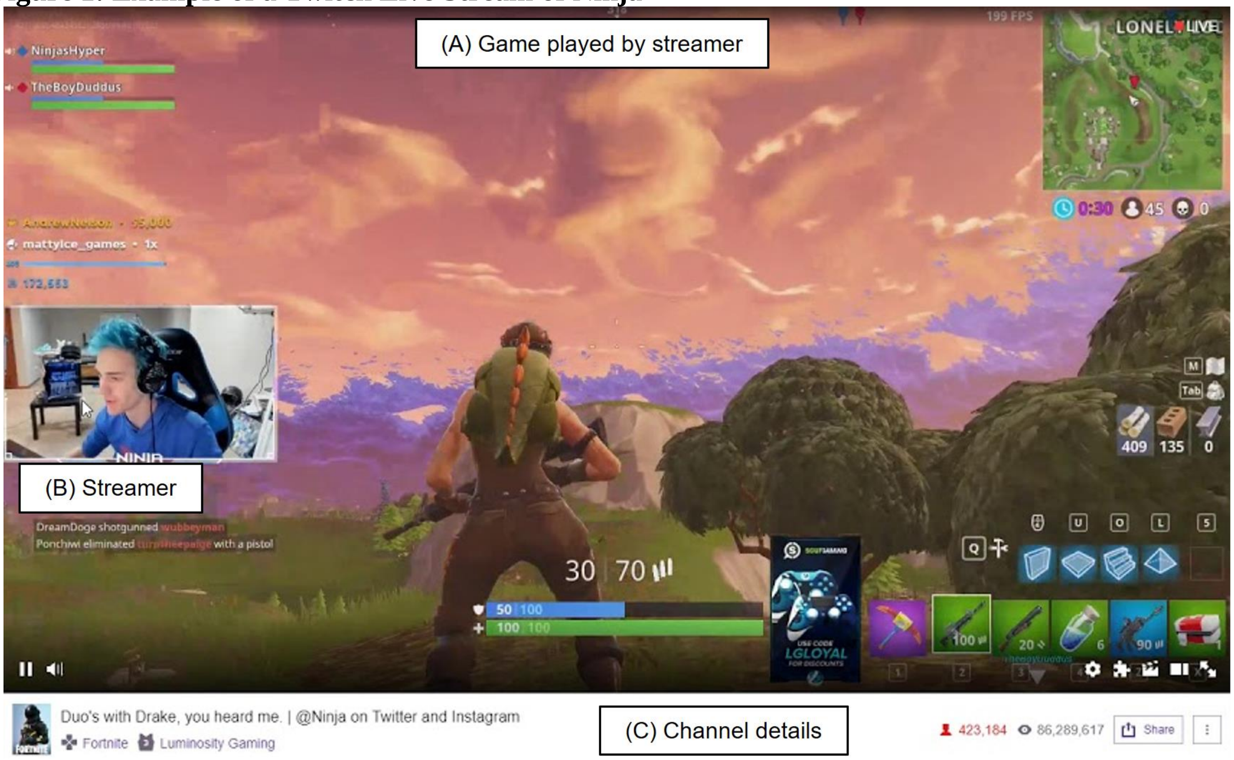
Note: N are channel-day observations. Fixed effects for hour-of-day, day-of-week, month included. Standard errors are heteroscedasticity robust and in parentheses. *, **, *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

Table 9: Summary of Difference-in-Differences Robustness Checks

	Log(Minutes streamed Fortnite)			
	(1) Placebo Treatment	(2) Placebo Time	(3) Two-period Aggregation	(4) With channel time-trend
Ninja left x Placebo	-0.602			
	(0.460)			
Placebo time x Affected		-0.022		
		(0.035)		
Ninja left x Affected			-0.207**	-0.100***
			(0.069)	(0.015)
Fixed effects				
Channel	Yes	Yes	Yes	Yes
Day of week	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Channel-specific trend	No	No	No	Yes
Observations	10,660	51,999	1,040	125,320
Number of channels	260	520	520	520
Estimator	OLS	OLS	OLS	OLS
adj. R-sq	0.003	0.052	0.018	0.386

