# Content Creator Multihoming and Attention Spillovers Across Platforms

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**Abstract**

Complementor multihoming is often viewed as weakening platforms by reducing differentiation and increasing consumer substitution. We revisit this perspective in the context of content creator multihoming. Using a unique seven-year panel tracking thousands of creators on Chinese TikTok and RedNote, we provide the first empirical evidence on creator multihoming behavior and its consequences. We first document that multihoming is widespread and strategic: Creators tend to adopt an additional platform after experiencing growth slowdowns on their incumbent platform, and they strategically cross-post selected content. We then study the impact of creator multihoming on their performance on the incumbent platform. Exploiting staggered platform adoption in a difference-in-differences design, we find that adopting a second platform benefits creators on the incumbent platform. Contrary to traditional platform concerns that multihoming diverts creators and thus users away from the incumbent platform and harms its performance, we show that adoption of a second platform leads to a 23.5% increase in followers and a 25.4% increase in engagement on the incumbent platform. Creators also increase content production and adjust their content topics toward styles characteristic of the new platform. Mechanism analyses show that the engagement gains are largely driven by audience expansion through cross-platform attention spillovers and increased viewership on the focal platform generated by exposure on the new platform. By highlighting this audience expansion channel in attention-driven markets, our paper helps clarify when complementor multihoming can benefit both complementors and incumbent platforms, with implications for creator strategy and platform governance.

**Keywords:** creator multihoming, social media, content creation, attention spillover

# 1 Introduction

Platform markets are now central to industries such as transportation, retail, software, and media (Gibson, 2024). A common feature of these markets is that complementors (firms or individuals providing complementary products or services) often adopt multiple platforms, a behavior known as complementor multihoming (Abolfathi, 2026; Li and Zhu, 2021). Drivers work simultaneously for Uber and Lyft; app developers publish across multiple app stores; and merchants list products on several marketplaces. A large literature emphasizes that complementor multihoming reduces platform value by reducing platform differentiation and thus increasing consumer substitution (Landsman and Stremersch, 2011). Consistent with this logic, platforms often seek to limit multihoming through exclusive contracting (Corts and Lederman, 2009; Lee, 2013) or by raising switching costs (Karhu et al., 2018).

Content platforms, however, present a different setting. Platforms such as YouTube, TikTok, and Instagram have grown rapidly and now command a substantial share of consumer attention (Qian and Jain, 2024). This landscape is shaped by the rapid expansion of the creator economy: more than 200 million creators are active worldwide, and the market is projected to reach $480 billion by 2027 (GoldmanSachs, 2023; Grand View Research, 2025). Because creators supply the content that generates engagement and monetization, they are a central source of platform value (Bhargava, 2022). Yet as creators increasingly post across content platforms, platforms often lower the cost of multihoming, for example, by enabling direct sharing of content to other platforms and converging on similar content formats.[1] Why would a social media platform relax restrictions on multihoming when it appears not to benefit the platform? Answering this puzzle requires understanding how creator multihoming affects the focal platform.

Content creators differ from traditional complements (e.g., Uber/Lyft drivers). Creators function as portable social brands because digital content is a non-rivalrous information good with near-zero redistribution costs. When creators expand their presence on an additional platform, they may build brand stock and increase discovery, generating cross-platform attention spillovers (i.e., incremental viewership on the focal platform driven by exposure on the other platform). At the same time, multihoming through cross-posting

[1]For example, TikTok offered a "Share to Facebook and Instagram" feature (https://techcrunch.com/2022/08/17/a-new-tiktok-feature-lets-creators-share-tiktok-stories-to-facebook-and-instagram/ (Accessed on March 25th 2026)) Instagram launched Reels as a direct response to TikTok's popularity, offering a short-form video format with similar features (https://www.wired.com/story/instagram-reels-tiktok-clone-launches/ (Accessed on March 25th 2026). Twitch announced that it would no longer enforce its livestream exclusivity agreement, meaning partnered creators could stream on other platforms (https://esports.gg/news/streamers/twitch-exclusivity-removal/) (Accessed on March 25th, 2026)

can make platforms closer substitutes for viewers (consumers), shifting consumption away from the focal platform. These opposing forces make the effect of creator multihoming theoretically ambiguous: it may strengthen the focal platform through audience expansion or weaken it by increasing cross-platform substitutability. Determining which force dominates is an open question with implications for platform governance choices such as portability tools, format convergence, and exclusivity.

In this paper, we link the platform-level strategic puzzle to a creator-level analysis. We begin with **RQ1**: *What is the current landscape of creator multihoming on social media platforms?* Specifically, how common is it? When do creators adopt an additional platform? And which types of content do they choose to cross-post? This question is important because the implications of multihoming for platform competition depend not only on whether creators multihome, but also on the form that multihoming takes. We then turn to our central **RQ2**: *How does adopting a new platform affect a creator's outcomes of interests on the focal platform?* Yet an average effect alone may obscure important heterogeneity, and this motivates **RQ3**: *What are the heterogeneous effects among creators?* Finally, knowing that effects exist and vary naturally points us toward **RQ4**: *Through which mechanisms do these effects operate?* While a full welfare or long-run equilibrium analysis would require modeling endogenous responses by viewers, creators, and platforms, our study provides short-run evidence on the immediate effects of creator multihoming on the focal platform. By identifying whether multihoming expands creators' audiences and raises engagement on the incumbent platform, our paper also sheds light on policy debate over when relaxing multihoming restrictions may benefit the incumbent platform.

Our empirical setting is Douyin (hereafter, TikTok) and Xiaohongshu (hereafter, RedNote), two leading social media platforms in China that compete for user attention and creators (Suciu, 2025). Founded in 2016, Chinese TikTok has grown into China's dominant short-video platform and reached approximately 766 million daily active users (Curry, 2025). RedNote, founded in 2013, operates as a lifestyle and social-commerce community, with more than 300 million daily active users (Lu and Miao, 2025). We assemble a large-scale panel data that tracks creators on both platforms over seven years, allowing us to observe their platform adoption, growth, and subsequent strategic adjustments. The data combine creator-level outcomes (e.g., daily follower dynamics) with complete post-level information (e.g., engagement and sponsorship activities), covering thousands of creators. We also compile platform-level app download data to capture broader market dynamics.

Studying creator multihoming at scale presents measurement challenges, because we need to link creator identities across platforms and to identify cross-posting behavior. To this end, we match creator accounts on TikTok to their corresponding RedNote profiles using detailed creators' information. This matching procedure is validated through extensive manual checks. We then classify posts as cross-posted versus platform-specific by comparing title similarity within the same creator across platforms. These steps allow us to characterize both the extensive and intensive margins of multihoming.

We begin by documenting several stylized facts about creator multihoming and providing answers to our RQ1. First, multihoming is prevalent: 48% of creators in our sample are active on both platforms. Second, creators often expand to an additional platform following a slowdown in follower growth on the incumbent platform, consistent with multihoming as a response to diminishing marginal returns from remaining single-homed. Third, creators generally maintain a consistent topical focus across platforms, reflecting stable creator "brands", but they do not replicate all content mechanically. Instead, they selectively cross-post around 30 percent their most engaging content, implying deliberate curation of what is shared across platforms. Fourth, cross-posted content receives higher engagement than platform-specific content and is released nearly simultaneously on both platforms, consistent with coordinated timing and content allocation chosen ex ante rather than reactive reposting after observing performance. These patterns show that creator multihoming is a strategic and selective choice over content supply and distribution across platforms.

We next examine how adopting an additional platform affects creators' performance on the focal platform, which is our RQ2. As discussed earlier, multihoming can generate both audience expansion and substitution, so the net effect is theoretically ambiguous. To discipline this ambiguity, we introduce a simple conceptual framework to clarify the opposing forces (see Section 3). We then take the framework to the data, exploiting staggered adoption of the new platform across creators to identify the effect. Specifically, we use a difference-in-differences (DiD) design that compares changes in outcomes for TikTok creators who adopt RedNote to changes for observably similar creators who have not yet adopted. Event-study analyses show no evidence of pre-trends, supporting the parallel trends assumption underlying our DiD approach.

Our study shows that creator multihoming is associated with improved outcomes on the incumbent platform along multiple dimensions. Most importantly, after adopting a second platform, creators' average engagement on the incumbent rises by 25.4 percent. Consistent with an audience expansion mechanism, creators also experience sizable follower gains by 23.5 percent. In addition, creators publish more sponsored posts, reflecting higher monetization intensity. Finally, creators' content shifts in a direction that is more aligned with the new platform's prevailing style, suggesting endogenous adaptation in content positioning.

Understanding heterogeneity in multihoming returns is important not only for creators deciding whether and when to expand across platforms, but also for platforms designing governance policies and incentive structures that account for the diverse needs of their creator ecosystems. We thus investigate our RQ3 and explore two key dimensions of heterogeneity: creator size and category competitiveness. First, smaller creators benefit more from multihoming, consistent with diminishing marginal returns to audience expansion for already-established creators. This pattern suggests that multihoming may reduce concentration by disproportionately helping smaller creators grow, which can be beneficial for platforms that value a broader and more resilient supply base. Second, creators in highly competitive content categories experience weaker engagement gains, indicating that the returns to multihoming are shaped by creators' initial positions and the cross-platform competition.

A potential concern is that creators may strategically time multihoming in anticipation of changes in their TikTok performance. However, we find that creators are more likely to adopt an additional platform after periods of stagnating follower growth, which is inconsistent with adoption being driven by anticipated positive shocks. If anything, such selection would bias our estimates downward, implying that the positive effects we document before should be interpreted as conservative lower bounds of the true impact.

Having established the net positive effect of multihoming, we turn to our final RQ4. We investigate the mechanism and provide evidence consistent with an audience expansion channel driven by cross-platform attention spillovers. Our main finding is that engagement gains after multihoming are largely mediated by increases in follower size on the incumbent platform, suggesting that improved performance primarily reflects a larger audience. These follower gains can arise through two spillover margins: (i) an extensive margin, where new users discover the creator on the new platform and then follow them on the incumbent platform; and (ii) an intensive margin, where existing multihoming users, who already use both platforms, begin following and engaging with the creator more on the incumbent. Using app download data, we show that TikTok experiences a meaningful increase in new users following a wave of creator adoption of RedNote, providing suggestive support for the extensive margin spillover. We further show that multihoming creators' gains do not crowd out non-multihoming creators' engagement or follower growth, mitigating concerns that the results are driven primarily by within-platform cannibalization. Taken together, those evidence is consistent with attention spillovers and audience expansion as the dominant forces.

Our paper makes both empirical and theoretical contributions. Empirically, we provide the first evidence on creator multihoming by constructing a unique seven-year panel of creators on TikTok and RedNote.

Exploiting staggered adoption, we estimate how adopting a second platform affects creators' outcomes on the incumbent platform. This evidence speaks to the growing creator economy literature, where multihoming is a first-order strategic choice shaping growth and career sustainability, and to the multihoming literature, which has been empirically constrained by limited cross-platform activity data. Theoretically, we develop and test a mechanism for multihoming in attention-driven (social media) platforms. We highlight a cross-platform attention spillover force, which potentially benefits the incumbent platform. This mechanism helps reconcile why prior work yields mixed predictions about whether complementor multihoming benefits or harms the incumbent.

