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BEHIND THE MILLION PLAYS: GENDER DIFFERENCES IN CREATOR INFLUENCE ON CHINESE SHORT-VIDEO PLATFORMS

ChengXi Bai, ZhiPeng Yang*, JiaYi Lv
School of International Economics, China Foreign Affairs University, Beijing 100037, China.
**Corresponding Author: ZhiPeng Yang*

Abstract: This paper examines gender differences in creator influence on Chinese short-video platforms using creator-video micro-data from Chanmama and Douyin. The analysis treats platform influence as an interaction-diffusion process shaped by account resources, content categories, creator tiers, and creative effort. The results show that the average female coefficient is negative but not uniformly significant after controlling for account size and video characteristics. Gender differences are instead conditional: they are concentrated in humanities and social sciences content, among tail creators, and in the weaker conversion of recent publishing effort into likes, comments, and composite interaction-diffusion outcomes. The findings indicate that gender inequality on short-video platforms is not only an outcome gap but also a process-level return gap in the transformation of comparable creative inputs into platform interaction.
Keywords: Short-video platforms; Creator economy; Gender inequality; Platform labor; Interaction-diffusion; Effort-reward conversion

1 INTRODUCTION

Short-video platforms have become central spaces for content production, social interaction, and public communication. Creator influence is not determined only by talent or content quality; it is produced through platform recommendation, account resources, content tracks, user feedback, and monetization opportunities. Existing studies of creator economies show that platforms organize visibility, relationships, monetization, and governance rather than simply providing neutral publishing infrastructure [1,2].

This platform-based production of influence makes gender a key dimension of analysis. Female and male creators may encounter different audience expectations, credibility judgments, emotional-labor demands, and returns to comparable publishing effort. The paper therefore examines whether similar account bases, content categories, video features, and posting intensity yield comparable likes, comments, shares, and composite interaction-diffusion performance.

The study uses creator-level and video-level data from Chanmama and Douyin. Its contribution is not a simple comparison of raw popularity. Instead, it measures gender inequality at the process level of platform influence and identifies the tracks, creator tiers, and effort-conversion mechanisms through which gender differences become visible.

2 LITERATURE REVIEW AND MECHANISMS

Creator-economy research emphasizes that platforms actively shape influence through distribution systems, connection management, monetization, and rule formulation. The concept of relational labor explains why creators must maintain ongoing communication and emotional connection with audiences in order to transform attention into durable social relationships [3]. The concept of aspirational labor further shows that many content producers, especially women, invest substantial low-paid or unpaid labor under the discourse of “doing what you love” [4].

Gendered visibility research suggests that platforms are not gender-neutral. Female creators must often appear authentic enough to attract attention while avoiding stronger scrutiny, shame, harassment, and reputational discipline [5]. Platform governance can also produce unequal visibility through formal moderation and informal algorithmic invisibility, and marginalized creators may rely more heavily on emotional and relational labor while facing greater vulnerability [6,7].

Empirical studies of the creator economy indicate that female creators often enter platforms later, cluster in gender-stereotyped categories, and receive lower recognition and returns [8]. In the Chinese short-video context, Douyin cultivates creators through traffic rewards, algorithmic visibility, and advertiser satisfaction, while the wanghong economy contains a clear gender hierarchy in labor and institutional power [9,10].

Platform governance also shapes whether creator effort is converted into rewards. Tiered governance gives different rules and protections to creators with different size and commercial value [11]. Douyin’s playful and gamified governance communicates platform rules through entertaining official accounts, and algorithmic pedagogy teaches creators to understand traffic success through platform-provided operational knowledge [12,13]. These mechanisms suggest that posting more frequently does not automatically produce proportional returns.

Related labor-market studies show that gender gaps can persist even in online and digital labor markets where tasks appear standardized or anonymous [14,15]. Creator platforms add another layer of complexity because independent-contractor arrangements, tiered governance, monetization rules, and algorithmic evaluation may shape labor returns and creator incentives [11-13].

