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Ningzhe Zhou
*Peking University*, inze_zhou@foxmail.com

Xinyan Yao
*The Hong Kong Polytechnic University*, yaoxinyan512@163.com

Chong (Alex) Wang
*Peking University Guanghua School of Management*, alex.wang@cityu.edu.hk

Hongju Liu
*Peking University Guanghua School of Management*, hliu@gsm.pku.edu.cn

# Bilateral Relationships in Live Streaming: A Power-Dependence Perspective

*Completed Research Paper*

**Ningzhe Zhou**
Peking University
Beijing, China
ningzhe_zhou@stu.pku.edu.cn

**Xinyan Yao**
The Hong Kong Polytechnic University
Hong Kong, China
yaoxinyan512@163.com

**Chong (Alex) Wang**
City University of Hong Kong, Peking University, China
alex.wang@cityu.edu.hk

**Hongju Liu**
Peking University
Beijing, China
hliu@gsm.pku.edu.cn

## Abstract

*Live streaming services are an important part of today's entertainment industry. This paper applies power dependence theory to investigate the bilateral relationship between streamers and viewers, focusing on both asymmetric and joint dependence, and examines its influence on tipping behavior. Additionally, the paper examines how those in disadvantaged positions attempt to restructure power dynamics. Using data from a large Chinese live streaming platform over a two-week period, the findings suggest that viewers in a relatively advantageous position tend to tip less. Conversely, an increase in joint dependence generally leads to higher tipping by viewers. To address power imbalances, streamers may reduce their dependency by decreasing their streaming frequency and forming alliances, while viewers might cut back on their viewing time. This study provides insights into power dynamics, streamer-viewer interactions, and tipping behavior on live streaming platforms.*

**Keywords:** Live streaming, Power, Resource dependence, Tipping

## Introduction

Live streaming services (LSS) have emerged as an influential segment of the global entertainment industry and have captured a substantial audience, especially attracting a large number of young people. For instance, 52.42% of Chinese university students enjoy watching live streaming for entertainment.[1] The economic potential of LSS is considerable, with the global market valued at $70.2 billion in 2023,[2] of which China accounts for a significant portion, with the Chinese market size reaching $26.2 billion in 2022.[3]

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[1] This statistical data is derived from a 2022 survey conducted by the China Youth Network on Chinese university students. Details: https://t.m.youth.cn/transfer/baobao/Dp7pWGIn.html
[2] This data is reported by IMARCGroup. Details: https://www.imarcgroup.com/live-streaming-market
[3] This data comes from the China Online Performance Industry Development Report (2022-2023). Details: https://www.capa.com.cn/news/showDetail/76001#/index/NewsDetail?activeName=%E5%B8%82%E5%9C%BA%E8%A7%82%E5%AF%9F&id=1659380221253586945

Live streaming platforms serve as a two-sided marketplace that connects viewers and streamers. Existing research on LSS primarily centers around understanding the engagement of both viewers and streamers. Regarding viewer engagement, these studies mainly focused on exploring viewers' motivation for engagement and identifying influencing factors (Hilvert-Bruce et al., 2018; Lu et al., 2021; Yao et al., 2024; Zhao et al., 2023) . In contrast, there is limited research on motivators of streamers' behavioral choices in LSS, such as interaction strategies with viewers and the frequency of streaming content provision (Bharadwaj et al., 2022; Lin et al., 2021) . In particular, few studies have delved into the characteristics and dynamics of the bilateral relationship between streamers and viewers.

Bilateral relationships exist naturally and have the potential to play a significant role in understanding the dynamics of LSS. The real-time interactivity of LSS fosters the development of rich bilateral relationships between streamers and viewers. The importance of bilateral relationships has been widely documented in traditional business contexts and social media platforms (Kapoor et al., 2018; Palmatier et al., 2013; Shamsollahi et al., 2021). While LSS is considered a new form of social media, its unique characteristics further strengthen the importance of characterizing bilateral relationships (i.e., streamer-viewer relationships). Real-time interaction and the parasocial presence of streamers (Wohn et al., 2018) heighten the significance of establishing and nurturing these relationships within LSS. Maintaining and developing such relationships is crucial for many practitioners on the live streaming platform.[4] To shed light on the potential role of bilateral relationships in LSS, this paper employs the lens of Power-Dependence Theory (PDT) to construct a comprehensive framework to elucidate the dynamics of the streamer-viewer relationship.

Power and dependence are two critical concepts in PDT. An actor is considered to depend on another when she/he relies on another to achieve her/his goals and gratifications (Emerson, 1962). Power resides implicitly in the dependency of one actor on another, and the other actor has power over those who depend on her/him. In the context of LSS, PDT provides insights into the power dynamics between streamers and viewers. The viewer's dependence on the content provided by the streamer gives the streamer power over the viewer. In turn, the streamer may depend on the viewer's tip (financial support for the streamer), which grants power to the viewer.

It is worth noting that power and dependence are bidirectional within a relationship and may be at different levels. This bidirectional nature allows us to explore the power structure within relationships. By analyzing the difference and sum of dependencies in both directions, we derive two key metrics for measuring power distribution in relationships: asymmetric dependence and joint dependence. Specifically, asymmetric dependence results from an imbalance in power between the actors, while joint dependence refers to the combined power held by both actors (Casciaro & Piskorski, 2005). Understanding the power structure within relationships clarifies how actors with varying levels of power act. Those with greater power can leverage their position to influence the weaker party and secure a larger share of benefits. In response, less powerful actors may take steps to correct the power imbalance.