Our results have implications for both creators and platforms. For creators, multihoming emerges as an effective growth strategy, particularly for those experiencing stagnating growth on a single platform. Expanding to an additional platform allows creators to increase visibility, reach new audiences, and scale monetization opportunities without sacrificing performance on the incumbent platform. For platforms, our findings suggest that restricting creator multihoming may be costly in markets where attention spillovers dominate attention substitution. More broadly, the evidence is consistent with platform competition shifting away from exclusivity in content creation and toward investments in distribution and discovery and complementary services that help creators convert visibility into revenue.

## 2 Related Literature

**Multihoming strategies.** Homing decisions are a core primitive in platform economics because they determine how platforms compete and how value is created and captured in two-sided markets (Armstrong, 2006; Rochet and Tirole, 2003). We focus on complementor multihoming because complements are a direct source of platform differentiation and user value (Cennamo et al., 2018; Corts and Lederman, 2009; Landsman and Stremersch, 2011).[2] Platform competition and governance, in turn, shape complementors' multihoming incentives (Abolfathi, 2026; Loh and Kretschmer, 2023; Nagaraj and Piezunka, 2024).

From the complementor's perspective, existing work emphasizes that complementor multihoming involves a trade-off between reach and cost. On the benefit side, operating on multiple platforms can expand market access and allow complementors to spread fixed costs across a larger user base and reuse capabilities across platforms, generating economies of scale and scope (Bresnahan et al., 2014; Cennamo et al.,

[2] A large and related literature also studies consumer multihoming, showing how users' participation on multiple platforms affects pricing, competition, and welfare (Boudreau and Hagiu, 2009; Bryan and Gans, 2019; Choi, 2010)

2018; Corts and Lederman, 2009). Multihoming can also reduce dependence on any one platform, mitigating platform-specific risk (Belleflamme and Peitz, 2019; Rysman, 2007), and may facilitate learning and knowledge transfer, particularly when platforms share similar complements or user demands (Polidoro Jr and Yang, 2024; Venkataraman et al., 2018). On the cost side, complementors adapting to different architectures and governance regimes can increase coordination and development costs (Cennamo et al., 2018). Moreover, platform responses, such as tightening policies or privileging exclusivity, can erode limit the net returns to multihoming (Chung et al., 2024).

From the platform's perspective, the implications of complementor multihoming are ambiguous and context-dependent. Classic platform theory suggests that multihoming could lower platform differentiation and weaken user lock-in, which helps explain why platforms often discourage multihoming through exclusivity clauses or higher switching costs (Chen et al., 2022; Karhu et al., 2018). Consistent with a "differentiation loss" mechanism, evidence from video game consoles shows that declining porting costs encouraged developer multihoming, weakened platform differentiation and reduced platform dominance (Corts and Lederman, 2009; Landsman and Stremersch, 2011). At the same time, complementor multihoming can improve ecosystem efficiency and expand demand. In ride-hailing market, multihoming by drivers and riders reduces idleness and "dead mileage" by speeding up matching, lowering service times and increasing market size (Bryan and Gans, 2019). In the daily deals market, restricting merchant multihoming can backfire by limiting deal variety and inducing consumers to multihome or switch to rivals, ultimately undermining the focal platform's performance (Li and Zhu, 2021).

Our paper contributes to the literature in two respects. First, to the best of our knowledge, we provide the first empirical evidence on creator multihoming by assembling a unique dataset across two major social media platforms. This addresses a main data constraint in the multihoming literature: the lack of granular, comparable outcomes observed simultaneously across competing platforms. Second, we document a cross-platform attention spillover mechanism that can offset cross-platform substitution. This mechanism helps explain why multihoming can raise creator performance on the incumbent platform and clarifies when platforms may benefit from complementor multihoming in attention-based information goods markets.

**Creator economy.** Our paper also contributes to the growing literature on the creator economy. Prior work studies the effectiveness of influencer marketing (e.g., Leung et al., 2022; Yang et al., 2025) and how firms should choose creators to improve campaign performance (e.g., Doosti et al., 2025; Mallipeddi et al., 2022).

From the creator perspective, research examines strategic choices, such as topic specialization (Gong, 2021), collaboration and co-creation (Yang et al., 2023), and joining influencer agencies (Hao and Li, 2026), and how they shape engagement. From the platform perspective, studies show how platform design, including advertising policy (Ren, 2024), monetization programs (El-Komboz et al., 2023), recommendation (Qian and Jain, 2024) affects creator participation and content supply. Much of this literature abstracts from creators adopting multiple platforms. Our paper documents creator multihoming as a first-order strategic choice and has implications for many standard questions, such as which creators' brands should partner with and how platforms should design incentives and governance when creators multihome.

**Attention spillover in digital platforms.** Our proposed mechanism relates to the work on attention spillovers in digital platforms, where user attention can travel across boundaries. For example, Bairathi et al. (2024) demonstrates that music exposure on TikTok affects streaming on Spotify. Closer to our setting, Zhao et al. (2023) document that when streamers switch to a new content category within the same platform, the incumbent category can benefit due to attention spillovers. Our study differs by examining creators' entry into a new platform and focusing on cross-platform spillovers rather than within-platform spillovers. Krijestorac et al. (2020) also complement our paper by showing that introducing viral content on a new platform can increase consumption on the original platform, though their focus is on product release strategies rather than creator multihoming.

## 3 Conceptual Framework

We present a parsimonious model of user attention allocation to clarify the economic forces underlying creator multihoming. This is a partial-equilibrium demand-side model: holding platform attributes fixed, we study how a creator's multihoming choice affects attention on the incumbent through (i) cross-platform brand stock and (ii) cross-platform substitutability. The net effect on incumbent platform outcomes depends on the balance between brand expansion and attention substitution.

**Environment.** A representative consumer allocates attention across two content platforms: an incumbent platform $I$ (e.g., TikTok) and an entrant platform $E$ (e.g., RedNote). Consider a single focal creator. Let $a_I \geq 0$ and $a_E \geq 0$ denote the consumer's attention allocated to the creator on platforms $I$ and $E$, respectively (e.g., minutes watched or engagement intensity).

**Preferences.** Consumer utility from allocating attention $(a_I, a_E)$ to the creator is

$$U(a_I, a_E; B, \gamma) = (v_I + B)\, a_I + (v_E + B)\, a_E - \frac{1}{2}\left(a_I^2 + a_E^2 + 2\gamma a_I a_E\right), \tag{1}$$

where $v_I$ and $v_E$ capture platform-specific baseline matches (e.g., feed relevance or audience preferences). The term $B \geq 0$ is the creator's brand stock that increases the marginal utility of consuming the creator on any platform where the consumer encounters the creator. We adopt a quadratic cost of attention, a standard workhorse that imposes diminishing returns and yields smooth, closed-form demands with an explicit substitution parameter (Singh and Vives, 1984). In the cost term, the own cost terms $-\frac{1}{2}a_I^2$ and $-\frac{1}{2}a_E^2$ capture diminishing returns to attention. The cross-term $-\gamma a_I a_E$ captures substitution across platforms. The parameter $\gamma \in [0, 1)$ governs cross-platform substitutability in attention: larger $\gamma$ implies stronger rivalry in attention (time spent on one platform crowds out attention on the other more strongly). This specification can be viewed as an approximation to a richer time-allocation problem (Becker, 1965).

**Creator multihoming, brand formation, and substitution.** The creator chooses whether to multihome across platforms. Let $m \in \{0, 1\}$ indicate multihoming, where $m = 1$ means the creator is active on both platforms and $m = 0$ means the creator is active only on the incumbent platform.[3] Multihoming increases the creator's brand stock:

$$B(m) = B_0 + \Delta m, \tag{2}$$

where $B_0$ is baseline brand and $\Delta > 0$ is the incremental brand gain from being present on a second platform. At the same time, multihoming may make the two platforms closer substitutes for the creator's audience, for example, by reducing differentiation. We capture this by allowing the cross-platform substitutability parameter to depend on multihoming:

$$\gamma(m) = \gamma_0 + \psi m, \tag{3}$$

where $\gamma_0 \in [0, 1)$ is baseline substitutability absent multihoming and $\psi \geq 0$ measures the increase in substitution induced by multihoming. We assume $\gamma_0 + \psi < 1$ to ensure concavity.

[3] For simplicity, we abstract from content choice and treat multihoming as affecting the creator's brand stock and, potentially, the degree of cross-platform substitution faced by users.

**Attention demand.** Given $(B, \gamma)$, the consumer chooses $(a_I, a_E)$ to maximize $U(a_I, a_E; B, \gamma)$ subject to $a_I, a_E \geq 0$. The first-order conditions yield the (interior) attention demands:

$$a_I(B,\gamma) = \frac{(v_I + B) - \gamma(v_E + B)}{1-\gamma^2}, \qquad a_E(B,\gamma) = \frac{(v_E + B) - \gamma(v_I + B)}{1-\gamma^2} \tag{4}$$

$a_I(B,\gamma)$ is the consumer's attention on the incumbent platform (and analogously for $a_E(B,\gamma)$).

**Attention spillover to the incumbent.** Combining (2)–(4), the effect of creator multihoming on incumbent platform attention decomposes into two components:

$$\frac{da_I}{dm} = \underbrace{\frac{\partial a_I}{\partial B} \cdot \frac{\partial B}{\partial m}}_{\text{brand expansion}} + \underbrace{\frac{\partial a_I}{\partial \gamma} \cdot \frac{\partial \gamma}{\partial m}}_{\text{substitution intensification}} = \Delta \cdot \frac{\partial a_I(B,\gamma)}{\partial B} + \psi \cdot \frac{\partial a_I(B,\gamma)}{\partial \gamma}, \tag{5}$$

evaluated at $(B,\gamma) = (B(m), \gamma(m))$. Since

$$\frac{\partial a_I(B,\gamma)}{\partial B} = \frac{1}{1+\gamma} > 0,$$

the brand expansion term is always positive.

$$\frac{\partial a_I(B,\gamma)}{\partial \gamma} = \frac{2\gamma(v_I + B) - (1+\gamma^2)(v_E + B)}{(1-\gamma^2)^2}$$

The sign of $\frac{\partial a_I(B,\gamma)}{\partial \gamma}$ is determined by the relative strength of the incumbent and entrant platforms. Let $V_I = v_I + B$ and $V_E = v_E + B$ represent the brand-adjusted baseline match for the incumbent and entrant platforms, respectively. The derivative is negative if $\frac{V_I}{V_E} < \frac{1+\gamma^2}{2\gamma}$ (see details in Online Appendix A). In such cases, higher substitutability reallocates attention toward the entrant platform and reduces incumbent attention. Thus, multihoming does not always increase attention on the incumbent platform; while brand expansion provides positive spillovers, incumbent attention may fall if multihoming primarily intensifies cross-platform substitution.

**Interpretation and empirical implications.** Multihoming generates two countervailing forces for the incumbent platform. On the one hand, multihoming increases the creator's brand stock, raising users' willingness to consume the creator and tending to expand attention on the incumbent platform. On the other hand, multihoming may make platforms closer substitutes for the audience, intensifying attention substitution and attenuating, or potentially even reversing, incumbent gains.