The paper therefore proposes three mechanisms. The track-entry mechanism states that gender differences may arise because male and female creators are distributed across content categories with different audience structures and evaluation standards. The interaction-diffusion mechanism states that, conditional on similar accounts and videos, female creators may receive different user feedback. The effort-reward mechanism states that comparable recent publishing intensity may generate weaker marginal interaction returns for female creators.

Hypothesis 1 states that part of the gender gap in influence arises from differences in the distribution of male and female creators across content categories. After controlling for content category, the gender coefficient should be attenuated. Hypothesis 2 states that after controlling for account size, creator tier, content category, video age, duration, and release time, female creators' interaction-diffusion outcomes may differ from male creators' outcomes. Hypothesis 3 states that the marginal effect of recent publishing intensity may differ by gender, with a negative interaction indicating weaker effort-reward conversion for female creators.

3 DATA, VARIABLES, AND MODELS

The data come from public Douyin pages and Chanmama. Douyin information verifies creator homepages, account identities, video links, release times, titles, and public interaction outcomes. Chanmama provides industry, creator, and video information, including gender, fan size, number of works, release date, likes, comments, and shares. The sample covers five representative categories: fashion, fitness, food, humanities and social sciences, and sannong. These categories differ in gender structure and interaction logic, making them suitable for testing whether gender differences are category-specific.

$$C = \{fashion, fitness, food, humanities\text{−}social\ sciences, sannong\} \tag{1}$$

The selection of these five industries follows the original sample design. All are stable categories on Douyin and Chanmama with comparatively complete creator- and video-level data. They also differ in gender structure and audience expectations: fashion and food include many active female creators, sannong is relatively male-concentrated, and fitness plus humanities and social sciences involve more mixed or complex gender distributions.

Creators are stratified by industry, gender, and tier. Female equals one for female creators and zero for male creators. Creator tiers are constructed from fan-count rankings and divided into head, waist, and tail tiers. The theoretical sampling structure contains 5 × 2 × 3 = 30 cells, and the final analysis uses creator-video observations from 177 creators. Because outcomes are cumulative values observed at the data-collection date, the models control for video age to reduce comparability problems caused by different accumulation periods.

The basic unit of observation is a video posted by a sampled creator. If a creator has several observable videos during the collection window, that creator contributes multiple video-level observations. This design makes it possible to control for observable account and video characteristics while testing whether videos posted by female creators receive different interaction-diffusion outcomes from comparable videos posted by male creators.

The main dependent variables are log likes, log comments, log shares, and the composite observed interaction-diffusion index. Likes, comments, and shares are log-transformed using ln(1 + Y). The composite index standardizes the logged indicators and averages them so that likes do not dominate the measure.

$$EngIndex^{obs}_{iv} = (Z^{L}_{iv} + Z^{c}_{iv} + Z^{s}_{iv}) / 3 \tag{2}$$

The rationale for constructing the composite index is that likes, comments, and shares all reflect user interaction but differ in magnitude and meaning. Likes are low-cost feedback, comments reflect deeper participation, and shares directly capture content diffusion. Standardization assigns balanced weights to these different behaviors.

The core explanatory variable is creator gender. Account-level controls include fan count, creator tier, total posted works, number of videos in the collection period, MCN affiliation, verification status, and region. Video-level controls include video age, duration, number of hashtags, commercial-title indicators, tutorial-title indicators, and title length. Industry fixed effects control for systematic differences in audience size, interaction norms, commercial value, and recommendation logic across the five categories.

The baseline model estimates the gender difference in video-level interaction-diffusion after controlling for account size, video age, duration, title features, creator tier, industry effects, and release-time effects. Standard errors are clustered at the creator level because one creator can contribute multiple videos.

$$\begin{Bmatrix} ln(1+Y_{iv})=\beta Female_{i}+\gamma_1 lnFans_{i}+\gamma_2 ln(1+Age_{iv})+\gamma_3 ln(1+Duration_{iv})+ \\ \gamma_4 Hashtag_{iv}+\gamma_5 CommercialTitle_{iv}+\gamma_6 Tutorial_{iv}+\theta Tier_{i}+\mu c+\lambda t+\varepsilon_{iv} \end{Bmatrix} \tag{3}$$

$$\begin{Bmatrix} EngIndex^{obs}_{iv}=\beta Female_{i}+\gamma_1 lnFans_{i}+\gamma_2 ln(1+Age_{iv})+\gamma_3 ln(1+Duration_{iv})+ \\ \gamma_4 Hashtag_{iv}+\gamma_5 CommercialTitle_{iv}+\gamma_6 Tutorial_{iv}+\theta Tier_{i}+\mu c+\varepsilon_{iv} \end{Bmatrix} \tag{4}$$

Here, Ziv denotes the vector of account-level, video-level, title, tier, industry, and release-time controls included in the baseline specification.