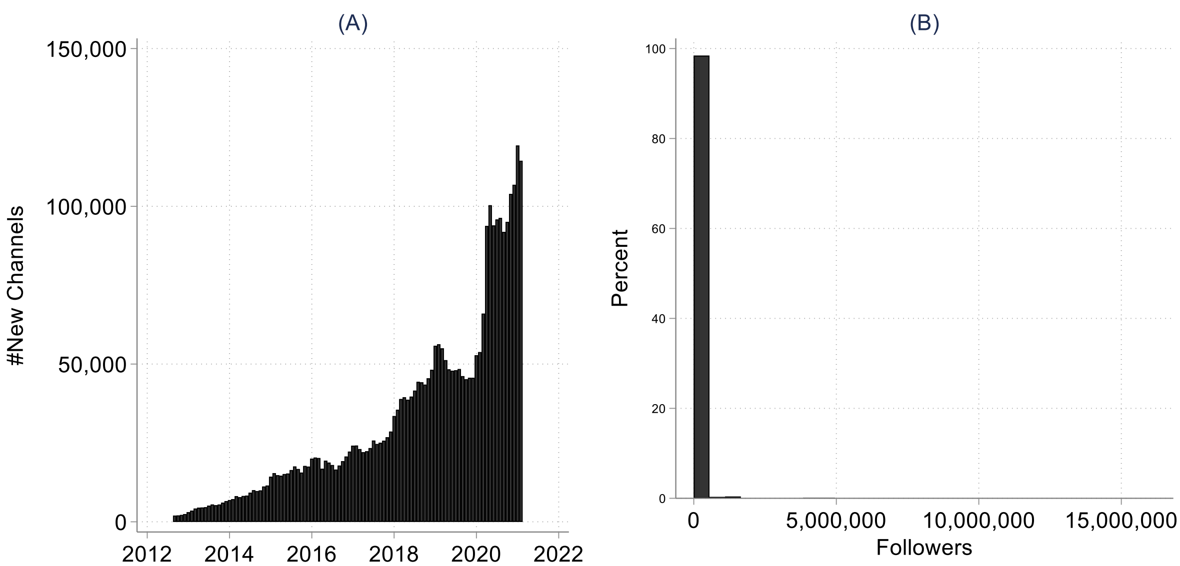
Note: N are channel-day observations. Sample includes 90 days before and after Ninja left Twitch. Standard errors are heteroscedasticity robust and in parentheses. *, **, *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

Figure 1: Example of a Twitch Live Stream of Ninja



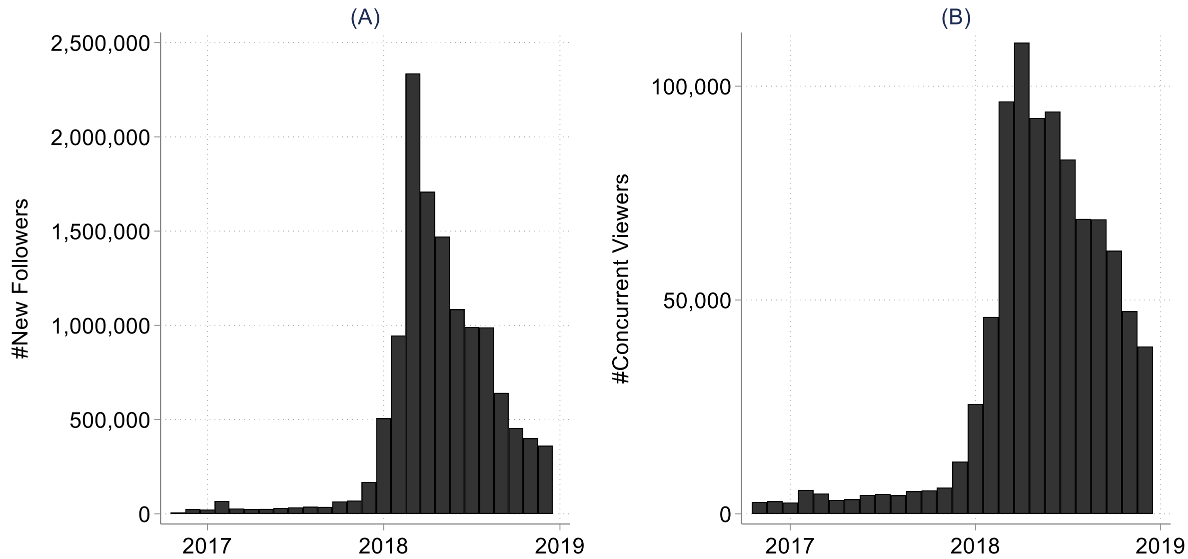
Note: The is a screenshot taken during one of Ninja’s live casts on Twitch. The majority of the screen (A) displays the game currently played (Fortnite); the streamer is displayed in a smaller section to the left of the screen (B); various further channel characteristics are shown at the bottom, including the number of concurrent viewers (C).