# 4 Empirical Context and Data

In this section, we first introduce the research context. We then describe our data collection procedures. Next, we explain how we process the unstructured data and construct key measures. Finally, we describe how we identify cross-posting.

## 4.1 Two Leading Content Platforms in China: TikTok and RedNote

This study uses data from two major social media platforms in China: TikTok and RedNote. TikTok, launched in 2016, rapidly became China's dominant short-video platform. The platform has reached approximately 766 million daily active users by the end of 2024 (Curry, 2025). RedNote, launched in 2013, has similarly grown into one of China's most active lifestyle and social-commerce communities, attracting over 300 million daily active users (Lu and Miao, 2025). Both platforms are discovery-driven social media that rely on algorithmic recommendations (Casner and Teh, 2025).

Although TikTok and RedNote originated with distinct positioning, their differentiation has narrowed over time. TikTok initially focused on entertainment-driven short-form videos, while RedNote emphasized product reviews or lifestyle content in photo-based posts. However, both platforms have broadened their capabilities over time: in August 2020, RedNote introduced a short video channel feature,[4] and in October 2021, TikTok launched a photo-and-text posting option.[5] These updates have enabled both platforms to support both video and photo content, and this convergence in formats and functionality has made two platforms increasingly substitutable from both the creator and user perspectives. For creators, greater format compatibility reduces repurposing costs and facilitates multihoming. For users, the growing similarity in content offerings increases the likelihood of cross-platform usage or even migration. As a result, platform competition intensifies for user attention and creator participation.

TikTok and RedNote provide a well-suited empirical setting to study creator multihoming. They con-

[4]Source: https://xh.newrank.cn/help/z/6BF6E06744A05C2D7FE09C554708FE84 (In Chinese. Accessed on March 25th 2026)

[5]Source: https://www.21jingji.com/article/20240725/herald/2d2857d2b59e6ab6547897d3be3e6f1e.html (In Chinese. Accessed on March 25th 2026)

stitute two of China's most influential discovery-driven social media platforms and among the most active venues for influencer sponsorships. Their increasingly overlapping functionality and content formats makes them natural complements for creators to maintain parallel presences. While creators can also multihome on other platforms such as Kuaishou and Bilibili, [6] such behavior is less prevalent. Kuaishou caters to a distinct audience segment and creator ecosystem, and Bilibili is oriented toward longer form and more professionally produced video content. Accordingly, an important scope of our analysis is that we study creator multihoming between these two dominant platforms: TikTok and RedNote. Finally, we focus on the Chinese market because the market offers unusually rich and granular creator-level and content-level data, enabling precise measurement of multihoming behavior and performance outcomes.

## 4.2 Source of Data

The ideal dataset for answering our research questions would track the same creators and their content across competing platforms over time, together with detailed measures of engagement and platform-level activity. To approximate this ideal, we assemble a comprehensive dataset along three dimensions. First, we collect creator-level information. Second, we gather post-level data, capturing the full universe of posts. Third, we compile platform-level download data for mechanism discussions.

**Creator-level data.** We construct a sample of TikTok content creators and then identify which of these creators also adopt RedNote (i.e., multihome). For this step, we randomly sample 16,164 creators from TikTok's creator-advertiser transaction marketplace. Joining this marketplace requires accounts to meet minimum thresholds for follower counts and cumulative video likes (Gasner, 2025). These eligibility requirements screen out small or inactive users, ensuring that our sample consists of sizable and commercially active creators. In our data, sampled creators average approximately 2 million followers (see Table 1).

Next, we identify which creators multihome. We define multihoming as a content creator starts to post content on both TikTok and RedNote. Operationally, the onset of multihoming is identified as the month in which a creator publishes their first post on the new platform, regardless of whether the content shared across platforms is identical or distinct. So our definition captures cross-platform participation rather than the

[6] Kuaishou is a short video platform launched in 2011 that primarily serves users in lower-tier Chinese cities. It has approximately 400 million daily active users as of 2024 and is known for its emphasis on social connections and grassroots content. Bilibili is a video sharing platform launched in 2009 that originated as a community for anime and gaming content. It has since expanded into a broader range of long-form and mid-form video categories.

specific content-level replication decision. Conceptually, multihoming is related to, but broader than, cross-posting. Cross-posting refers to the simultaneous sharing of the same content across multiple platforms, whereas our definition of multihoming includes a broader range of behaviors, including posting entirely different or partially adapted content across platforms. Multihoming also differ from platform migration, which involves creators abandoning one platform in favor of another.

We use a two step matching algorithm to match TikTok creator accounts with their corresponding RedNote accounts. In the first stage, we perform automated matching based on creator nicknames and geographic locations based on IP address. Because these attributes are not unique and may generate multiple plausible matches, we conduct a second stage manual verification. We cross check profile images, biography descriptions, and primary content categories across platforms. Through this process, we identify 7,676 creators with accounts on both platforms, indicating that approximately 48% of creators in our sample engage in multihoming. Figure 1 provides an example of a creator who maintains profiles on both TikTok (left) and RedNote (right).

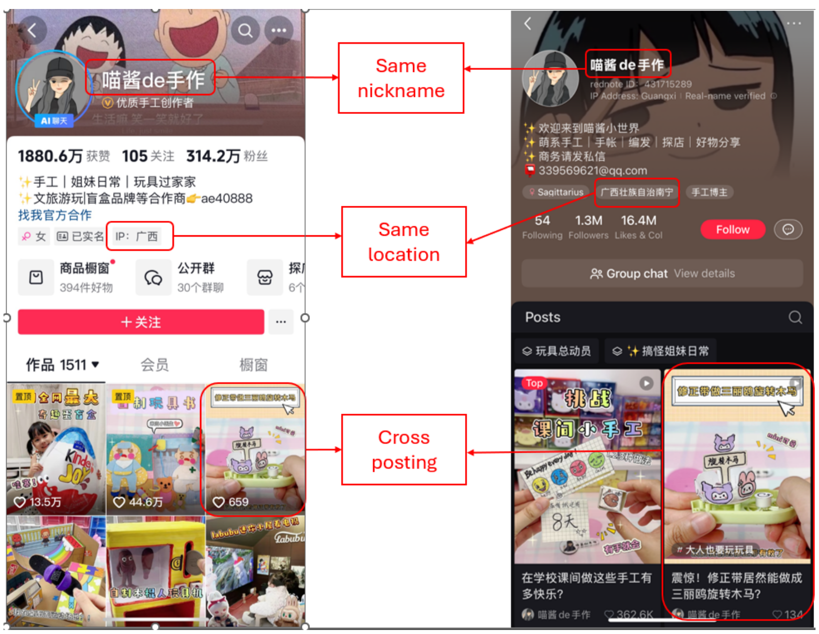



Figure 1: **The example of a multihoming content creator.**

Notes: The left screenshot shows the creator's TikTok account, while the right screenshot shows the corresponding RedNote account. The two profiles share the same nickname and geographic location, which allows us to identify this creator as a multihoming creator. In addition, the screenshots indicate that the creator has cross-posted at least one piece of content across the two platforms.

A potential concern is that creators may use different identifiers across platforms, which could lead us to miss some true cross-platform matches. In practice, most multihoming creators typically maintain consistent nicknames and content positioning across platforms to preserve creator brand recognition and facilitate audience expansion. In addition, creators may multihome across platforms outside our setting (e.g., Kuaishou or Bilibili). Our analysis defines multihoming with respect to TikTok and RedNote and does not attempt to measure creators' full multihoming portfolio. Both concerns, if present, would mainly lead us to understate how prevalent multihoming is in the creator population, and our main findings on the impact of second-platform adoption on the incumbent platform are unlikely to be affected.

For each sampled TikTok creator, we collect detailed creator-level information, including nickname, age, gender, and IP location. We also obtain their TikTok-defined content categories, daily follower counts since account inception (which allows us to track follower changes over a long horizon), and advertising quotation rates for brand sponsorships. For creators identified as multihoming, we also collect the same set of measures from RedNote.

**Post-level data.** We collect complete post-level data for each sampled creator on TikTok and RedNote. For tractability, we randomly select 1,583 multihoming content creators out of 7,676 content creators. We then retrieve metadata for each of their posts, including posting time, title, description, hashtags, and engagement measures. Later in Section 4.3, we use the textual data to classify content topics and to infer whether a post contains sponsorship.

A legitimate concern is that our data collection procedure might miss posts that content creators later delete. In practice, such deletions represent only a small fraction of total posts and almost always target low-performance content with limited engagement, outdated styles, or inconsistent quality (Branch, 2024). We do not expect such deletions to be systematically related to the timing of multihoming and to bias our estimates. Consistent with this interpretation, we find that creators' overall posting activity increases significantly after multihoming (Table 2), suggesting that creators are unlikely to disproportionately delete low-performing posts in the post-multihoming period.

Panels A and B of Table 1 report summary statistics at the creator and post levels for TikTok and RedNote, respectively. On average, creators post about eight times per month on each platform, indicating comparable levels of content production. Engagement per post average follower size is higher on TikTok, consistent with its position as the more established platform with a larger user base.

Table 1: **Summary Statistics.**

| | Mean | Std_Dev | 10th Percentile | 90th Percentile |
|---|---|---|---|---|
| **Panel A: creator level** | | | | |
| Monthly average number of posts on TikTok | 8.77 | 11.94 | 0 | 19 |
| Monthly average number of posts on RedNote | 8.11 | 9.94 | 0 | 19 |
| Average follower size on TikTok | 2,661,691 | 4,036,863 | 334,752 | 6,188,942 |
| Average follower size on RedNote | 414,420 | 701,563 | 18,641 | 1,031,078 |
| **Panel B: post level** | | | | |
| Average likes on TikTok | 125,854 | 398 | 3,242 | 310,111 |
| Average likes on RedNote | 12,648 | 72 | 134 | 26,506 |

Note: All statistics are computed using all periods in our sample and therefore reflect averages over time. Mean denotes the average, Std. Dev. the standard deviation.

**Platform-level data.** We collect monthly mobile app download data for TikTok and RedNote from Sensor Tower. Sensor Tower is the leading source of mobile app, digital advertising, retail media, and audience insights for the largest brands and app publishers across the globe.[7] These data provide a comprehensive view of platform-level inflows, serving as an aggregate indicator of growth and market penetration over time.

## 4.3 Data Processing

Many downstream tasks in our analysis are content-based. For example, determining whether a post is identical across platforms and measuring changes in topics and sponsorship. While deep learning methods could extract these attributes directly from video and image content, doing so at scale is computationally costly. We therefore use textual metadata (e.g., titles, descriptions, and hashtags) as a proxy for content. These fields typically summarize the core elements of a post and often contain explicit cues about topic and commercialization. For example, Ershov et al. (2025) infer sponsorship status directly from such metadata.

We first generate embeddings from the textual metadata using Sentence-BERT, a transformer-based model designed to produce semantically meaningful sentence representations (Reimers and Gurevych, 2019). These embeddings provide the basis for our content-similarity measures, which we use to identify cross-posting.