Additional models test track heterogeneity, creator-tier heterogeneity, fan-base conversion, and creative-effort conversion. The track model interacts Female with industry dummies; the tier model interacts Female with waist and tail tier indicators; the fan-base model interacts Female with log fan count; and the effort model interacts Female with the log number of videos posted in the 30 days before a video's release.

$$Y_{iv}=\beta_0 Female_i+\sum c\delta c Female_i\times Industry_i c+X'_{iv}\Gamma+\theta Tier_i+\mu c+\varepsilon_{iv} \quad (5)$$

$$Y_{iv}=\beta_0 Female_i+\sum k\theta k Female_i\times Tier_i k+X'_{iv}\Gamma+\mu c+\varepsilon_{iv} \quad (6)$$

$$Y_{iv}=\beta_0 Female_i+\alpha lnFans_i+\pi Female_i\times lnFans_i+X'_{iv}\Gamma+\theta Tier_i+\mu c+\varepsilon_{iv} \quad (7)$$

$$Y_{iv}=\beta_0 Female_i+\rho ln(1+PriorPosts30_{iv})+\phi Female_i\times ln(1+PriorPosts30_{iv})+X'_{iv}\Gamma+\theta Tier_i+\mu c+\varepsilon_{iv} \quad (8)$$

4 EMPIRICAL RESULTS

The baseline results in Table 1 show that the coefficient on Female is negative across likes, comments, shares, and the composite index. Under creator-level clustered standard errors, the average effect is not uniformly significant, indicating that a simple full-sample female disadvantage is not robustly identified. This motivates the heterogeneity and mechanism tests.

Table 1 Baseline Regression: Creator's Gender and Video Interaction-diffusion Performance

	(1)ln_likes	(2)ln_comments	(3)ln_shares	(4)eng_index
female	-0.1100	-0.2770	-0.1196	-0.0733
female	(0.2677)	(0.2129)	(0.2694)	(0.0988)
ln_fans	0.1984	0.2060*	0.1062	0.0724
ln_fans	(0.1714)	(0.1214)	(0.1590)	(0.0612)
ln_age_days	0.6409***	0.4575***	0.7089***	0.2474***
ln_age_days	(0.0984)	(0.0837)	(0.0932)	(0.0359)
ln_duration_sec	0.5930***	0.6022***	0.6308***	0.2538***
ln_duration_sec	(0.1038)	(0.0855)	(0.1050)	(0.0389)
hashtag_count	-0.0339	-0.0299	0.0209	-0.0066
hashtag_count	(0.0671)	(0.0561)	(0.0750)	(0.0259)
title_length	-0.0001	0.0022	-0.0018	0.0001
title_length	(0.0033)	(0.0024)	(0.0038)	(0.0012)
control variables	Yes	Yes	Yes	Yes
Observations	3075	3075	3075	3075
R^2	0.3136	0.3332	0.2948	0.3198

The baseline pattern is important because it prevents a one-dimensional interpretation of gender inequality. The direction of the coefficients suggests that gender may matter, especially for comments and composite interaction performance, but the lack of uniform significance under clustered inference means that gender differences should be studied as conditional differences rather than as a single average gap.

Table 2 shows that the gender difference is most pronounced in humanities and social sciences. The interaction between Female and this track is significantly negative for likes and the composite index, and directionally negative for comments and shares. The results suggest that the disadvantage is concentrated in knowledge- and opinion-based content rather than being uniform across tracks.