Figure 2: Twitch Growth and Superstar Distribution of Channels



Note: Panel A plots the monthly growth in channels on the Twitch platform. Panel B is a histogram of followers per channel.

Figure 3: Ninja's Growth in Followers and Viewers by Month



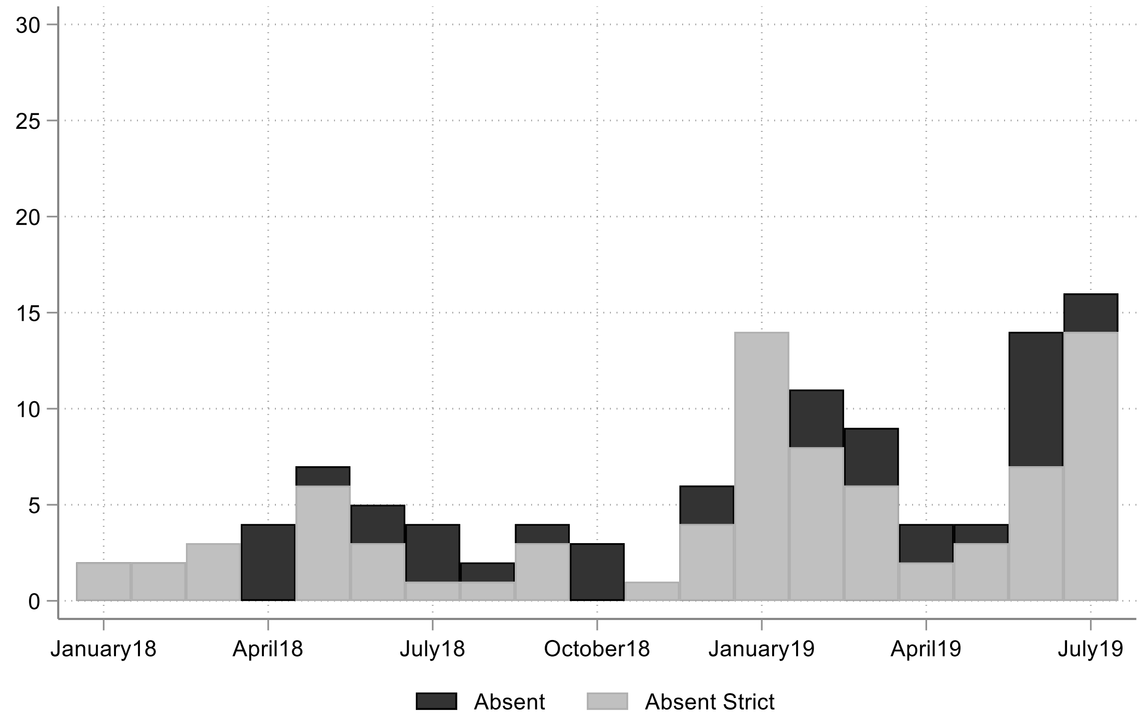
Note: Panel A displays the number of new followers of Ninja's Twitch channel by month. Panel B shows the number of concurrent viewers of Ninja's Twitch channel by month.