In addition, we identify the topics covered by each post. Although we observe platform-assigned content category labels, these labels are often too coarse and time-invariant. For example, a "beauty and cosmetics" content creator might also share travel or lifestyle-related content. To recover more granular, post-level topics, we apply topic modeling. Because our corpus consists primarily of short texts, we follow Yan et al. (2013) and employ the Biterm Topic Model (BTM), which is designed for short content. We set the number of topics,

[7] https://sensortower.com/

a key hyperparameter in BTM, to 80 to balance the trade-off between topic coherence and model perplexity. Each post is represented by an 80-dimensional topic vector.

Lastly, we identify whether a post is sponsored. Since neither TikTok nor RedNote requires content creators to explicitly disclose sponsorships, we rely on whether content creators mention brand names or promotional content in the text. To systematically identify such disclosures, we combine the textual information for each post and follow Ershov et al. (2025) to use OpenAI's GPT-4.1 large language model via API to evaluate whether the text contains brand mentions or promotional language (see Online Appendix Table D1 for examples). This process yields a binary variable for each post, indicating the presence of sponsorship or not.

### 4.4 Cross-Posting Identification

Although all content creators in our dataset operate accounts on both TikTok and RedNote, the content they post is not always identical across platforms. In other words, not all posts are cross-posted. To identify cross-posting, we compare content across the two platforms using the text-embedding representations described above. Specifically, for each creator, we perform pairwise comparisons between TikTok and RedNote posts that are published within the same calendar month. For each TikTok post $t$ and RedNote post $r$ created by creator $i$ within the same calendar month $m$, we compute the cosine similarity as:

$$\text{CosSim}_{i,m,t,r} = \frac{\left(\mathbf{e}^{T}_{i,m,t}\right)^{\top} \mathbf{e}^{R}_{i,m,r}}{\left\|\mathbf{e}^{T}_{i,m,t}\right\|_2 \left\|\mathbf{e}^{R}_{i,m,r}\right\|_2},$$

where $\mathbf{e}^{T}_{i,m,t}$ and $\mathbf{e}^{R}_{i,m,r}$ denote the $K$-dimensional embedding vectors for the TikTok post $t$ and RedNote post $r$, respectively. For each post, we then identify the best-matching post on the other platform, if the maximum cosine similarity exceeds a threshold. Because titles, descriptions, and hashtags can differ across platforms even for the same underlying video (see Online Appendix Table D2 for examples), we experiment with several similarity cutoffs (e.g., 0.75, 0.8, 0.85). For each threshold, we draw a subsample of matched pairs and manually verify whether they correspond to the same video across platforms. This validation exercise shows that 0.8 best separates genuinely cross-posted content from posts that are only topically related. Using this rule, we create a binary indicator equal to one if a post has a matched counterpart on the other platform (i.e., is cross-posted) and zero otherwise.

## 5 Facts About Creator Multihoming

### 5.1 How prevalent multihoming is?

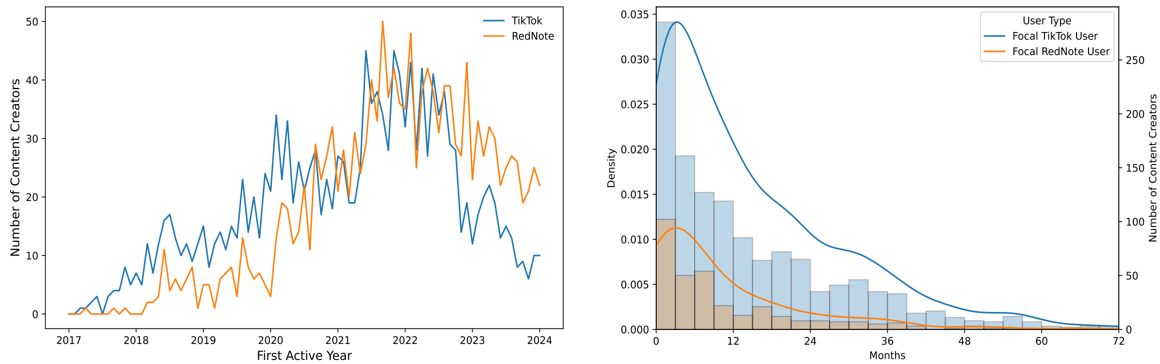
**Around half of creators multihome.** To establish the empirical relevance of our setting, we first document the prevalence of creator multihoming. As described earlier, we randomly select 16,164 content creators from Chinese TikTok and match them to RedNote accounts using usernames and location information. This procedure identifies 7,676 creators with accounts on both platforms, implying that about 48% of sampled TikTok creators engage in multihoming. As discussed before, this estimate should be interpreted as a lower bound on the true prevalence of multihoming. Nonetheless, the evidence suggests that multihoming is a common practice among content creators rather than a niche behavior.

### 5.2 When creators multihome?

**Creators multihome about one year after adopting the incumbent platform.** We examine the timing of creators' platform adoption and show that multihoming typically occurs within one year of initial platform entry. Figure 2a displays creators' joining dates on TikTok and RedNote. We next examine the interval between platform entry for 1,583 creators for whom we observe adoption on both platforms. Figure 2b shows that most creators begin multihoming within one year of joining their initial platform. This pattern holds for creators who joined TikTok first and those who joined RedNote first. This timing pattern suggests that multihoming reflects a delayed and selective expansion process. Prior research shows that agents often postpone expansion until they have accumulated sufficient experience (Jovanovic, 1982). In our context, creators may initially rely on the incumbent platform to learn platform-specific norms, refine their content strategy, and build an audience history before expanding to an additional platform.

**Creators tend to multihome when growth on the incumbent platform has plateaued.** To better understand the timing of multihoming, we analyze creators' follower dynamics prior to adoption and show that multihoming tends to occur when follower growth on the incumbent platform has plateaued.

Focusing on the 1,257 focal TikTok creators (who adopt TikTok first and subsequently join RedNote) in our main sample, we use daily follower counts to compute, for each creator, the change in TikTok followers during the 30 days (1 month) preceding the month in which they join RedNote. Let $d_{it}$ denote creator




(a) Joining Time (b) Time Difference

Figure 2: **Joining Time of content creators on TikTok and RedNote.**

Notes: Panel (a) plots the number of new creators joining each platform monthly from 2017 to 2024. Panel (b) plots the distribution of the time elapsed between a creator's registration on their first and second platform. For focal TikTok users, TikTok is the first platform joined; for focal RedNote users, RedNote is the first platform joined. The left y-axis reports density, and the right y-axis reports the number of creators.

$i$'s TikTok follower count on month $t$. We measure pre-multihoming follower growth as $\Delta\text{Followers}_{i,\text{pre}} = d_{i,t_i^*} - d_{i,t_i^*-1}$, where $t_i^*$ denotes the month in which creator $i$ first adopts the second platform. Online Appendix Figure E1a shows that these pre-multihoming follower changes are heavily concentrated around zero, indicating that many creators choose to multihome when their follower growth on TikTok has slowed or plateaued.

Online Appendix Figure E1b presents a complementary measure based on the monthly follower growth ratio, defined as $\text{GrowthRatio}_{it} = \frac{\Delta\text{Followers}_{i,\text{pre}}}{d_{i,t_i^*-1}}$. We observe a similar pattern, reinforcing the conclusion that multihoming tends to occur when follower momentum weakens. A plateau in follower growth implies diminishing marginal returns to remaining single-homed on the incumbent platform, as additional effort yields limited audience expansion. In this situation, expanding to a second platform becomes more attractive. This evidence complements our earlier finding on delayed multihoming, suggesting that creators tend to expand after growth opportunities on their initial platform plateau.

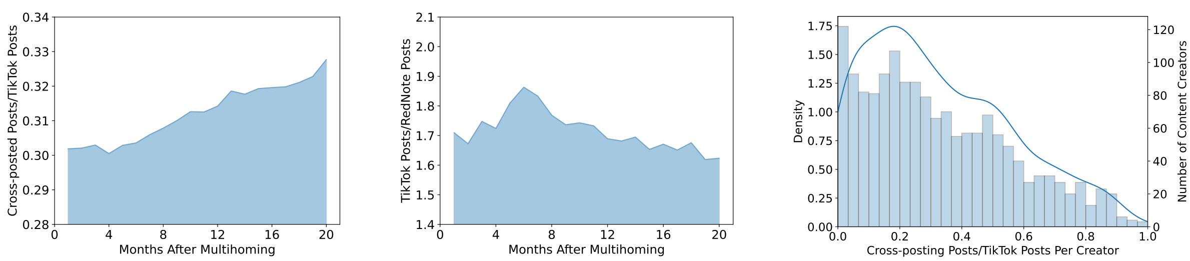
### 5.3 How creators multihome?

**Creators keep topic focus but cross-post about 30% of content.** We examine how creators adjust their content strategies when operating across TikTok and RedNote. We show that creators maintain similar content topic across platforms, selectively cross-posting content, indicating that cross-posting is a deliberate and selective strategy rather than mechanical duplication.

We first categorize content creators using platform-specific user tags and compare content types across

TikTok and RedNote. Because category labels are not defined identically, we manually calibrate tags across the two platforms (see Online Appendix Figure E2 for details). Overall, approximately 70% share at least one common tag across platforms, while the remaining creators exhibit minor differences, indicating substantial overlap in content focus.

We next use post-level data to examine how creators allocate content across platforms after multihoming. Analyzing all posts published on TikTok and RedNote between January 2017 and June 2024, we find that, on average, 31% of monthly TikTok posts are also shared on RedNote, while approximately 35% of RedNote posts are duplicated on TikTok, indicating a moderate reliance on content replication. We define the cross-posting ratio as the number of cross-posted posts divided by the total number of TikTok posts for each creator in a given month. Figure 3a plots the average cross-posting ratio by event time after multihoming. The figure shows that the cross-posting ratio increases gradually with time since multihoming, suggesting that creators rely more heavily on content replication as they gain experience operating on multiple platforms. We also plot the ratio of TikTok posts to RedNote posts over time to examine how creators allocate their overall effort across platforms. As shown in Figure 3b, this ratio exhibits a slight downward trend following multihoming, indicating a gradual shift in creators' activity toward RedNote. While a small subset of creators fully replicate content across platforms, most creators only partially cross-post and continue to produce largely distinct content for each platform. Figure 3c presents the density of creators' average cross-posting ratios, highlighting this variation.




(a) (b) (c)

Figure 3: **Monthly Changes of Cross-posting Ratio and TikTok Ratio.**

Notes: Panels (a) and (b) plot changes in the average cross-posting ratio and the ratio of TikTok posts to RedNote posts, respectively. In Panel (c), the left y-axis reports density and the right y-axis reports the number of creators.

A natural question is which posts creators choose to cross-post. If creators selectively replicate content across platforms, this decision is likely based on expected returns, such as platform fit, audience overlap, and engagement potential. To provide suggestive evidence, we compare cross-posted and non–cross-posted posts produced by the same creator within the same month, allowing for an apples-to-apples comparison (see Online Appendix Table D3). We find that cross-posted posts receive significantly more likes and are slightly more distinct from creators' recent topical focus. These patterns suggest that creators strategically select higher-performing or more broadly appealing content for cross-platform distribution.