Therefore, we focus on the context of entertainment live streaming platforms and collect data for two weeks, including 3,345,198 relationships formed between 10,461 streamers and 230,793 viewers. We first investigate the impact of power structure on viewers' tipping behavior. Our findings show that when viewers have relatively more power, they use it to maximize their benefits by reducing the *price* they pay for the content, which is reflected in lower tipping amounts. Besides, as the joint dependence rises, viewers become more willing to tip higher amounts. We further explore the power restructuring operations of actors at a power disadvantage. When streamers have relatively less power, they attempt to reduce their reliance on resources provided by viewers by reducing the frequency of streaming and forming coalitions with other streamers. When viewers are at a power disadvantage, they strive to minimize the perceived criticality of the resources provided by streamers by watching less streaming.

This research contributes to the live streaming literature by exploring the bilateral relationship between streamers and viewers, examining the impact of power structure on tipping behavior under the

[4] According to the China Online Performance Industry Development Report (2022-2023), 95.2% of streamers who rely on live streaming as their primary source of income earn less than 5,000 RMB (approximately 704 USD) per month. Additionally, the China Internet Audio-Visual Industry Development Report (2024) indicates that as of December 2023, the number of professional streamers in China has reached 15.08 million. Details:
http://tradeinservices.mofcom.gov.cn/article/yanjiu/hangyezk/202403/162615.html

Pay-What-You-Want (PWYW) pricing mechanism, and providing insights into streamers' behavior. Additionally, it enhances the application of power-dependence theory by empirically testing the concepts of asymmetric dependence and joint dependence within the one-to-many resource exchange context of LSS. And the study provides a comprehensive framework for analyzing power dynamics by considering actors' potential strategies for power restructuring within this context, thereby examining the entire process of power effects.

## Theoretical Background and Main Hypotheses

### *Live Streaming-related Literature*

In live streaming, understanding the motivations and influences at different levels is essential to understanding the dynamics between viewers, streamers, and the streamer-viewer relationship. At the viewer level, existing research has identified several important motivations that drive their engagement with live streaming platforms, including entertainment, social interaction, and enhancing social image (Bharadwaj et al., 2022; Hilvert-Bruce et al., 2018; Ma et al., 2022; Wohn et al., 2018; Yao et al., 2024; Zhao et al., 2023). Viewers are often drawn to live streaming content for its ability to provide engaging and interactive experiences, and various factors can influence viewer engagement, such as audience size (Lu et al., 2021) and emotional extremity (Chen et al., 2023) within live streaming content. However, while several studies have documented the impact of streamer's characteristics on viewer behavior (Bharadwaj et al., 2022; Lin et al., 2021; Zhao et al., 2021), there is a lack of research on the factors that motivate streamers' behavioral choices in live streaming, such as their interaction strategies with viewers or the frequency of streaming activities. Understanding these factors is critical for comprehending streamers' motivations, decision-making processes, and strategies to cultivate and maintain viewer engagement and loyalty.

At the streamer-viewer relationship level, few studies have focused on the characteristics of bilateral relationships between streamers and viewers. Some studies have been limited to single dimensions, such as loyalty (Yao et al., 2023), to capture the characteristics of streamer-viewer relationships. However, it is necessary to construct a more comprehensive framework to understand the intricate dynamics between streamers and viewers due to the bidirectional interactive nature of bilateral relationships.

### *Power-Dependence Theory*

Power-dependence theory (PDT), developed by Emerson (1962) within the framework of social exchange theory, provides a foundation for understanding power dynamics within relationships (Pfeffer & Salancik, 1978; Cook et al., 2013). According to PDT, power and dependence are seen as two sides of the same coin, where power is the ability to influence others, and dependence is the reliance on others for desired outcomes. The dependent actor's reliance on the more powerful actor strengthens the latter's power position. This interdependence between power and dependence creates a dynamic where both actors are affected by and influence each other. Two key factors determine the magnitude of power and dependence within a relationship: resource criticality and alternative availability (Emerson R, 1962; Hillman et al., 2009). Resource criticality refers to the importance of the resources controlled by one actor in satisfying the needs or goals of the other actor. Alternative availability relates to the extent to which actors have access to alternative sources of resources or relationships that can fulfill their needs.

Building upon Emerson's (1962) work, Casciaro & Piskorski (2005) introduced the concepts of asymmetric dependence (AD) and joint dependence (JD) to further understand bidirectional dependence within relationships. AD refers to situations where one party is more dependent on the other, while JD represents situations where both parties are mutually dependent on each other. They also defined two types of operations within power-dependence relationships: *power using* and *power restructuring* operations. Power using operations involve the exertion of power to influence the behavior or outcomes in the relationship. Power restructuring operations include changes in the power dynamics and dependencies within the relationship, either unilaterally or bilaterally.

While PDT is usually applied to organizational research, this study incorporates the concepts of AD and JD from PDT into individual-level research, examining the operations of different actors in different power positions (Hillman et al., 2009; Kim & Fortado, 2021). We introduced this theoretical perspective into the context of live streaming for two main reasons. First, the concepts of AD and JD, as well as power using and power restructuring derived from PDT are inherently based on individual studies. Second, streamers and viewers in live streaming are suppliers and buyers in this new service market setting. Power dynamics and dependence emerging in streamer-viewer interactions may be crucial in shaping their behaviors. Furthermore, LSS provides a unique opportunity to observe and analyze rich micro-data, allowing for the examination of different power operations of streamers and viewers.

## *Power-Dependence Relationship in Live Streaming*

In live streaming, a bidirectional dependence exists between streamers and viewers, which is closely tied to the resources they rely upon. Viewers depend on the content provided by streamers. They rely on streamers to produce engaging and captivating content that satisfies their entertainment needs and fulfills their desire for social connection. Meanwhile, streamers depend on the tips provided by viewers, which are a major source of income for streamers. This bidirectional resource dependence, where viewers rely on the content and streamers rely on the tips, sets the stage for the power dynamics within LSS. The availability and control of these resources creates a power dynamic where both streamers and viewers hold some degree of power. Streamers have power over streaming content that attracts and retains viewers, while viewers hold power through their ability to financially support the streamers. This bidirectional power dynamic forms the foundation for identifying AD and JD within a streamer-viewer relationship.