Table 2 Track Heterogeneity Regression Results

variable	(1) ln_likes	(2) ln_comments	(3) ln_shares	(4) eng_index
Female	0.2802	-0.0211	-0.0733	0.0250
Female	(0.3398)	(0.2963)	(0.3725)	(0.1278)
Female × Humanities and Social Sciences	-1.3449**	-0.9553	-0.9603	-0.4517*
Female × Humanities and Social Sciences	(0.6665)	(0.5960)	(0.6206)	(0.2480)
Female × Fitness	-0.3335	-0.0108	0.4108	0.0055
Female × Fitness	(0.5393)	(0.4391)	(0.5942)	(0.1970)
Female × Fashion	0.5296	0.2263	0.6520	0.1890
Female × Fashion	(0.8703)	(0.6529)	(0.7732)	(0.3066)
Female × Food	-0.8541	-0.5890	-0.3126	-0.2465
Female × Food	(0.9162)	(0.7034)	(1.1351)	(0.3630)
Account control variables	Yes	Yes	Yes	Yes
Video control variables	Yes	Yes	Yes	Yes

title control variable	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
level fixed effects	Yes	Yes	Yes	Yes
Observations	3,075	3,075	3,075	3,075
R^2	0.3306	0.3436	0.3064	0.3334

This result is consistent with the theoretical mechanism that knowledge-intensive and opinion-based tracks may impose higher credibility and authority thresholds on female creators. In lifestyle-oriented tracks, the interaction effects are not statistically stable, which indicates that content category mediates the gendered return process rather than merely reflecting the gender composition of creators.

Table 3 shows that gender differences vary sharply by creator tier. Head female creators are not weaker than head male creators; the Female coefficient is positive and significant for likes at the 10% level. The Female × tail interaction is significantly negative for all four outcomes. Gender differences therefore appear mainly during the growth stage, when creators rely more on initial recommendations and feedback from unfamiliar users.

Table 3 Results of Hierarchical Heterogeneity Analysis

variable	(1) ln_likes	(2) ln_comments	(3) ln_shares	(4) eng_index
Female	0.7570*	0.2529	0.6513	0.2236
Female	(0.4385)	(0.3229)	(0.4130)	(0.1545)
Female × waist	-0.7970	-0.5223	-0.7084	-0.2784
Female × waist	(0.6257)	(0.4770)	(0.6172)	(0.2264)
Female × tail	-1.7161**	-1.0133*	-1.5263**	-0.5822**
Female × tail	(0.6719)	(0.5305)	(0.6327)	(0.2422)
ln_fans	0.2680	0.2480**	0.1681	0.0961
ln_fans	(0.1782)	(0.1255)	(0.1617)	(0.0632)
Account control variables	Yes	Yes	Yes	Yes
Video control variables	Yes	Yes	Yes	Yes
title control variable	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
level fixed effects	Yes	Yes	Yes	Yes
Observations	3,075	3,075	3,075	3,075
R^2	0.3327	0.3420	0.3078	0.3344

The tier results also explain why the full-sample average effect is weak. If female head creators perform comparably to or better than male head creators, while female tail creators perform substantially worse than male tail creators, the two patterns partly offset each other in the pooled baseline model. Gender inequality on short-video platforms is therefore better understood as a growth-stage problem rather than a uniform disadvantage after success.

From a platform-operation perspective, head creators already possess stable fans, account reputation, mature production routines, and often team-based support. Tail creators rely more heavily on the initial recommendation of individual videos and early feedback from unfamiliar users. This is precisely where gendered evaluations of credibility, expression, and content legitimacy can more easily affect interaction-diffusion outcomes.

The mechanism tests clarify where the gap arises. Table 4 finds no significant disadvantage in fan-base conversion: Female × lnFans is positive but insignificant across outcomes. Once creators have a comparable fan base, female creators are not significantly weaker in converting existing fans into interactions.