Finally, we examine the timing of cross-posted content. Among the 148,130 cross-posted posts we identify, 65.1% are published on both platforms on the same day, and 86.7% appear within five days (see Online Appendix Figure E3). This tight timing pattern suggests that multihoming reflects coordinated, near-simultaneous content deployment rather than responses to realized performance on one platform. Taken together with our earlier results, the evidence suggests that creators strategically select content and rapidly deploy it across platforms to expand reach. These results together answer our RQ1.

# 6 Consequences of Multihoming

In this section, we examine the effects of multihoming using a DiD design to establish causal identification. We report the estimated impacts on audience growth, engagement, content production, monetization, and topic shift. Finally, we present a series of robustness checks.

## 6.1 Research Design

We exploit creators' staggered adoption of a new platform to estimate its impact on a multi-dimensional set of performance and engagement outcomes on the incumbent platform. Our primary estimand is the average treatment effect on the treated (ATT), the average change in outcomes for creators who choose to multihome, relative to how their outcomes would have evolved absent multihoming.

Multihoming is a strategic decision, and the DiD design does not require treatment assignment or treatment timing to be as good as random (de Chaisemartin and D'Haultfœuille, 2025). Instead, identification relies on the parallel trends assumption: absent multihoming, treated and control creators would have followed similar outcome trajectories on the incumbent platform. Under this assumption, the DiD estimator identifies the ATT.

It is useful to contrast our estimand with a "pure exposure" thought experiment: a strictly exogenous setting in which content is automatically cross-posted to the new platform by the platform itself, without any additional effort, strategic adjustment, or decision-making by the creator. Such an experiment would isolate the effect of platform exposure holding creator behavior fixed. While this mechanical exposure effect is conceptually interesting, it is not our object of interest. From a platform perspective, the economically relevant phenomenon is strategic multihoming, in which creators actively choose to expand across platforms and endogenously adjust their content strategies in response. Thus, our ATT captures the equilibrium, policy-relevant effect of creators' multihoming decisions—platform entry together with the induced behavioral responses—on outcomes on the incumbent platform.

We focus on creators whose initial presence is on TikTok and define treatment as the subsequent adoption of RedNote. We restrict attention to focal TikTok creators because TikTok is the more established platform, and the majority of creators initially operated exclusively on TikTok in our sample. The DiD design compares changes in outcomes for creators before and after they adopt RedNote to contemporaneous changes for creators who have not yet adopted RedNote. All outcomes are measured on TikTok, allowing us to isolate how multihoming affects creators' activity and performance on their incumbent platform.

We restrict the main analysis window to January 2020 through December 2022, a period during which adoption of RedNote became substantial (Ch, 2026). The treatment group consists of creators who adopted RedNote during this period. The control group comprises creators who remained TikTok-only throughout this window. All creators in our sample eventually multihome by June 2024; thus, the control group comprises later adopters whose treatment occurs strictly after the estimation period. This construction yields a stable and transparent control group and facilitates a clear interpretation of the DiD estimates.

A potential concern is that treated adopters may differ systematically from control adopters (i.e., later-treated creators in our setting) in ways that generate different underlying trends. To improve comparability between treated and control creators prior to treatment, we implement propensity score matching (PSM). Specifically, we estimate propensity scores using pre-treatment creator characteristics and perform one-to-one nearest neighbor matching without replacement. Each treated creator is matched to a control creator based on three variables: follower count, advertising price, and number of posts. As reported in Online Appendix Table D4, substantial imbalances between treated and control creators in the unmatched sample are largely eliminated after matching, indicating improved balance along key observables.

We aggregate all variables to the creator-month level for the main analysis, and estimate the following two-way fixed-effect (TWFE) model as our baseline DiD specification:

$$Y_{it} = \beta * 1(\text{ Early multihomer}_i) \times 1(\text{Post-multihoming period}_t) + \alpha_i + \delta_t + \epsilon_{it}, \quad (6)$$

where $Y_{it}$ denotes the outcomes of interest for content creators $i$ in month $t$, as defined in Section 6.3. We define $\text{Early multihomer}_i$ as an indicator equal to one for creators who ever adopt RedNote during January 2020 through December 2022 and zero for creators in the control group who adopt RedNote only at a later date. The indicator $\text{Post-multihoming period}_t$ equals one starting in the month when a treated creator first posts content on RedNote, and zero otherwise; for control creators, this indicator is always zero. The model includes creator fixed effects $\alpha_i$, which control for time-invariant individual characteristics, and month-fixed effects $\delta_t$, which account for common time shocks affecting all creators equally, such as platform-wide policy shifts. The parameter of interest $\beta$, captures the causal impact of multihoming on $Y_{it}$ under the standard DiD identification assumption. We estimate this model using ordinary least squares (OLS) and cluster standard errors at the creator level, the level at which treatment is assigned.

## 6.2 Identification Discussions

Our identification strategy relies on the parallel trends assumption, which is weaker than requiring treatment timing to be as good as random. But this assumption rules out selection into adoption timing based on creator unobserved heterogeneity that generate differential counterfactual trajectories. A concern would arise, however, if creators time their adoption in anticipation of changes in TikTok performance that would have occurred even in the absence of multihoming. For example, if creators begin multihoming precisely when expecting an improvement in engagement on TikTok. We address this concern in several ways. First, we implement an event-study specification and find no evidence of differential pre-trends in Section 6.5. This partially validates the parallel trends assumption.

Second, following Higgins (2024), we estimate a discrete-time hazard model predicting the timing of multihoming adoption. We find that outcome levels (e.g., followers, posts, likes) predict adoption timing, but their growth rates do not (see Online Appendix B for details). This distinction is key: in a DiD framework, selection on levels is absorbed by creator fixed effects, whereas selection on trends would threaten identification. The lack of association between adoption timing and growth rates mitigates concerns about differential pre-trends, and the negative sign on growth-rate coefficients implies our estimates are conservative lower bounds.

Another identification concern relates to potential violations of the Stable Unit Treatment Value Assumption (SUTVA). In our context, SUTVA would be violated if one creator's decision to multihome affects the TikTok outcomes of other creators. Such spillovers could arise, for example, if early adopters attract new users to TikTok or reallocate audience attention across creators. However, to the extent that these spillovers are positive, they would raise outcomes for control creators and thereby attenuate the estimated treatment effects toward zero. So our estimates are conservative lower-bound effects of multihoming.

Lastly, when treatment effects are heterogeneous and adoption is staggered, two-way fixed effects estimators can produce biased estimates due to negative weighting of treatment effects (Goodman-Bacon, 2021; Sun and Abraham, 2021). To address this concern, in Section 6.5, we complement the TWFE estimates with alternative DiD estimators that are robust to treatment effect heterogeneity across cohorts and over time.

### 6.3 Outcome variables

**Audience Size.** Social media platforms enable content creators to communicate directly with their audiences (Qiu and Subodha, 2017). Audience size serves as a primary indicator of a creator's reach and visibility on a given platform(Mallipeddi et al., 2022). We measure audience size using $\log(\text{Followers}_{it})$, defined as the logarithm of the number of TikTok followers for a creator $i$ in month $t$. This variable captures creators' overall reach and visibility on the platform. Audience size is a core outcome because multihoming can expand exposure through cross-platform discovery, translating attention gained on RedNote into follower growth on TikTok.

**Engagement.** We follow Bapna et al. (2019) and proxy content engagement using $\log(\text{Likes}_{it})$, defined as the logarithm of the average number of likes per post received by creator $i$ in month $t$. This measure reflects the perceived appeal of a creator's content and captures audience attention in a platform environment.

**Monetization Intensity.** As digital consumption continues to rise, social media video sponsorship, through which brands leverage content creators to engage audiences, has become an increasingly central component of modern marketing (Doosti et al., 2025). We measure monetization intensity using $\text{Number\_advertisement}_{it}$, defined as the number of sponsored posts published by creator $i$ in month $t$. Section 4.3 describes our procedure for identifying sponsored content using a large language model.

**Content Production.** We measure content production using $\text{Number\_Posts}_{it}$, defined as the number of posts published by creator $i$ in month $t$. This variable captures creators' production intensity and serves as a proxy for effort on the platform (Cao et al., 2024), allowing us to assess whether multihoming alters creators' content supply.

**Content Horizontal Quality.** We characterize creators' horizontal content strategies using two measures: Within-creator topic similarity$_{it}$ and Cross-platform content similarity$_{it}$. Within-creator topic similarity$_{it}$ captures within-creator topic consistency over time on the focal platform. To construct this measure, we first obtain post-level topic vectors using the BTM described in Section 4.3 and aggregate them to the creator-month level. We then compute the cosine similarity between creator $i$'s topic vector in their first observed month and their topic vector in month $t$. This approach follows prior work that uses topic-vector representations and cosine similarity to capture content focus and strategic consistency in digital platform settings (Zhao et al., 2023; Qian and Jain, 2024). Higher values indicate a more focused content strategy, whereas lower values reflect horizontal expansion into new topic areas.

Cross-platform content similarity$_{it}$ measures the similarity between the content produced by focal TikTok creator $i$ in month $t$ and the representative content of creators on RedNote. This measure captures whether, following multihoming, creators adjust their content on the incumbent platform to align more closely with the dominant content style of the newly adopted platform. For TikTok, we average embeddings at the creator–month level. For RedNote, we focus on the 326 focal RedNote creators and compute monthly average embeddings across all their posts, which serve as a representative benchmark for RedNote content in that month. We then calculate the cosine similarity between creator $i$'s TikTok embedding and the representative RedNote embedding in month $t$. Higher values indicate greater cross-platform content similarity.

These two measures capture complementary dimensions of creators' horizontal content strategies, allowing us to assess whether multihoming induces topic diversification within platforms and whether creators adjust their content to better align with audiences across platforms after multihoming.

**Summary.** These outcome variables capture distinct dimensions of a creator's activity and performance that differ in the degree of direct control. Audience size, engagement, and monetization intensity outcomes that creators seek to influence but cannot directly choose. In contrast, content production and content horizontal quality are endogenous strategic variables directly controlled by the creators themselves. Distinguishing between outcomes that are not directly chosen and actions under creators' control is essential for interpreting our results, as it allows us to separate the effects of multihoming on realized performance from creators' behavioral responses to platform expansion.

## 6.4 Main Results

**Effects on Audience Size.** Column 1 in Table 2 presents the estimated effect of multihoming on follower count. We find that adopting RedNote is associated with a 23.5% increase in follower count on the focal platform. In levels, the average number of followers before multihoming is approximately 1.64 million, which rises to about 1.74 million within three months after multihoming—an average gain of 100,000 followers. The result indicates that multihoming substantially expands creators' audience reach on the incumbent platform.

Table 2: **Effects of Multihoming.**

| VARIABLES | (1) log (Followers) | (2) log (Likes) | (3) Number of advertisement | (4) Number of posts | (5) Within-creator topic similarity | (6) Cross-platform content similarity |
|---|---|---|---|---|---|---|
| *Multihoming* | 0.235*** | 0.254** | 0.285*** | 2.244*** | -0.030** | 0.015*** |
| | (0.070) | (0.102) | (0.099) | (0.506) | (0.015) | (0.005) |
| *Constant* | 13.18*** | 10.42*** | 0.484*** | 6.388*** | 0.502*** | 0.811*** |
| | (0.028) | (0.040) | (0.034) | (0.173) | (0.006) | (0.002) |
| Individual fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,019 | 7,626 | 9,760 | 9,760 | 7,562 | 7,594 |
| R-squared | 0.922 | 0.674 | 0.550 | 0.596 | 0.733 | 0.535 |

Note: Robust standard errors are clustered at the creator level in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Effects on Engagement.** Columns (2) report the effect of multihoming on engagement. We find a positive and statistically significant effect: average likes per post increase by 25.4% following RedNote adoption. The magnitude is economically meaningful and suggests improved engagement after adopting the new RedNote. This increase may arise from audience expansion, improvements in content quality, or both. We investigate these mechanisms in Section 7.