### The Impact of Power Structure on Tipping Behavior

We first examine the impact of power structure within a streamer-viewer relationship on viewers' tipping behaviors. Tipping is the most critical viewer engagement behavior because the PWYW pricing mechanism plays a significant role in the business model of live streaming platforms. Tipping is a new form of pricing and negotiation for live streaming context where consumers have full control over the price they pay for streaming services. The impact of power structure on pricing has also been a central issue in traditional firm-level research related to PDT. Specifically, we use AD and JD to capture the power structure within each streamer-viewer relationship and explore how AD and JD would influence viewers' tipping behavior.

For asymmetric dependence, we define AD as the difference between the power held by the viewer and the power held by the streamer. Viewers' tipping decisions are significantly influenced by their perceived power within the relationship. Due to psychological factors arising from power, such as desire and greed, viewers may prioritize their own interests over the needs of others (Sturm & Antonakis, 2015). Therefore, when viewers possess pricing power and the content offered by the streamer is difficult to change, they are more likely to reduce the amount they tip to maximize their gains from streaming content. Consequently, we propose the following hypothesis:

**H1:** A decrease in the asymmetric dependence in a streamer-viewer relationship is positively associated with tip amounts the viewer gives to the streamer.

For joint dependence, we define JD as the sum of viewers' and streamers' power. A high level of JD in the relationship indicates a closer and more interdependent connection between actors (Gulati & Sytch, 2007). On the one hand, streamers and viewers are more likely to converge in their views. Viewers may have a greater appreciation for streamers' performance and the value they provide, thus giving more tips as a form of reciprocal exchange. On the other hand, emotions typically associated with close relationships, such as empathy, friendship, and loyalty, may emerge at high levels of JD. Both streamers and viewers may invest efforts to maintain and develop the relationship, which can be reflected in viewers giving more tips to support the streamer. Therefore, Hypothesis 2 is as follows.

**H2:** An increase in the joint dependence in a streamer-viewer relationship is positively associated with tip amounts the viewer gives to the streamer.

### Power Restructuring Operations in Live Streaming

When the power structure within a streamer-viewer relationship is asymmetric, the actor at a power disadvantage is often motivated to restructure her/his dependence. There are two types of power restructuring, i.e., unilateral and bilateral (Casciaro & Piskorski, 2005; Gulati & Sytch, 2007). We focus on investigating unilateral power restructuring as bilateral operations involving constraint absorption and cooptation do not seem to apply to the context of LSS. Specifically, unilateral operations include seeking alternative resources, reducing resource criticality, and coalition.

When streamers face a power disadvantage, they may seek alternative resources by adjusting their content, scheduling, and platform activities. First, streamers may adapt their content to better align with viewer preferences, aiming to attract more viewers and expand their support base. Second, streamers may reduce their dependence on streaming as a main source of livelihood. This can be achieved by reducing the frequency of their streams or exploring other means of generating income, such as creating short videos or engaging in traditional jobs. Third, streamers may seek formal or informal alliances with other streamers. This can be manifested through increased interaction and collaboration with other streamers, such as co-streaming or engaging in live battles. Therefore, we have the following Hypothesis 3 regarding the restructuring operations of streamers:

**H3:** An increase in the asymmetric dependence within a streamer-viewer relationship is positively associated with streamers engaging in power restructuring operations, i.e., seeking new viewers, increasing streaming intervals, and interacting more with other streamers.

Regarding viewers' unilateral operations in response to a power disadvantage within the streamer-viewer relationship, we mainly discuss strategies involving finding alternative resources and reducing resource criticality because we cannot observe viewers' interactions with other viewers. When viewers find themselves at a power disadvantage, they may try to actively search for other streamers who provide similar resources or content. Besides, viewers may choose to reduce their reliance on streaming and spend less time watching live streaming. These strategies allow them to reduce their dependence on a single streamer and increase their options for accessing the desired resources. Hypothesis 4 is as follows.

**H4:** A decrease in the asymmetric dependence within a streamer-viewer relationship is positively associated with viewers engaging in power restructuring operations, i.e., watching more streamers and decreasing their streaming watching time.

## Data and Empirical Strategy

### *Data*

We collected data from a large live streaming platform in China, where streamers primarily engage in talent-show performances, including singing, dancing, companionable chatting, and other talents. On the platform, viewers can freely watch live streaming and interact with streamers by tipping (in the form of sending virtual gifts) and chatting. We tracked all streamer-viewer relationships between March 6, 2017, and March 19, 2017, and collected records of the daily behavior of both streamers and viewers. As this study focuses on the action of the next period in response to the power structure of the previous period, we dropped observations of the streamer-viewer relationship that existed only once during the observation period. Therefore, we constructed panel data with 3,311,723 relationships between 7,815 streamers and 215,302 viewers.

### *Measurement*

#### Dependence, Asymmetric Dependence, and Joint Dependence

Dependence is determined by the joint effect of one actor's motivational investment in goals mediated by the other actor and the availability of those goals to one actor outside of this specific relationship (Emerson, 1962). Drawing on measures of dependence at the firm level (Casciaro & Piskorski, 2005; Gulati & Sytch, 2007; Patatoukas, 2012), we identify the streamer *i*'s dependence on viewer *j* on day *t* based on the following equation.

$$Dependence_{i \to j,t} = Resource\ Criticality \times Alternative\ Availability\ = (\frac{Tip_{ij,t}}{\sum_{n=1}^{N} Tip_{in,t}}) \times CR4_{i,t} \quad (1)$$

Tipping is the resource that streamers need to obtain from the viewers. Therefore, for streamer $i$, we measure the perceived resource criticality from viewer $j$ by calculating the proportion of the tip amount that viewer $j$ gives to streamer $i$ to the total tip amount that streamer $i$ receives on day $t$. And we use the four-viewer concentration ratio ($CR4_{i,t}$) to evaluate the availability of alternative resources for streamer $i$. $CR4_{i,t}$ represents the share of tip amounts from the four most important viewers in streamer $i$'s room on day $t$. A higher $CR4_{i,t}$ indicates that a significant portion of the tip amount comes from a few viewers. This suggests that it is challenging for streamer $i$ to obtain resources from alternative providers, which increases her/his dependence on viewer $j$.