Figure 4: Study Overview

Study 1: The Effects of Superstar Presence on Content Supply	**Study 2: The Effects of a Superstar Switch on Content Supply**
Research design: We compare streamer behavior on days of Ninja's presence to that on days of Ninja's unexpected absence from the platform	Research design: We compare streamer behavior before/after Ninja announces to leave Twitch and to exclusively stream on Microsoft Mixer
Method: Simple differences, exogenous time-varying shocks	Method: Difference-in-differences
Data: All partnered English-language channels that had streamed Fortnite at least once in calendar week 1 2018	Data: All partnered English-language (versus German) channels that had streamed Fortnite at least once in calendar week 1 2019
Timeframe: January 2018 – July 2019	Timeframe: January 2019 – October 2019

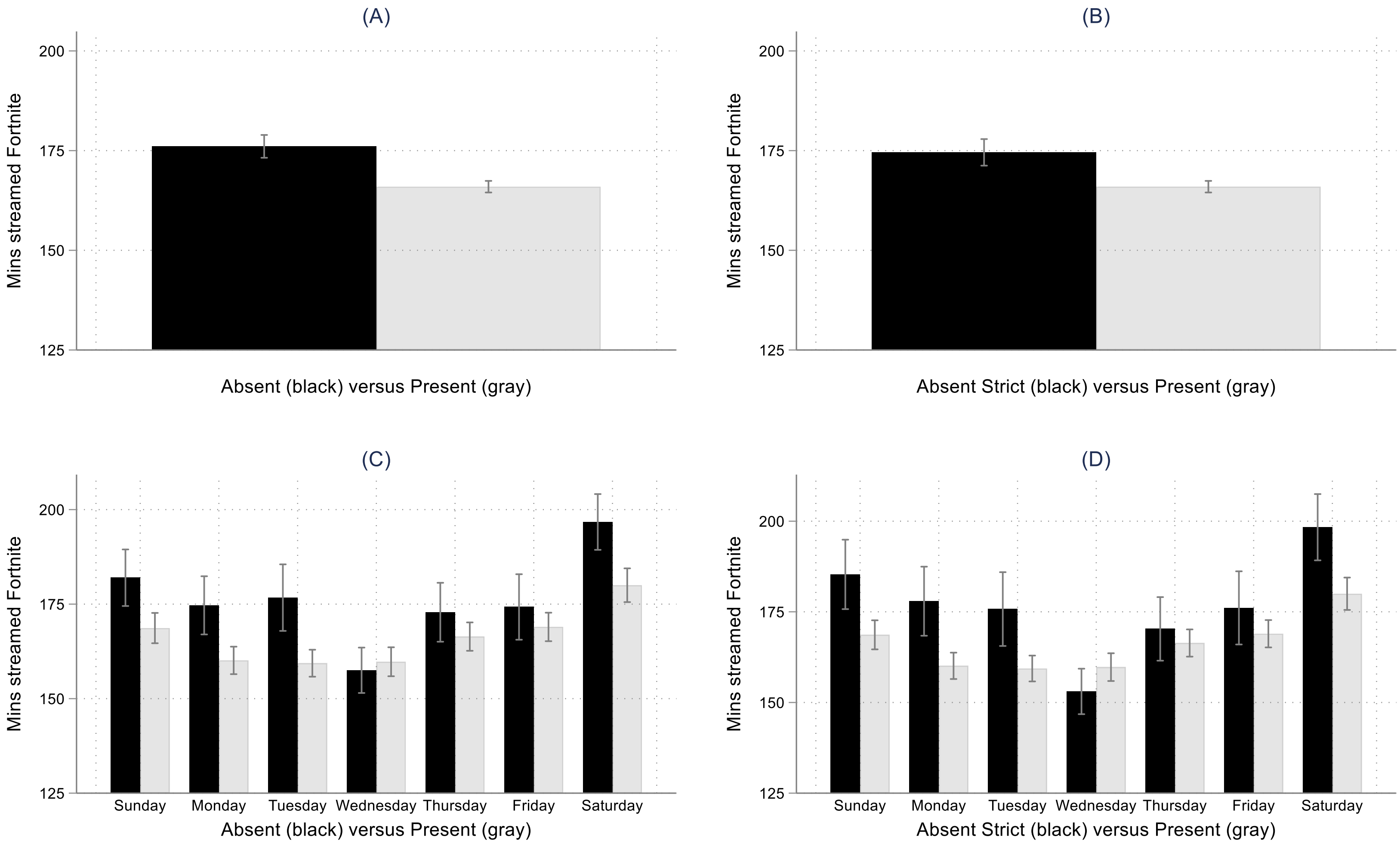
Note: The figure illustrates the research design. Study 1 investigates channels' streaming behavior in the absence versus presence of Ninja during his time as a star on the Twitch platform. Study 2 is focused on understanding the effects of a permanent star absence by investigating channels' streaming behavior before and after Ninja's exit in a difference-in-differences design.