**Effects on Monetization Intensity.** Column (3) shows that creators post a significantly greater number of sponsored posts after multihoming, suggesting an increase in monetization activity on the platform. We further examine the ratio of sponsored posts to total posts and find no statistically significant change following multihoming. This indicates that creators do not increase the share of advertising content; instead, the increase in sponsored posts is driven by higher overall content production.

**Effects on Content Production.** As shown in Column (4), we observe a statistically significant increase of 2.244 posts per month following the adoption of RedNote. This result indicates that multihoming is associated not only with audience expansion and higher engagement, but also with increased content supply on the incumbent platform.

**Effects on Content Horizontal Quality.** Column (5) indicates a negative correlation between multihoming and within-creator topic similarity, suggesting that creators broaden the range of topics they cover after adopting RedNote. One plausible explanation is that exposure to a new platform introduces creators to different audience preferences, content norms, and recommendation incentives, encouraging experimentation beyond their established topical niche on TikTok.

Column (6) reports the results for cross-platform content similarity and indicates a significant increase following multihoming. This pattern suggests that while creators diversify their topical portfolio, they also adjust their content on TikTok to better align with what they post on RedNote. Rather than fully duplicating content, creators appear to engage in strategic coordination by making incremental content adjustments that improve cross-platform compatibility. Such coordination likely reflects creators' attempts to manage cognitive and production costs while maintaining a coherent cross-platform presence.

These behavioral responses have important implications for platform competition. Topic diversification may intensify within-platform competition by increasing overlap in content categories and reducing differentiation among creators, potentially raising audience substitution across creators. At the same time, increased cross-platform alignment can weaken content exclusivity and blur platform boundaries, reducing platforms' ability to differentiate themselves through unique creator ecosystems. From a competitive perspective, multihoming thus shifts rivalry from platform-level content differentiation toward competition over discovery algorithms, monetization tools, and creator support, reshaping how platforms compete for both creators and user attention.

**Summary.** Overall, the results indicate that multihoming behavior is associated with systematic shifts in creators' performance and strategic behavior. The adoption of a second platform is linked to a substantial increase in audience size. Furthermore, multihoming is associated with higher engagement at the post level and an expanded volume of sponsored posts. Alongside these shifts in audience and engagement, creators appear to adjust their content strategies by increasing production supply and broadening topical coverage. The simultaneous increase in cross-platform content alignment suggests a pattern of strategic coordination rather than indiscriminate duplication. Taken together, these results answer our RQ2, confirming that creator multihoming generates broad and systematic benefits on the incumbent platform.

## 6.5 Robustness Checks

We perform a series of robustness checks to validate our main findings. Our strategies for addressing potential endogeneity concerns and ensuring the stability of our estimates are summarized in Table 3.

Table 3: **Robustness Checks Summary.**

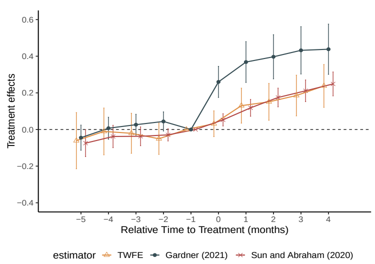
| **Potential issues** | **Adopted methods** | **Findings** |
|---|---|---|
| Pre-treatment trends | Relative-time (event-study) model | Pre-treatment estimates are statistically indistinguishable from zero, supporting the parallel trends assumption. |
| Heterogeneous treatment effects and staggered adoption | Robust staggered DiD estimators (Gardner et al., 2024; Sun and Abraham, 2021) | Post-treatment estimates remain statistically significant and corroborate the main findings. |
| Inaccurate multihoming definition | A stricter definition based on first instance of cross-platform content duplication | Empirical results remain consistent under this more conservative definition of multihoming. |
| Platform-specific context bias | Symmetric analysis using RedNote as the focal platform | Results mirror the TikTok analysis, showing increased activity and engagement on the focal platform. |

### 6.5.1 Relative Time Model and Staggered DiD

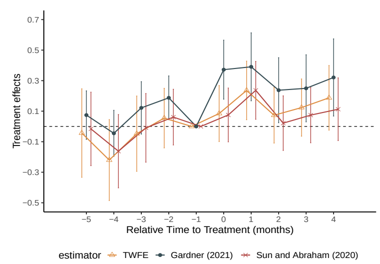
We first present a conventional TWFE event-study specification to visualize dynamic treatment effects and assess pre-trends. Specifically, we extend Equation (6) by replacing the treatment interaction term with a set of event-time indicators that capture leads and lags relative to a creator's multihoming adoption date. We normalize the coefficient for the period immediately prior to adoption to zero so that each event-time coefficient measures the change in outcomes relative to this baseline. Additional implementation details are provided in the Online Appendix C, and the orange line in Figure 4 plots the TWFE event-study estimates with 95% confidence intervals.

Goodman-Bacon (2021) shows that TWFE DiD can be biased under staggered treatment adoption when treatment effects are heterogeneous over cohorts or over time, because the TWFE estimator implicitly reweights comparisons across early- and late-treated groups. To address this concern, we re-estimate dynamic effects using recent staggered DiD estimators that are robust to heterogeneous treatment effects (Gardner et al., 2024; Sun and Abraham, 2021). Specifically, Sun and Abraham (2021) recover cohort-specific event-time effects by interacting event-time indicators with treatment-cohort indicators, while Gardner et al. (2024) implement a two-stage procedure that first residualizes outcomes using untreated observations and then estimates treatment effects from the residual variation. We apply both estimators and report the estimates in Figure 4 as well.

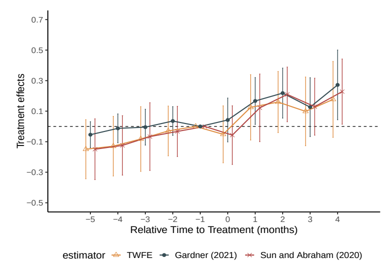
Figure 4 yields two key takeaways. First, the pre-treatment coefficients are small and statistically indistinguishable from zero, providing evidence against differential pre-trends. Second, the post-treatment estimates are statistically significant and corroborate our main findings: after creators start multihoming, performance improves in terms of follower growth, engagement, and sponsorship activity, while content topics become more diversified (lower topic similarity) and cross-platform content overlap increases (higher cross-platform similarity).



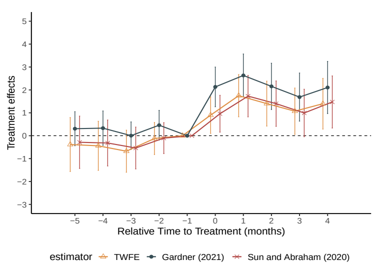

(a) log(Followers)



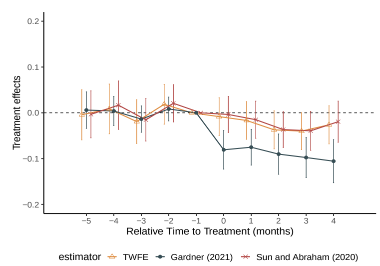

(b) log(Likes)



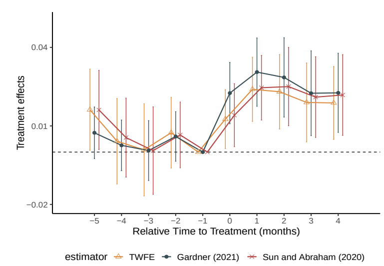

(c) Number of advertisement




(d) Number of posts




(e) Within-creator topic similarity




(f) Cross-platform content similarity

Figure 4: **Dynamic DiD Results.**

Notes: This figure illustrates the dynamic treatment effects of creator multihoming across six key outcome variables using an event-study framework. The horizontal axis represents the number of months relative to the initial adoption of the RedNote, where the month immediately preceding adoption ($k = -1$) is omitted and utilized as the reference period. We plot estimates from three distinct econometric specifications: the yellow line represents the standard TWFE model, the black line represents the Gardner et al. (2024) two-stage procedure, and the red line represents the Sun and Abraham (2021) cohort-interaction estimator.

### 6.5.2 Different Multihoming Definition

We also consider an alternative definition of the multihoming. In our primary analysis, treatment begins in the month a creator first becomes active on the second platform, regardless of post content. However, one might argue that multihoming is only fully realized when a creator begins to leverage both platforms for similar content (i.e., cross-posted posts). We thus redefine the treatment onset as the month in which a creator first duplicates content across TikTok and RedNote. As shown in Online Appendix D5, our empirical results remain consistent under this more conservative definition, suggesting that the observed effects are not driven solely by the initial platform entry but by the broader strategy of dual-platform engagement.

### 6.5.3 Symmetric Analysis on RedNote

We conduct a symmetric analysis using RedNote as the focal platform. The sample consists of creators who joined RedNote first and subsequently joined TikTok. We examine the impact of joining TikTok on creators' performance on RedNote along three dimensions: the number of posts, engagement measured by RedNote likes, and within-creator topic similarity. As reported in Online Appendix Table D6, the results mirror those obtained in the TikTok analysis. Specifically, creators experience an increase in posting activity and engagement, accompanied by a decline in topic similarity.

## 6.6 Heterogeneous Effect

Heterogeneity in multihoming returns carries meaningful implications for both creators calibrating their expansion decisions and platforms seeking to design governance structures that serve a diverse creator base. Identifying the conditions under which multihoming yields the greatest benefits enables more targeted strategies for both parties in the ecosystem. Hence, we employ a triple interaction model to examine how specific creator-level characteristics moderate the impact of multihoming on platform outcomes, which answers our RQ3. This approach allows us to identify whether the treatment effect varies systematically across different types of creators.

**Follower Size.** We first examine how pre-multihoming popularity on TikTok, measured by initial follower count, moderates the effects of platform expansion. The columns (1) and (2) in Table 4 reveal a negative and statistically significant interaction between multihoming and initial follower size for both growth and engagement. This pattern implies that, although multihoming increases performance on average, the gains are substantially larger for creators with smaller initial audiences. This pattern suggests that multihoming serves as a leveling mechanism in the creator economy. Highly popular creators likely face audience saturation and diminishing marginal returns to algorithmic exposure, whereas smaller creators benefit more from relaxing their visibility constraints through a second platform.