Streaming content is the resource that viewers rely on streamers to provide. We measure the viewer $j$'s dependence on streamer $i$ on day $t$ by the following equation, following the same logic as for the streamer's dependence. The resource criticality in the dependence of viewer $j$ on streamer $i$ is measured by the ratio of the time spent watching streamer $i$ to viewer $j$'s total watching time on day $t$. And the four-streamer concentration ratio ( $CR4_{j,t}$ ) of the same streaming type as streamer $i$ indicates the availability of alternatives.[5]

$$Dependence_{j \to i,t} = Resource\ Criticality \times Alternative\ Availability\ = (\frac{Watch_{ij,t}}{\sum_{m=1}^{M} Watch_{mj,t}}) \times CR4_{j,t} \quad (2)$$

Based on measure of dependence of streamer $i$ and viewer $j$ on each other, we measure asymmetric and joint dependence in the $i$-$j$ relationship by subtracting and adding the two dependencies, respectively. $AD_{ij,t}$ indicates the extent of viewer $j$'s power over streamer $i$'s power in the $i$-$j$ relationship. A higher $AD_{ij,t}$ suggests that viewer $j$ has a larger power advantage. $JD_{ij,t}$ represents the overall dependence strength of the $i$-$j$ relationship, independent of how much power is in the relationship.

$$AD_{ij,t} = Dependence_{i \to j,t} - Dependence_{j \to i,t} \quad (3)$$

$$JD_{ij,t} = Dependence_{i \to j,t} + Dependence_{j \to i,t} \quad (4)$$

Table 1(A) provides the summary statistics of $AD_{ij,t}$ and $JD_{ij,t}$. In our sample, $AD_{ij,t}$ is negative for over 90% of the relationships, indicating that streamers generally hold a power advantage. This may be due to the distinctive feature of live streaming, that streamers can exchange products with a marginal cost close to zero for viewers' tip.

Moreover, for discussing power restructuring operations that streamers and viewers undertake in response to an imbalance in the power structure, we aggregate data observations at the streamer and viewer level to better focus on the behavioral choices of streamers or viewers, respectively.

Specifically, we use the tip amount within relationships in period $t$ as weights to compute asymmetric dependence and joint dependent at the streamer level, i.e., $AD_{i,t}$ and $JD_{i,t}$. As shown in Table 1(B), the value of $AD_{i,t}$ is significantly higher than asymmetric dependence at the relationship level due to the influence of large viewers who often give substantial tips. This interesting pattern suggests that, although a streamer may hold a power advantage in most of the relationships they establish with viewers, the distribution of power in a few disadvantaged relationships is what really affects the overall asymmetric dependence perceived by streamers. Similarly, we aggregate the data into viewer-level observations weighted by viewing time within each relationship, and obtain $AD_{j,t}$ and $JD_{j,t}$ for viewer $j$. The distribution of $AD_{j,t}$ shown in Table 1(C) indicates that viewers generally find themselves in a power disadvantage position.

## Other Variables

For examining the impact of power structure on viewers' tipping behavior, the dependent variable is $Tip_{ij,t}$ which represents tip amount that viewer $j$ gives to streamer $i$ in period $t$. We also construct several

[5] In our analysis, the dependence indicators in both directions range from 0 to 100. These values represent relative power magnitudes.

control variables, including the total amount of time viewer $j$ watches streamer $i$ in period $t$ ($Watch_{ij,t}$), and the duration of the $i$-$j$ relationship ($Tenure_{ij,t}$), which accounts for potential long-term continuities within the same relationship (Ma et al., 2022).

| Variable Name | Variable Definition | Mean | St. Dev. |
|---|---|---|---|
| A. Relationship level | | | |
| $AD_{ij,t}$ | Asymmetric dependence of $i$-$j$ relationship in period $t$ | -1.00 | 7.13 |
| $JD_{ij,t}$ | Joint dependence of streamer $i$-viewer $j$ relationship in period $t$ | 2.38 | 7.74 |
| $Tip_{ij,t}$ | The tip amount is given by viewer $j$ to streamer $i$ in period $t$ | 350.22 | 39323.79 |
| Num. Relationships | 3,311,723 | | |
| Num. Observations | 7,387,619 | | |
| B. Streamer level | | | |
| $AD_{i,t}$ | Total asymmetric dependence of streamer $i$ in period $t$ | 51.58 | 29.27 |
| $JD_{i,t}$ | Total joint dependence of streamer $i$ in period $t$ | 61.54 | 28.77 |
| $ViewerSize_{i,t}$ | The number of viewers watching streamer $i$ in period $t$ | 325.14 | 810.02 |
| $StreamingInterval_{i,t}$ | The number of days between streamer $i$'s current streaming and the next streaming | 1.02 | 0.18 |
| $Chat_{i,t}$ | The total number of chat messages sent by streamer $i$ to other streamers in period $t$ | 37.15 | 81.41 |
| Num. Streamers | 7,815 | | |
| Num. Observations | 65,161 | | |
| C. Viewer level | | | |
| $AD_{j,t}$ | Total asymmetric dependence of streamer $i$ in period $t$ | -5.39 | 9.51 |
| $JD_{j,t}$ | Total joint dependence of streamer $i$ in period $t$ | 8.07 | 10.14 |
| $StreamerSize_{j,t}$ | The number of streamers watched by viewer $j$ in period $t$ | 13.25 | 22.49 |
| $WatchingTime_{j,t}$ | The total duration of streaming watched by viewer $j$ in period $t$ | 0.90 | 2.76 |
| Num. Viewers | 215,302 | | |
| Num. Observations | 1,511,181 | | |