Figure 5: Ninja's Absences from Twitch January 2018 to July 2019



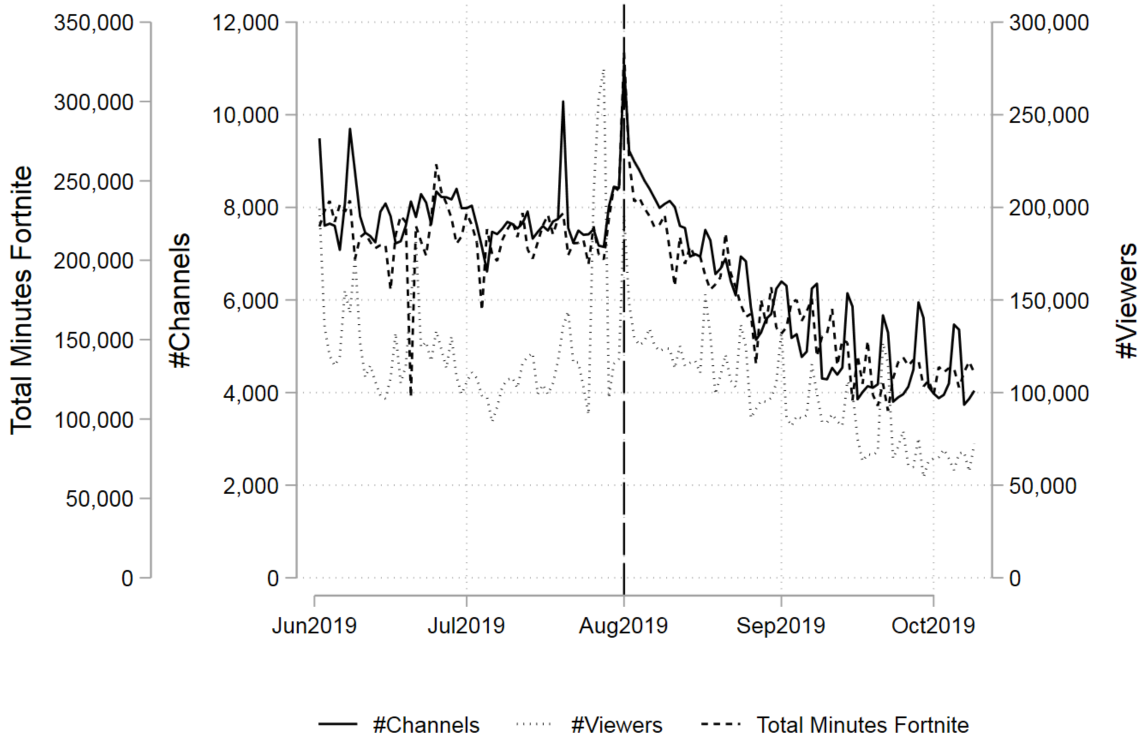
Note: Panel A plots the number of monthly active days of Ninja on Twitch. Panel B displays the immediate observation period from January 2018 to July 2019, wherein days with black bars indicate absences and gray bars overlaid indicate absences coded as exogenous.

Figure 6: Content Production on Days of Ninja's Unexpected Absence versus Presence