Table 4: **Moderating Effects: Followers on TikTok and Category Competition on RedNote.**

| **VARIABLES** | (1) log (Followers) | (2) log (Likes) | (3) Number of advertisement | (4) log (Likes) | (5) Within-creator topic similarity |
|---|---|---|---|---|---|
| Multihoming | 2.825*** | 4.714*** | -2.385 | 0.457*** | -0.001 |
| | (0.531) | (1.137) | (1.738) | (0.145) | (0.018) |
| *Multihoming*Follower size* | -0.193*** | -0.351*** | 0.204 | | |
| | (0.0396) | (0.0817) | (0.139) | | |
| *Multihoming*High_competition* | | | | -0.476*** | -0.068*** |
| | | | | (0.201) | (0.026) |
| Constant | 13.32*** | 10.71*** | 0.479*** | 10.43*** | 0.504*** |
| | (0.019) | (0.029) | (0.033) | (0.039) | (0.006) |
| Individual fixed effect | Yes | Yes | Yes | Yes | Yes |
| Month fixed effect | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,947 | 5,814 | 7,347 | 7,626 | 7,562 |
| R-squared | 0.920 | 0.648 | 0.579 | 0.674 | 0.734 |

Note: Robust standard errors are clustered at the creator level in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Category Competition on RedNote.** We next examine how competitive intensity in content categories on RedNote moderates the effects of multihoming. Based on creator density, we identify the most competitive categories as life, humor, fashion, travel, and food. The columns (4) and (5) in Table 4 show that the interaction between multihoming and high competition is negative and statistically significant for both engagement and within-creator topic similarity.

These findings suggest that intense competition on the new platform limits the marginal visibility gains of multihoming, making it harder for creators to stand out. Furthermore, heightened competition induces creators to adjust their content strategies more aggressively, leading them to experiment with new topics or shift away from established niches to differentiate themselves. Therefore, while multihoming relaxes platform-level constraints, category-level competition remains a critical factor in shaping both performance outcomes and strategic content adjustments.

# 7 Mechanisms

Our central finding is that creator multihoming increases audience size and engagement on the incumbent platform. This result raises our RQ4: through which mechanisms do these effects operate? Guided by our conceptual framework, the net impact of multihoming reflects a balance between brand expansion and attention substitution. Because we observe a net increase in audience size and engagement, our results suggest that the brand expansion channel dominates any offsetting effects from attention substitution. In the following section we provide empirical evidence supporting the audience expansion mechanism.

## 7.1 Audience Expansion

In our study, audience expansion across platforms operates through what we call cross-platform attention spillovers. By operating on an additional platform, creators are exposed to a broader pool of users, some of whom subsequently follow and engage with the creator on the incumbent platform. Therefore, multihoming allows the new platform to serve as a discovery channel that reaches previously untapped audiences and expands creators' overall audience reach, which in turn increases engagement on existing platforms.

These attention spillovers arise through several ways. First, users on RedNote may discover creators whose content they value and subsequently choose to follow them on TikTok. Second, creators often explicitly list their TikTok accounts on their RedNote profile pages, which lowers cross-platform search costs and increases the salience of following the creator on the incumbent platform. Online Appendix Figure E4 illustrates how a creator self-promotes her TikTok account on her TikTok profile page. Finally, platform algorithms may reinforce exposure to the same creators. Although recommendation systems are platform-specific, they often rely on similar user signals (i.e., content characteristics), which can lead different platforms to surface the same creators to overlapping user populations. Such repeated exposure increases familiarity and salience, enhancing creator recognition and ultimately raising the likelihood of following on the incumbent platform.

### 7.1.1 Evidence for Audience Expansion

We present two pieces of evidence consistent with the audience expansion mechanism. First, we show that the engagement gains from multihoming are largely mediated by increases in audience size. To assess the mediating role of audience expansion, we augment Equation 6 by controlling for follower size. As shown in

Table 5: **Add Follower Size as Control Variable.**

| **VARIABLES** | (1) log(Likes) | (2) log(Likes) |
|---|---|---|
| *Multihoming* | 0.254*** | -0.107 |
| | (0.102) | (0.0757) |
| Log(Followers) | | 0.319*** |
| | | (0.0532) |
| Constant | 10.42*** | 6.607*** |
| | (0.040) | (0.710) |
| Individual fixed effect | Yes | Yes |
| Month fixed effect | Yes | Yes |
| Observations | 7,626 | 5,966 |
| R-squared | 0.674 | 0.728 |

Note: Robust standard errors are clustered at the creator level in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5, once follower size is controlled for, the estimated effect of multihoming on engagement becomes statistically insignificant. This attenuation suggests that the positive engagement effect of multihoming operates primarily through audience expansion.

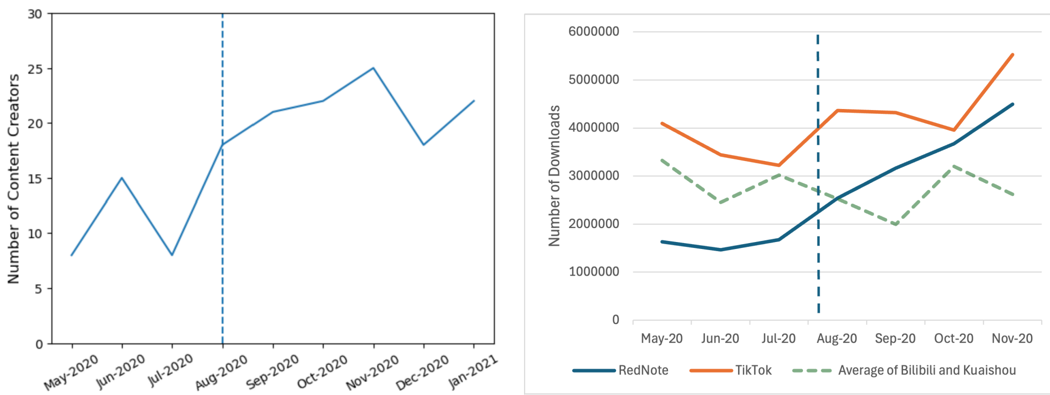
Next, we examine whether the strength of attention spillovers depends on the intensity of multihoming. If spillovers operate through cross-platform discovery, creators who multihome more actively (i.e., cross-post a larger share of content) should generate larger attention inflows and benefit more from these spillovers. We exploit variation in the share of cross-posted content as a moderating factor. Specifically, we construct a cross-posting ratio, defined as the monthly percentage of a creator's posts that are cross-posted. As reported in Online Appendix Table D8, creators with higher cross-posting ratios experience significantly larger gains in both follower counts and engagement. This pattern is consistent with cross-platform attention spillovers: more intensive multihoming increases the frequency with which users encounter the same content across platforms, reinforcing attention and recognition.

### 7.1.2 Sources of New Followers

Building on our finding that multihoming creators attract new followers, we next examine the sources of these follower gains and their broader implications for the incumbent platform. These gains operate through two margins. The intensive margin captures existing multihoming users who already use TikTok but had not followed the focal creator and subsequently begin following them. The extensive margin reflects new TikTok adopters who join the platform for the first time after encountering the creator on the entrant platform.

**Existing multihomed Users.** For users who already use both TikTok and RedNote, cross-platform attention spillovers operate by inducing them to follow and engage with multihomed creators on TikTok. This process can take two forms. In one case, users expand their attention or total media consumption time on TikTok (within-platform attention expansion). In the other, users reallocate a fixed attention budget toward multihomed creators at the expense of other creators (within-platform attention cannibalization). This distinction is important from the platform's perspective, as attention reallocation across creators may not translate into meaningful increases in overall platform performance.

We assess the relevance of cannibalization by examining whether engagement for non-multihomed creators declines following an exogenous surge in creator multihoming. Specifically, we exploit the RedNote policy change that relaxed content restrictions, lowered the cost of multihoming, and triggered a large number of TikTok creators to adopt RedNote (see Figure 5a) (Tian et al., 2022). Consistent with our earlier results, multihomed creators experience substantial engagement gains after this shock. However, we find no significant decline in engagement for non-multihomed creators (Online Appendix Table D7). This suggests limited evidence of attention substitution/reallocation across creators.




(a) Number of Creators Joining RedNote from TikTok

(b) Number of Downloads

Figure 5: **RedNote Policy Impacts.**

Notes: The blue dashed line in both Figure 5a and 5b indicates the implementation of the RedNote policy change, which relaxed content restrictions and lowered multihoming costs. The green dashed line in Figure 5b represents the baseline control, calculated as the average download volume of Bilibili and Kuaishou.

**New Users.** We provide suggestive evidence consistent with the possibility that multihoming may draw new users into TikTok, generating a potential market expansion effect for the incumbent platform. To examine this possibility, we analyze iOS app download volumes for four major social media platforms in China—TikTok, RedNote, Bilibili, and Kuaishou—around RedNote's policy change that lowered the cost of creator multihoming. Among these platforms, TikTok is most similar to RedNote in terms of user demographics and functionality, whereas Bilibili and Kuaishou serve more distinct user segments.

Using the average download volumes of Bilibili and Kuaishou as a baseline control, we observe a clear increase in RedNote downloads following the policy change, consistent with reduced multihoming frictions inducing more users and creators, particularly from TikTok, to adopt RedNote. Importantly, we also observe a contemporaneous increase in TikTok downloads (see Figure 5b). While this pattern is not sufficient to establish causality, it is consistent with cross-platform discovery: as more TikTok creators adopt RedNote, some RedNote users may be exposed to these creators and subsequently choose to download TikTok.

Altogether, cross-platform attention spillovers might benefit the incumbent platform through two complementary channels. First, among existing users, multihoming generates within-platform attention expansion rather than merely reallocates attention across creators. Second, multihoming may attract new users to the platform. Although the relative importance of these channels may vary, both operate through increases in audience stock and attention inflows, suggesting that creator multihoming can potentially enhance incumbent-platform outcomes.

### 7.2 Alternative Explanations

**Quality improvement through learning.** Multihoming may enhance creator performance through learning and subsequent improvements in content quality, particularly when creators operate across platforms with similar complements and strong cross-platform interdependencies (Cennamo et al., 2018; Polidoro Jr and Yang, 2024; Venkataraman et al., 2018). If such learning-driven quality improvements were a first-order mechanism, multihoming should increase engagement even after controlling for follower size in Table 5. However, we find little evidence consistent with this channel. Moreover, our event study results (see Figure 4) show that engagement effects emerge immediately after multihoming adoption, whereas learning-based quality improvements would be expected to occur more gradually over time. So learning-induced quality improvements play, at most, a secondary role in our setting.

# 8 Conclusion

This paper studies the strategic drivers and performance implications of creator multihoming. While traditional platform literature often emphasizes the risks of eroded exclusivity and the threat of user substitution (Corts and Lederman, 2009; Karhu et al., 2018), we identify a countervailing benefit of complementor multihoming arising from cross-platform attention spillover. Using a unique seven-year panel of thousands of creators on TikTok and RedNote, we document several key findings. First, multihoming is prevalent and strategic: approximately 48% of sampled creators are active on both platforms, and adoption typically follows a period of stagnating follower growth on the incumbent platform. Second, using a DiD design exploiting staggered platform adoption, we find that multihoming leads to an increase in followers and engagement on the incumbent platform, along with higher content production and increased monetization. Our empirical results demonstrate that expansion to a second platform catalyzes significant short-run gains on the incumbent platform. Third, mechanism analyses reveal that these gains are primarily driven by audience expansion through cross-platform attention spillovers.