**Table 1. Descriptive Statistics of Key Variables**

***Notes:*** *The unit of the tip amounts is the virtual currency used for tipping on this live streaming platform.*

Concerning the investigation of power restructuring operations that streamers and viewers undertake in response to an imbalance in the power structure, we consider three dependent variables for streamers' actions, i.e., the total number of viewers for streamer $i$ in period $t$ ($ViewerSize_{i,t}$), the interval days between streamer $i$'s two consecutive streams ($StreamingInterval_{i,t}$), and the total number of chat messages the focal streamer sends to other streamers in period $t$ ($Chat_{i,t}$). We control for a set of streamer-level covariates, including the number of viewers who have given a positive number of tips to the streamer ($TipperSize_{i,t}$), the streamer's involvement in a streaming guild ($StreamingGuild_{i,t}$), and the total amount of tips received by the streamer in past streams ($CumulativeTipReceive_{i,t}$).

For viewers' restructuring operations, we consider two dependent variables, i.e., the number of streamers a viewer watches in period $t$ ($StreamerSize_{j,t}$) and the total streaming watching time ($WatchingTime_{j,t}$). We further control the number of streamers to whom a viewer has given tips ($StreamerTipSize_{j,t}$), as well as the viewer's cumulative tip amount ($CumulativeTipGive_{j,t}$).

## *Model Specification*

To examine the impact of power structure on viewers' tipping behaviors, we estimate the following model.

$$Tip_{ij,t+1} = \alpha + \beta_1 AD_{ij,t} + \beta_2 JD_{ij,t} + Tip_{ij,t} + \boldsymbol{X}\theta + \mu_i + \pi_j + \tau_t + \varepsilon_{ij,t} \quad (5)$$

$Tip_{ij,t+1}$ represents the tip amount from viewer $j$ to streamer $i$ in period *t+1*.[6] The key independent variables, $AD_{ij,t}$ and $JD_{ij,t}$ are the key independent variables, indicating the asymmetric dependence and joint dependence between viewer $j$ and streamer $i$ in period $t$, respectively. Additionally, we control for the current tip amount from viewer $j$ to streamer $i$ ($Tip_{ij,t}$) to absorb unobservable biases related to power structure and next time tip amount. This control also isolates tipping behavior's potential cross-period path dependency from the power-dependence relationship. $\boldsymbol{X}$ represents a set of covariates that account for the time-variant characteristics of the streamer-viewer relationship. To further mitigate the potential impacts of unobservable characteristics of streamers and tippers, such as streaming style and emotional expression (Chen et al., 2023; Lin et al., 2021), we incorporate individual fixed effects for both the streamer ($\mu_i$) and the viewer ($\pi_j$), as well as time fixed effects ($\tau_t$). $\varepsilon_{ij,t}$ denotes the random error conforming to a normal distribution. In regression analysis, we cluster standard errors at the streamer level to address potential within-group correlation and heteroskedasticity.

We construct similar specifications based on observations at the streamer and viewer level to estimate their restructuring operations, respectively.

$$Y_{i,t+1} = \alpha + \beta_1 AD_{i,t} + \beta_2 JD_{i,t} + Y_{i,t} + \boldsymbol{X}\theta + \mu_i + \tau_t + \varepsilon_{i,t} \quad (6)$$

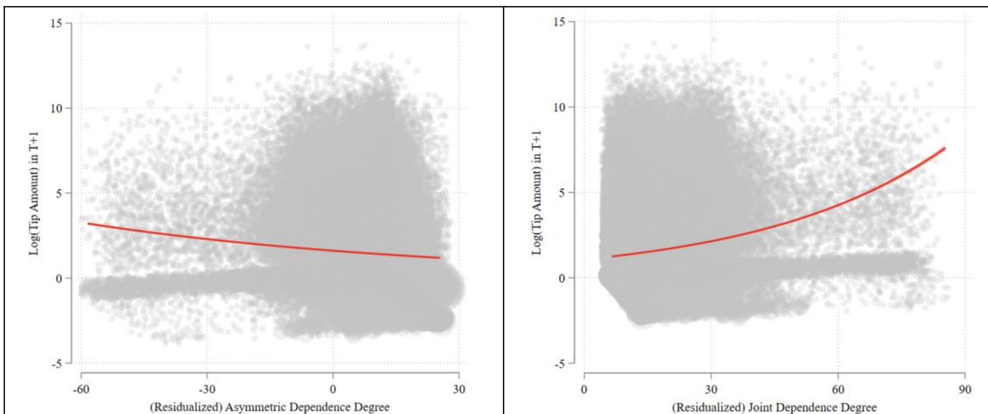
$$Y_{j,t+1} = \alpha + \beta_1 AD_{j,t} + \beta_2 JD_{j,t} + Y_{j,t} + \boldsymbol{X}\theta + \pi_j + \tau_t + \varepsilon_{j,t} \quad (7)$$

In the above models, $Y_{i,t+1}$ represents the three streamer level outcome variables in period *t+1,* i.e., $ViewerSize_{i,t+1}$, $StreamingInterval_{i,t+1}$, and $Chat_{i,t+1}$. And $Y_{j,t+1}$ includes the two focal outcomes at the viewer level, i.e., $StreamerSize_{j,t+1}$ and $WatchingTime_{j,t+1}$.

## Results

### *The Impact of Power Structure on Tipping Behavior*

For the impact of power structure within a streamer-viewer relationship on viewers' tipping behavior, Figure 1 provides model-free results. We estimate the relationship between asymmetric dependence and joint dependence and tipping in the next period at the relationship level.