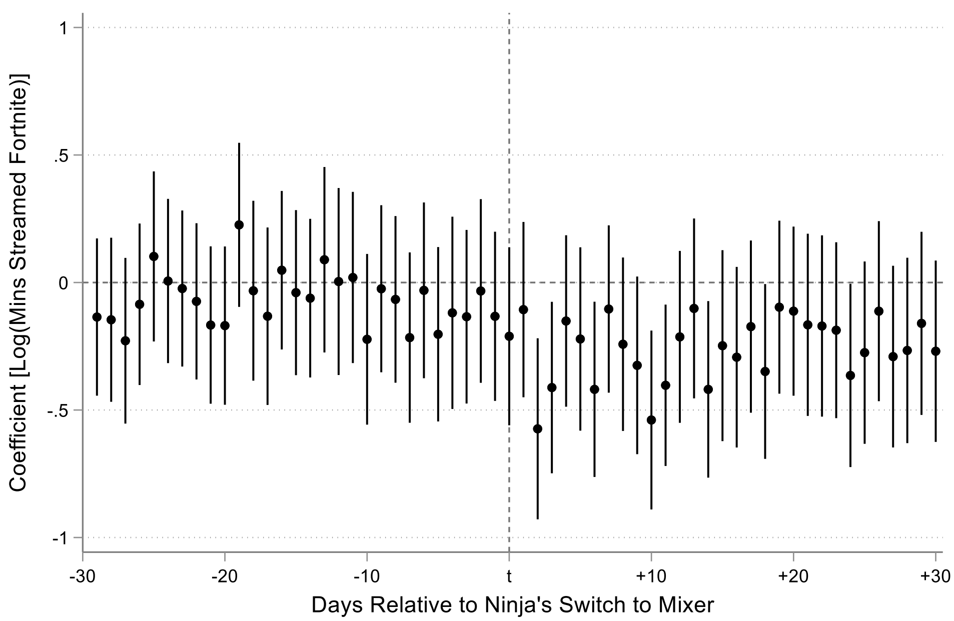
Note: Panel A plots channels' provision of Fortnite content on days of Ninja's absence (black) versus his presence (gray). Panel B is identical but restricted to strict absences. Panel C uses the same data as Panel A but distinguishes content production by day-of-week. Panel D uses the same data as Panel B but distinguishes content production by day-of-week. Whiskers indicate 95% confidence intervals around the mean.

Figure 7: Fortnite Minutes Streamed, Channels, and Viewers on Twitch Around Ninja's Switch



Note: The figure plots the number of Fortnite channels (dashed line) and viewers (solid line) from June 2019 to October 2019. The long-dashed vertical denotes Ninja's switch to Mixer.

Figure 8: Coefficient Plot of Relative-Time Difference-in-Differences Estimation



Note: The figure plots the coefficients on the interaction term (p') of the relative-time difference-in-differences estimation of Ninja's switch to Mixer. The time window is [-30,+30] days around the switch.

The Effects of Platform Superstars on Content Production: Evidence from Ninja

Appendices

Appendix A: Examples of Ninja's Tweets and their Coding into Types of Absences

Tweet	Date	Time	Code
No stream today as my eye is disgusting and I look like a red eyed pirate. On antibiotics so hopefully I'll be better tomorrow.	6.7.2019	5:07 pm	Sickness
Woke up with my throat super sore and some body aches. Sickness never fully went away and it's back. Slept all night and am taking vitamins and chugging water. Hopefully feeling better by Friday.	3.7.2019	5:22 pm	Sickness
Happy valentine's day everyone! There will be no stream today I am spending all day with my love @JGhosty If you are not with a special someone today that is ok! it is important to love yourself before loving another!	14.2.2019	5:58 pm	Family
Alright guys! Decision for the day is... NO stream. Gunna spend time and take care of @JGhosty <3	2.3.2018	10:29 pm	Family
Got people fixing some stuff in the house and my stream room is being fixed today (cameras and mic) so I am taking the day off :D Happy Martin Luther king jr. Day	21.1.2019	4:58 pm	Technical issues

Appendix B: Mediation Test Framework

To test the mechanisms, we rely on an indirect effect mediation test for linear models (Imai et al., 2011). We estimate an indirect effects linear model with the demand variables being introduced as mediating (MEDIATOR) variables. This approach also has the benefit of reporting the proportion of the effect that is explained by MEDIATOR (denoted as M).

The procedure consists of four steps that are carried out sequentially. First, we begin by estimating the following equations:

$$M_{i,t} = \alpha \quad + \beta_1 NINJA\_PRESENT_t + \epsilon_{i,t} \tag{1}$$

$$Y_{i,t} = \alpha \quad + \beta_1 NINJA\_PRESENT_{i,t} + \beta_2 M_{i,t} + \epsilon_{i,t} \tag{2}$$

With variables and indexes being defined as in the main body of the paper. M is then the variable that holds the mediator, in terms of channel demand.