Table 4 Mechanism Test: Fan Base-interaction Reward Conversion Mechanism

variable	(1) ln_likes	(2) ln_comments	(3) ln_shares	(4) eng_index
Female	-3.3076	-2.2546	-2.6727	-1.1354
	(3.0049)	(2.1898)	(2.8205)	(1.0640)
ln_fans	0.0519	0.1154	-0.0107	0.0237
	(0.1992)	(0.1440)	(0.1995)	(0.0720)
Female × ln_fans	0.2317	0.1433	0.1850	0.0770
	(0.2149)	(0.1546)	(0.2009)	(0.0757)
Account control variables	Yes	Yes	Yes	Yes
Video control variables	Yes	Yes	Yes	Yes

title control variable	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
level fixed effects	Yes	Yes	Yes	Yes
Observations	3,075	3,075	3,075	3,075
R^2	0.3172	0.3351	0.2968	0.3224

The fan-base result suggests that accumulated account resources can buffer gender differences. Once a creator has built a comparable audience base, the marginal return from that base is not significantly lower for female creators. This finding is consistent with the head-tier result and shows that the main gap is not simply that female creators fail to mobilize existing followers.

Table 5 provides the central mechanism result. Recent posting intensity is positively associated with interaction-diffusion performance, but Female × lnPriorPosts30 is negative. The coefficient is significant for likes, comments, and the composite index, showing that the marginal return to sustained publishing effort is weaker for female creators. This effort-reward conversion gap helps explain why the disadvantage is concentrated among tail creators.

Table 5 Mechanism Test: Creative Effort-interactive Return Transformation Mechanism

variable	(1) ln_likes	(2) ln_comments	(3) ln_shares	(4) eng_index
Female	0.7092**	0.2886	0.2061	0.1665
Female	(0.2742)	(0.2611)	(0.3683)	(0.1117)
ln_prior_posts_30d	0.1515*	0.1452*	0.1974*	0.0681**
ln_prior_posts_30d	(0.0814)	(0.0737)	(0.1046)	(0.0327)
Female × ln_prior_posts_30d	-0.2609**	-0.1859*	-0.0969	-0.0764*
Female × ln_prior_posts_30d	(0.1018)	(0.0967)	(0.1393)	(0.0412)
ln_fans	0.3343	0.1411	0.3028	0.1053
ln_fans	(0.2046)	(0.1821)	(0.2338)	(0.0786)
Account control variables	Yes	Yes	Yes	Yes
Video control variables	Yes	Yes	Yes	Yes
title control variable	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
level fixed effects	Yes	Yes	Yes	Yes
Observations	1,643	1,643	1,643	1,643
R^2	0.3341	0.3218	0.3225	0.3258

This finding shifts the interpretation from a static outcome gap to a dynamic return gap. Publishing more frequently generally improves interaction outcomes, but female creators receive smaller marginal gains from the same recent posting intensity. For creators in the tail tier, weaker returns to effort can slow account growth and reduce the likelihood of moving into higher tiers.

The robustness checks support the stability of the main pattern. Table 6 shows that winsorizing interaction outcomes at the 99th percentile or dropping extreme observations leaves the gender coefficient numerically close to the baseline estimate. Table 7 shows that HC3 standard errors produce the same negative direction and make comments and the composite index statistically significant, although creator-level clustering remains the primary inference benchmark.

Table 6 Winsor and Truncation Test Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(4)
	ln_likes	ln_comment	ln_shares	eng_index	ln_likes	ln_comment	ln_shares	eng_index
female	-0.1162	-0.2742	-0.1263	-0.0752	-0.1469	-0.2596	-0.1475	-0.0772
female	(0.2669)	(0.2123)	(0.2681)	(0.0994)	(0.2652)	(0.2103)	(0.2642)	(0.0976)
ln_fans	0.1936	0.2012*	0.1012	0.0710	0.1655	0.1836	0.0858	0.0625
ln_fans	(0.1699)	(0.1199)	(0.1580)	(0.0612)	(0.1638)	(0.1151)	(0.1567)	(0.0588)
ln_age_days	0.6360***	0.4580***	0.7045***	0.2486***	0.6146***	0.4592***	0.6897***	0.2405***
ln_age_days	(0.0973)	(0.0833)	(0.0925)	(0.0360)	(0.0958)	(0.0822)	(0.0909)	(0.0352)
ln_duration_sec	0.5952***	0.5995***	0.6349***	0.2565***	0.6083***	0.5966***	0.6428***	0.2576***
ln_duration_sec	(0.1035)	(0.0852)	(0.1041)	(0.0390)	(0.1037)	(0.0844)	(0.1015)	(0.0382)
hashtag_count	-0.0358	-0.0300	0.0198	-0.0071	-0.0408	-0.0320	0.0176	-0.0090
hashtag_count	(0.0668)	(0.0558)	(0.0745)	(0.0260)	(0.0659)	(0.0551)	(0.0724)	(0.0254)
title_length	-0.0001	0.0022	-0.0018	0.0001	0.0001	0.0021	-0.0019	0.0000
title_length	(0.0032)	(0.0024)	(0.0038)	(0.0012)	(0.0032)	(0.0022)	(0.0036)	(0.0012)
control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3075	3075	3075	3075	3045	3045	3045	3045