A. Asymmetric Dependence

B. Joint Dependence

**Figure 1. Next Period Tip Amount and Degree of Power-Dependence**

***Notes:*** *In estimating the trend shown in Figure 1(A), we calculate the residuals of AD by regressing AD on JD, plot these residuals against the log-transformed tip amounts (plus one) for the subsequent period in a scatter plot, and fit the red trend curve using Poisson distributions. Figure 1(B) follows a similar approach, utilizing the residuals from JD.*

6 The term *period t+1* does not indicate a specific date but rather serves to identify the performance of this relationship the next time it appears in the data sample.

Figure 1(A) shows the tip amounts for different levels of asymmetric dependence, controlling only for joint dependence. As the degree of asymmetric dependence increases, the future tip amount tends to decrease. There is a positive correlation between joint dependence and future tip amount, as shown in Figure 1(B). It hints that a higher degree of joint dependence is beneficial for fostering the growth of reciprocal tipping behavior.

Table 2 presents the estimation results based on our model specification. As there is a large number of zero values in $Tip_{t+1}$, we employ several estimation methods to address this issue. Column (1) shows the results with a log-transformed plus one method for the dependent variable. Following the recommendation of Cohn et al. (2022), column (2) shows the estimation results based on the Poisson Pseudo Maximum Likelihood method, which is considered less biased compared to the *log-plus-one* method and allows for valid semi-elasticity interpretations. In column (3), we construct a variable for the strength of tipping behavior ($Tip\_Strength_{ij,t+1}$) using the ratio of tip amount to watching time within a relationship, estimated by PPML as well.

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | $Log(Tip_{ij,t+1}+1)$ | $Tip_{ij,t+1}$ | $Tip\_Strength_{ij,t+1}$ |
| $AD_{ij,t}$ | -0.0022** | -0.0166*** | -0.0144* |
| | (0.001) | (0.003) | (0.008) |
| $JD_{ij,t}$ | 0.0110*** | 0.0202*** | 0.0144** |
| | (0.001) | (0.004) | (0.006) |
| $Log(Tip_{ij,t}+1)$ | 0.3029*** | 0.0711* | 0.0950*** |
| | (0.003) | (0.040) | (0.020) |
| $Log(Watch_{ij,t})$ | 0.0276*** | 0.1296*** | 0.1325*** |
| | (0.001) | (0.028) | (0.025) |
| $Log(Tenure_{ij,t})$ | 0.0445*** | 0.5639*** | 0.4042*** |
| | (0.001) | (0.079) | (0.037) |
| Time Fixed Effects | YES | YES | YES |
| Streamer Fixed Effects | YES | YES | YES |
| Viewer Fixed Effects | YES | YES | YES |
| Observations | 7,387,619 | 3,927,007 | 3,927,007 |

**Table 2. The Impact of Power Structure on Tipping Behavior**

***Notes:*** *Column (1) employs a linear estimation with fixed effects, while columns (2) and (3) use Poisson estimation. All three columns control for individual fixed effects and time fixed effects, along with three relationship characteristics variables. We cluster standard errors at the streamer level. Regarding the significance levels, * denotes a p-value less than 0.1, ** indicates a p-value less than 0.05, and *** signifies a p-value less than 0.01.*

The results shown in Table 2 support Hypotheses 1 and 2. In column (2), estimated coefficients indicate that an increase in $AD_{ij,t}$, which represents a rise in the viewer's relative power advantage, leads to a decrease in the tip amount given by the viewer in the subsequent period. More specifically, a decrease in $AD_{ij,t}$ by one standard deviation (streamer power advantage increasing) results in an average increase of 11.3% in the tip amount given to the streamer in the next period, which is quite a large share (one standard deviation of AD in the relationship level data is 7.13, as shown in Table 1). For joint dependence, the results show that when JD increases by one standard deviation, the tip amount rises by 16.9%. The consistency among results shown in columns (1)-(3) supports the robustness of our findings. In particular, the coefficients for $Tip\_Strength_{ij,t+1}$ in column (3) reflects how the changes in power structure influence the unit price that viewers are willing to pay for streamers' content. There is also a negative impact of $AD_{ij,t}$ on $Tip\_Strength_{ij,t+1}$.

## *Power Restructuring Operations*

### Streamer Power Restructuring

This section discusses the potential power restructuring behaviors that disadvantaged actors within power relationships might adopt. First, we examine whether streamers take actions to counteract the viewers' power advantage based on the streamer-level observations. The results in Table 3 basically support our hypotheses regarding the streamers' power restructuring operations. Columns (1) to (3) in Table 3 represent three possible restructuring strategies streamers might adopt when they are at a power disadvantage.

Results shown in columns (2) and (3) indicate that a one standard deviation rise in $AD_{i,t}$ leads to an average 0.88% increase in the streamers' streaming intervals and a 5.4% increase in the number of chat messages with other streamers. These results suggest that when facing an imbalanced power situation, streamers might choose to reduce their focus on the criticality of resources from viewers or increase their interactions with other streamers to mitigate the constraints of the power structure. However, the coefficient of $AD_{i,t}$ in column (1) is insignificant. It may be because controlling viewers' size is challenging for streamers. Even if streamers wish to attract more viewers, it may not always be feasible during streaming sessions. Therefore, Hypothesis 3 is partially supported.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Alternative Source | Resource Criticality | Coalition |
| VARIABLES | $ViewerSize_{i,t+1}$ | $StreamingInterval_{i,t+1}$ | $Chat_{i,t+1}$ |
| $AD_{i,t}$ | 0.0006 | 0.0003*** | 0.0018*** |
| | (0.001) | (0.000) | (0.001) |
| $JD_{i,t}$ | 0.0000 | -0.0002*** | -0.0014** |
| | (0.001) | (0.000) | (0.001) |
| $Log(ViewerSize_{i,t})$ | 0.0393*** | -0.0053*** | 0.0298*** |
| | (0.011) | (0.001) | (0.011) |
| $Log(TipperSize_{i,t})$ | 0.0590*** | 0.0005 | 0.0688*** |
| | (0.015) | (0.001) | (0.015) |
| $StreamingGuild_{i,t}$ | 0.0730 | -0.0023 | 0.0181 |
| | (0.050) | (0.009) | (0.050) |
| $Log(CumulativeTipReceive_{i,t})$ | -0.0322*** | -0.0023** | -0.0133 |
| | (0.010) | (0.001) | (0.010) |
| Time Fixed Effects | YES | YES | YES |
| Streamer Fixed Effects | YES | YES | YES |
| Observations | 65,161 | 65,161 | 55,027 |