Second, we compute the direct and indirect components of the effects. These components are defined as follows:

1) Direct Effects (DE)

$$\xi_i \equiv Y_i\big(1, M_i(t)\big) - Y_i(0, M_i(t))$$

2) Indirect Effect (IE)

$$\delta_i \equiv Y_i\big(t, M_i(1)\big) - Y_i(t, M_i(0))$$

3) Total effect

$$\tau_i \equiv Y_i\big(1, M_i(1)\big) - Y_i(0, M_i(0))$$

Third, a Monte-Carlo bootstrapping procedure is carried out. In a final step, a sensitivity analysis is conducted. Sensitivity analysis allows to state how an estimated quantity would change for different degrees of violation of the identification assumption. Because the key assumption in this case—sequential ignorability (Imai et al., 2011)—cannot be tested directly, a sensitivity analysis is usually recommended.

<u>References</u>

Imai, K., Keele, L., Tingley, D., and Yamamoto, T. 2011. "Unpacking the Black Box of Causality: Learning About Causal Mechanisms from Experimental and Observational Studies," American Political Science Review (105:4), pp. 765-789.

Appendix C: Robustness Check With European Streamers

We conduct arobustness check of the effects of Ninja's switch that relies on an alternative control group, namely European streamers. In particular, we use German, French, Swedish, Norwegian, Italian, Greek, Finnish, Dutch, and Danish channels as a base for constructing the control group. We do not use Spanish and Portuguese streamers to avoid including American Hispanic and South American channels. As in the main paper, we employ coarsened exact matching and rely on the same matching variables.

Parallel to our main paper, Table C1 displays the comparison in means and trends across the groups. The results, after matching, do not indicate significant differences in trends, which corroborates the use of this control group under the assumption of parallel trends. Although some mean differences are still significant after matching, this does not confound the DID analysis as long as the parallel trends assumption holds.

Table C2 replicates Table 7 from the paper, in terms of the direct effects of Ninja's switch on the content production. The results are consistent, yet the effect magnitudes are smaller than in our baseline estimation.

Table C1: Pre-Switch Comparison and Trends (Alternative Control Group)

	Before matching		After matching	
	Difference in means	Difference in trends	Difference in means	Difference in trends
Log(Mins streamed Fortnite)	0.079	0.050	-0.040	0.070
Log(Mins streamed)	0.061	0.055	-0.007	0.076
Log(Average viewers)	0.254***	0.040	-0.023	0.043
Log(Followers)	0.491***	0.060	0.030	0.068
Streamed Fortnite	-0.006*	0.003	-0.007	0.005
Log(Age)	0.022	0.025	0.003	0.036
Number of channels	4,924	4,924	1,456	1,456

Note: Sample restricted to the pre-switch period. Difference in trends gives the coefficient when regressing the comparison variable on the interaction between the group indicator and a linear time trend. Standard errors are heteroscedasticity robust and in parentheses. *, **, *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

Table C2: Effects of Ninja's Switch to Mixer (Alternative Control Group)

	Log(Minutes streamed Fortnite)				Streamed Fortnite
	(1)	(2)	(3)	(4)	(5)
Ninja left x Affected	-0.121**	-0.124**	-0.111**	-0.121**	-0.021**
	(0.042)	(0.044)	(0.038)	(0.042)	(0.008)
Controls: Fixed effects					
Channel	Yes	Yes	Yes	Yes	Yes
Day of week	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes
Window	[-30, +30]	[-20, +20]	[-60, +60]	[-60, +60]	[-20, +20]
Observations	88,816	59,696	176,176	88,816	88,816
Number of channels	1,456	1,456	1,456	1,456	1,456
Mean of DV	2.27	2.27	2.27	2.27	2.27
Estimator	OLS	OLS	OLS	OLS	OLS
adj. R-sq	0.002	0.002	0.005	0.003	0.002

Note: N are channel-day observations. Window reported in days. Standard errors are heteroscedasticity robust and in parentheses. $^{+}$, *, **, *** indicate significance at the 10%, 5%, 1%, and 0.1% levels, respectively.