R^2	0.3132	0.3341	0.2980	0.3212	0.3045	0.3308	0.3011	0.3196

Table 7 OLS-HC3 Regression Results with Robust Standard Errors

variable	(1) ln_likes	(2) ln_comments	(3) ln_shares	(4) eng_index
Female	-0.1100	-0.2770***	-0.1196	-0.0733**
	(0.0756)	(0.0644)	(0.0819)	(0.0289)
ln(Fans)	0.1984***	0.2060***	0.1062**	0.0724***
	(0.0547)	(0.0410)	(0.0523)	(0.0200)
ln(Video Age)	0.6409***	0.4575***	0.7089***	0.2474***
	(0.0364)	(0.0319)	(0.0391)	(0.0140)
ln(Duration)	0.5930***	0.6022***	0.6308***	0.2538***
	(0.0367)	(0.0311)	(0.0389)	(0.0140)
Hashtag count	-0.0339	-0.0299	0.0209	-0.0066
	(0.0238)	(0.0201)	(0.0273)	(0.0093)
Title length	-0.0001	0.0022**	-0.0018	0.0001
	(0.0013)	(0.0009)	(0.0016)	(0.0005)
Video FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes
Observations	3,075	3,075	3,075	3,075
R-squared	0.3136	0.3332	0.2948	0.3198

Because multiple videos from the same creator are likely correlated, the creator-clustered specification remains the main inference benchmark. HC3 standard errors mainly correct for heteroskedasticity and high-leverage observations and do not address within-creator dependence. Taken together, the robustness tests support the direction of the gender coefficient while also showing that statistical significance depends on the standard-error structure.

5 CONCLUSION

This study demonstrates the feasibility of evaluating gender differences in creator influence by combining creator-video micro-data with process-level regression analysis. Instead of relying only on raw fan counts or total traffic, the framework controls for account resources, creator tier, content category, video characteristics, and release-time factors, making it possible to examine whether comparable creative inputs are converted into comparable interaction-diffusion outcomes.

The empirical results show that the gender gap on Chinese short-video platforms is conditional and process-based. The average female coefficient is negative but not uniformly significant under creator-clustered inference, while clearer disadvantages appear in humanities and social sciences content, among tail creators, and in the weaker conversion of recent publishing effort into likes, comments, and the composite interaction-diffusion index. These findings indicate that platform inequality is not only a final-outcome gap but also an effort-reward conversion gap during creator growth.

The feasibility of the research design is further supported by the robustness checks. Winsorization, truncation, and HC3 robust standard-error specifications preserve the main direction of the gender coefficient, and the mechanism models consistently locate the gap in specific tracks, tiers, and effort-return processes. The approach therefore provides an operational empirical basis for platform governance, creator-support policies, and the evaluation of whether different creator groups receive comparable returns from comparable work.

Future research should expand the sample to more content categories and longer observation windows, incorporate exposure, playback completion, recommendation position, advertising cooperation, livestreaming, and e-commerce conversion data, and use longitudinal causal designs or platform-audit experiments to separate algorithmic distribution from audience response. These extensions would make it possible to track long-term creator mobility, identify when tail creators move into higher tiers, and design more equitable recommendation and support mechanisms for the short-video creator economy.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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