**Table 3. Streamer Power-Restructuring Operations**

***Notes:*** *Results are based on Poisson estimation, as these three outcome variables are count data, and notably, the chat counts in column (3) exhibit many zeros. All columns control for individual fixed effects and time fixed effects, along with four streamer time-varying characteristic variables. We employ heteroscedasticity-robust standard errors. Regarding the significance levels, * denotes a p-value less than 0.1, ** indicates a p-value less than 0.05, and *** signifies a p-value less than 0.01.*

### Viewer Power Restructuring

Table 4 presents the impact of a viewer-side power imbalance on the use of power restructuring operations. Column (2) in Table 4 indicates that viewers reduce their daily streaming watch time by 0.04% when $AD_{i,t}$ decreases by one standard deviation, which weakens viewers' relative power. However, similar to the results for streamers' alternative seeking in Table 3, we find insufficient evidence to suggest that viewers expand the sizes of streamers they watch as their degree of power disadvantage increases. These results partially support Hypothesis 4.

| | (1) | (2) |
|---|---|---|
| | Alternative Source | Resource Criticality |

| VARIABLES | $StreamerSize_{j,t+1}$ | $Log(WatchingTime_{j,t+1})$ |
|---|---|---|
| $AD_{j,t}$ | 0.0000 | 0.0004*** |
| | (0.000) | (0.000) |
| $JD_{j,t}$ | 0.0003* | -0.0001** |
| | (0.000) | (0.000) |
| $Log(StreamerSize_{j,t})$ | -0.0167*** | -0.0002 |
| | (0.002) | (0.001) |
| $Log(StreamerTipSize_{j,t})$ | 0.0571*** | 0.0369*** |
| | (0.003) | (0.001) |
| $Log(WatchingTime_{j,t})$ | 0.0457*** | 0.0296*** |
| | (0.003) | (0.002) |
| $Log(CumulativeTipGive_{j,t})$ | -0.0068*** | -0.0058*** |
| | (0.001) | (0.000) |
| Time Fixed Effects | YES | YES |
| Viewer Fixed Effects | YES | YES |
| Observations | 1,511,181 | 1,511,181 |

**Table 4. Viewer Power-Restructuring Operations**

***Notes:*** *Columns (1) to (2) represent seeking alternative resources and reducing the focus on the criticality of resources. Column (1) employs Poisson estimation because the number of streamers is a count variable, while column (2) uses linear estimation as the watching time is treated as a continuous variable. Both columns control for individual-fixed effects and time-fixed effects, along with four viewer time-varying characteristic variables. Heteroscedasticity-robust standard errors are in the parentheses. Regarding the significance levels, * denotes a p-value less than 0.1, ** indicates a p-value less than 0.05, and *** signifies a p-value less than 0.01.*

## *Robustness Checks*

To further check the robustness of our results, we first re-estimate all the main findings using a different measure of power dependence. Considering that the CR4 may be inaccurate when fewer than four viewers give tips in a streaming room, we use the Herfindahl-Hirschman Index (HHI) to measure the availability of alternatives instead of the CR4. Then, we construct AD and JD based on the HHI measure. The results shown in Table 5(A) are consistent with the main findings.

Second, we re-estimate the models by controlling for more fixed effects. As streamers and viewers might adopt different streaming and watching strategies during weekdays and weekends, we interact individual fixed effects with weekend fixed effects. The results shown in Table 5(B) are the same as the main results.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | $Tip_{ij,t+1}$ | $StreamingInterval_{i,t+1}$ | $Chat_{i,t+1}$ | $Log(WatchingTime_{j,t+1})$ |
| A. Sensitivity Test - Change Independent Variable | | | | |
| $AD\_HHI_t$ | -0.1062*** | 0.0018*** | 0.0154** | 0.0022*** |
| | (0.029) | (0.001) | (0.007) | (0.000) |
| $JD\_HHI_t$ | 0.1081*** | -0.0017*** | -0.0148** | -0.0016*** |
| | (0.028) | (0.001) | (0.007) | (0.000) |
| Characteristic Control | YES | YES | YES | YES |
| Time Fixed Effects | YES | YES | YES | YES |
| Streamer Fixed Effects | YES | YES | YES | |
| Viewer Fixed Effects | YES | | | YES |
| Observations | 3,927,007 | 65,161 | 55,027 | 1,511,181 |
| B. Specification Test - Add Fixed Effects | | | | |
| $AD_t$ | -0.0201*** | 0.0003*** | 0.0015** | 0.0007*** |
| | (0.005) | (0.000) | (0.001) | (0.000) |
| $JD_t$ | 0.0220*** | -0.0002*** | -0.0011* | -0.0000 |
| | (0.005) | (0.000) | (0.001) | (0.000) |

| | | | | |
|---|---|---|---|---|
| Characteristic Control | YES | YES | YES | YES |
| Time Fixed Effects | YES | YES | YES | YES |
| Streamer-Weekend Fixed Effects | YES | YES | YES | |
| Viewer-Weekend Fixed Effects | YES | | | YES |
| Observations | 3,601,406 | 63,244 | 51,467 | 1,439,941 |

**Table 5. The Sensitivity and Specification Tests**

***Notes:*** *All estimations focus on Tip, StreamingInterval, Chat, and WatchingTime, and except for the mentioned setting changes, all other settings remain consistent with those in the primary analysis. Regarding the significance levels, * denotes a p-value less than 0.1, ** indicates a p-value less than 0.05, and *** signifies a p-value less than 0.01.*

Third, one may be concerned that many zero values of the tip amount would affect the estimation results. We address this concern by employing Poisson estimation in our main analyses. Here, we further re-estimate the model using zero-inflated negative binomial regression following Chen et al. (2023) , which is suitable for over-dispersed non-negative count variables with an excessive number of zeros. The results shown in Table 6(A) are consistent with the main analyses.

| | A. Zero-Inflated Negative Binomial | | B. Selection Model | |
|---|---|---|---|---|
| | Logit | Negative Binomial | Probit | PPML |
| | (1) | (2) | (3) | (4) |
| VARIABLES | *Zero-Inflation* | $Tip_{ij,t+1}$ | *I(Days>1)* | $Tip_{ij,t+1}$ |
| $AD_{ij,t}$ | -0.0156*** | -0.0484*** | -0.0097*** | -0.0147*** |
| | (0.000) | (0.001) | (0.000) | (0.003) |
| $JD_{ij,t}$ | 0.0243*** | 0.0636*** | 0.0078*** | 0.0200*** |
| | (0.000) | (0.001) | (0.000) | (0.004) |
| $Log(Tip_{ij,t}+1)$ | -0.6879*** | 0.1169*** | 0.0859*** | 0.0107 |
| | (0.004) | (0.001) | (0.001) | (0.046) |
| $Log(Watch_{ij,t})$ | -0.1987*** | -0.1772*** | 0.0945*** | 0.0329 |
| | (0.002) | (0.003) | (0.000) | (0.050) |
| $Log(Tenure_{ij,t})$ | -0.0091*** | 0.2791*** | 0.3719*** | 0.2431*** |
| | (0.002) | (0.003) | (0.000) | (0.068) |
| $Log(Chat_{ij,t})$ | -0.4529*** | | 0.2304*** | |
| | (0.003) | | (0.001) | |
| $Log(ViewerSize_{ij,t})$ | 0.4223*** | | 0.0600*** | |
| | (0.002) | | (0.000) | |
| $Log(ViewerSize_{ij,t})$ | 0.3421*** | | 0.0764*** | |
| | (0.002) | | (0.000) | |
| $Time_{ij,t}$ | -0.0987*** | | | |
| | (0.001) | | | |
| $IMR$ | | | | -1.9814*** |
| | | | | (0.343) |
| Likelihood-Ratio Test | 0.0000 | | | |
| Vuong Test | 0.0000 | | | |
| Time Fixed Effects | | | | YES |
| Streamer Fixed Effects | | | | YES |
| Viewer Fixed Effects | | | | YES |
| Observations | 7,387,619 | 7,387,619 | 22,771,008 | 3,927,007 |

**Table 6. Zero-Inflated Negative Binomial and Sample Selection Tests for Tipping Behavior**

***Notes:*** *Table 6(A) shows the results of zero-inflated negative binomial regression. This estimation employs a Logit estimation in stage one (column (1)) to address the issue of zero values. Stage two (column (2)) uses negative* *binomial regression to estimate the adjusted tip amount. Table 6(B) shows the results of a two-stage sample selection model. In stage one (column (1)), we use a probit model to estimate the probability of a relationship entering the sample, i.e., being observed more than once, and calculate the Inverse Mills Ratio (IMR). In stage two (column (2)), we re-estimate the model by controlling for the IMR. Regarding the significance levels, * denotes a p-value less than 0.1, ** indicates a p-value less than 0.05, and *** signifies a p-value less than 0.01.*

Finally, as our discussion focuses on the behavior choices of streamers and viewers in the next period, observations of relationships observed only once during the sample period are naturally dropped from the estimation. To address the potential selection bias that may arise from "retaining only samples that have more than one observation record during the sample period," we employ a two-stage model to estimate the Inverse Mills Ratio (IMR) and control for IMR in the second stage following Lu et al. (2021) . The first-stage results indicate that relationships are more likely to persist when streamers exhibit greater relative power, as the streamers' power essentially reflects the viewers' dependence. With controlling for unobservable factors affecting relationship continuity, the results of the second stage support our main conclusions regarding tipping behavior. These results are consistent in both magnitude and statistical significance.

## Conclusion and Implication

This study employs the power-dependence perspective to explore the power relationships between streamers and viewers within live streaming context. Our comprehensive analysis of a large-scale dataset reveals that the power structure at the relationship level significantly influences viewers' tipping behavior. Viewers with power advantages tend to reduce tip amounts, potentially to maximize their gains. The degree of joint dependence within streamer-viewer relationships positively correlates with tip amounts, indicating that closer relationships foster reciprocal tipping. Furthermore, both streamers and viewers engage in power restructuring behaviors when they are at a power disadvantage. Streamers will reduce their streaming frequency and collaborate with other streamers, while viewers will spend less time watching live streaming.

The findings provide essential managerial insights for live streaming platforms and the various participants within these platforms. Streamers are suggested to remain acutely aware of power dynamics, using them strategically to maximize benefits and increase revenue. Viewers should manage their relationships carefully to prevent over-dependence and potential overspending. For platforms, monitoring the dynamics between streamers and viewers in real time has clear benefits. These insights can guide the development of targeted management policies and platform activities that enhance user engagement and satisfaction.

There are some limitations of this paper, which provide avenues for future research. First, the influence of power structures on other types of engagement behaviors, such as the content of chats identified in fine-grained data, warrants further exploration. Second, more diverse power-restructuring operations could be discussed, including potential bilateral operations where disadvantaged parties might introduce new resources to mitigate unfavorable conditions.

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