## 8.1 Managerial Implications

For creators, multihoming is a deliberate strategy to restart growth after reaching an audience plateau on a single platform. Our results suggest that creators should consider expanding to a second platform not as a signal of abandonment, but as a strategic investment in audience development. The evidence indicates that creators can increase their visibility, reach new audiences, and scale monetization opportunities without sacrificing performance on the incumbent platform. Unlike traditional "gig economy" multihoming (e.g., Uber and Lyft), digital multihoming has very low marginal costs because content is non-rivalrous and can be shared across platforms at near-zero cost once produced. However, the decision to expand is not frictionless; it entails some implicit costs, including account management and the need to adapt to different platform architectures and governance regimes. Effective multihoming therefore requires creators to balance the growth benefits of expanding to additional platforms with the operational and coordination costs involved.

Our paper sheds light on platform competition in environments with low multihoming costs. When a competing platform reduces the cost of multihoming in an attempt to attract creators from an incumbent platform, those creators do not simply divert attention away. Instead, multihoming creators also bring attention back to the incumbent platform through cross-platform spillovers. As a result, competition for creators need not be zero-sum in terms of attention on the focal platform. Rather than investing in exclusivity agreements or raising switching costs, platforms may benefit more from facilitating multihoming, for example, by providing portability tools, cross-posting features, and format convergence that lower the cost of multi-platform presence.

### 8.2 Limitations and Future Research Directions

Despite these insights, our study has several limitations. First, we cannot directly observe the full follower histories of individual users for each creator, which prevents us from cleanly distinguishing between new TikTok adopters and existing multihoming users. As a result, we are unable to separately quantify the extensive and intensive margins of market expansion at the user level. Second, our analysis captures multihoming as an endogenous strategic choice by creators rather than as a strictly exogenous experimental shock. Finally, our analysis focuses on short-run outcomes following multihoming adoption and does not speak to longer-run equilibrium effects.

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# Online Appendix

## A Model Details

In our conceptual framework, the sign of the substitution intensification term $\psi \cdot \frac{\partial a_I(B,\gamma)}{\partial \gamma}$ determines whether increased platform competition helps or hurts the incumbent. This sign is governed by the derivative of incumbent attention with respect to substitutability:

$$\frac{\partial a_I(B,\gamma)}{\partial \gamma} = \frac{2\gamma(v_I + B) - (1+\gamma^2)(v_E + B)}{(1-\gamma^2)^2} \tag{7}$$

The sign of this derivative is determined by the relationship between the brand-adjusted platform strengths, $V_I = v_I + B$ and $V_E = v_E + B$, and the threshold function:

$$f(\gamma) = \frac{1+\gamma^2}{2\gamma} \tag{8}$$

The function $f(\gamma)$ is convex, reaching its minimum value of 1 at $\gamma = 1$ and approaching infinity as $\gamma \to 0$. Because $f(\gamma) \geq 1$ for all values of $\gamma \in (0,1)$, the "bar" for the incumbent to benefit from substitution is mathematically high.

**Case 1: Entrant Dominance ($V_E \geq V_I$)** When the entrant platform is as strong as or stronger than the incumbent ($V_E \geq V_I$), the ratio $V_I/V_E$ is naturally less than or equal to 1. Since $f(\gamma) \geq 1$, the condition for a negative derivative $\frac{V_I}{V_E} < f(\gamma)$ is *always satisfied*. In this scenario, any increase in competition through multi-homing unambiguously reallocates user attention toward the entrant, lowering engagement on the incumbent platform.

**Case 2: Negative Effects When the Incumbent is Stronger ($V_I > V_E$)** A negative substitution effect can occur even when the creator is "stronger" on the incumbent platform ($V_I > V_E$), particularly at lower levels of substitutability ($\gamma$). In our context, this explains why even dominant TikTok creators may face reduced engagement when entering RedNote:

- **Exploration of New Niches:** Even if $V_I > V_E$, a user may find a creator's RedNote content more relevant for specific tasks like product reviews. If the platforms are highly differentiated (low $\gamma$), the user reallocates time to this “specialized” experience, hurting TikTok’s engagement.

- **The “Dilution” of Attention:** Expanding to a differentiated platform splits the consumer’s total attention across two distinct experiences. Unless the incumbent’s advantage is massive enough to overcome the “pull” of the new platform’s unique environment, the reallocation remains negative for the incumbent.

# B Discrete-Time Hazard Model Results

We formally test whether the timing of multihoming is correlated with the levels or trends of observable characteristics. Following Higgins (2024), we estimate a discrete time hazard model, where the dependent variable indicates whether a creator adopts multihoming in a given month. The model includes both time-invariant covariates, such as gender and advertising prices, and time-varying covariates, including follower size, number of posts, number of likes, and their corresponding growth rates. As reported in Table B1, the levels of followers, posts, and likes are significantly associated with the timing of multihoming, whereas their growth rates are not statistically significant. This distinction is important for identification. In a DiD framework, selection on outcome levels is permissible and absorbed by creator fixed effects. In contrast, selection on short-run trends would threaten the parallel trends assumption. The absence of a systematic relationship between adoption timing and growth rates suggests that differential pre-trends are unlikely to drive our results. Moreover, the estimated coefficients on growth rates are negative, implying that even if some residual trend-based selection remains, our estimates would constitute conservative lower bounds.

Table B1: **Discrete-Time Hazard Model Results.**

| Variable | (1)<br>Mean | (2)<br>SD | (3)<br>Discrete time hazard |
|---|---|---|---|
| Gender | 1.417 | 0.493 | 0.034 |
| | | | (0.026) |
| log(Advertising price) | 10.383 | 0.913 | 0.026 |
| | | | (0.018) |
| log(Followers) | 13.788 | 1.238 | −0.027** |
| | | | (0.013) |
| Growth rate of followers | 0.132 | 0.168 | −0.075 |
| | | | (0.068) |
| log(Number of posts) | 2.213 | 0.674 | 0.044*** |
| | | | (0.017) |
| Growth rate of post counts | −0.170 | 0.675 | −0.005 |
| | | | (0.010) |
| log(Likes) | 10.943 | 1.435 | 0.042*** |
| | | | (0.010) |
| Growth rate of likes | −0.346 | 1.736 | −0.000 |
| | | | (0.003) |

Note: Columns 1 and 2 show the mean and standard deviation of characteristics. Column 3 tests whether these characteristics predict the timing of multihoming in a single regression, using a linear probability discrete time hazard with time-fixed effects. The dependent variable in the model is a dummy variable indicating if creator i has been treated at time t. Standard errors are clustered at the creator level.

# C Relative Time Model

Let $\text{Month}_{k,it}$ denote a dummy equal to one if month $t$ is the $k^{\text{th}}$ month relative to creator $i$'s multihoming month, where $k \in \{-5, \cdots, -2, 0, \cdots, 4\}$; we further include $\text{Month}_{<-5,it}$ and $\text{Month}_{>4,it}$ to bin months more than five periods before or more than four periods after the multihoming event. The model specification is presented in following:

$$Y_{it} = \beta_{<-5}\,\text{Month}_{<-5,it} + \sum_{k=-4}^{4} \beta_k\,\text{Month}_{k,it} + \beta_{>4}\,\text{Month}_{>4,it} + \alpha_i + \delta_t + \epsilon_{it} \tag{9}$$

The indicator $\text{Month}_{k,it}$ equals one if month $t$ is the $k^{\text{th}}$ month relative to creator $i$'s multihoming month and zero otherwise. We examine a window of five months before and five months after the event. For treated creators, $\text{Month}_{k,it}$ is set to one when month $t$ matches the $k^{\text{th}}$ month since treatment and remains zero otherwise, while for control creators all event-time indicators remain zero throughout the sample period. The variables $\text{Month}_{<-5,it}$ and $\text{Month}_{>4,it}$ group observations that occur more than five months before treatment or more than four months after treatment, respectively. The coefficient for $k = -1$ is omitted and serves as the reference period, so coefficients for $k < 0$ capture deviations from the pre-treatment trend and coefficients for $k \geq 0$ trace the month-by-month evolution of treatment effects after multihoming.

# D Additional Tables

Table D1: **Examples of Posts with Advertisements.**

| **Content** |
|---|
| 今年的” 年味照片” 就这样拍！很难不出片！# 麦当劳祝你今年金拱门 # 麦当劳快闪店 # 拍照 # 东方美学 # 深圳 |
| This is how you take 'New Year's flavor photos' this year! Hard not to get great shots! #McDonald's Wishes You Golden Arches #McDonald's PopUp Store #Photography #Eastern Aesthetics #Shenzhen |
| 听好了, 今年夏天我只教一遍 # 拍照姿势不重样 # 来拍照了 # 氧气感照片 # 水之蔻 # 水之蔻身体乳 |
| Listen up, I'm only teaching this once this summer #Different Poses EveryTime #Come For Photos #Fresh Look Photos # ShuiZhiKou #ShuiZhiKou BodyLotion |
| 素颜也能出片, 学到就是赚到！# 拍照姿势 # 素颜拍照 # 宅家拍出氛围感 # 欧诗漫珍白因美白套装 # 欧诗漫精准养白 |
| Great photos even without makeup—learning this is earning! #Photo Poses #No Make up Photos #At Home Ambience #OSM WhiteningSet #OSM Precision Whitening |
| 假期旅游不会拍？实战演练教到你们会！# 拍照技巧 # 旅游拍照 # 来拍照了 # 珀莱雅无限空间 |
| Don't know how to take photos on vacation? Hands-on practice until you get it! #PhotoTips #TravelPhotos #ComeForPhotos #PROYAInfiniteSpace |

Notes: In each pair of rows, the first row presents the Chinese title, and the row below provides its English translation.

Table D2: **Examples of Identified Cross-platform Posts.**

| **Posts from TikTok** | **Posts from RedNote** |
|---|---|
| 冷都女烟熏黑道千金风 # 美妆百万新星计划 # 单眼皮 | 冷都女烟熏黑道千金风 # 单眼皮眼妆 # 今日妆容 # 妆前妆后 |
| Cold city girl smoky dark gangster chic look | Cold city girl smoky dark gangster chic look #Monolid-Makeup #TodaysMakeup #BeforeAndAfterMakeup |
| 当方圆脸尝试网红芭比妆，走进现实能看吗？# 方脸 # 方圆脸 # 美妆博主回归现实 | 当方圆脸尝试网红感芭比妆，现实中能看吗？# 方圆脸 # 方脸 # 芭比 # 网红妆容回归现实 # 新手化妆技巧 # 完美底妆这样画 #UD 定妆喷雾 |
| When a square/round face tries the trendy Barbie makeup, does it look good in reality? | When a square/round face tries the trendy Barbie-style makeup, does it look good in real life? |
| 无睫毛　超详细跟练版韩系姐姐气质单眼皮 # 单眼皮 # 新手化妆教程 | 无睫毛　超详细跟练版气质单眼皆真的超级无敌简单易学！# 单眼皮眼妆 # 新手化妆 # 妆前妆后大对比 |
| No false lashes—super detailed follow-along Korean-style elegant monolid look | No false lashes—super detailed follow-along elegant monolid look, truly super easy to learn! |

Notes: In each pair of rows, the first row presents the Chinese title, and the row below provides its English translation.

Table D3: **T-test Result.**

| | Number of posts | Likes | Within-creator topic similarity |
|---|---|---|---|
| Difference | -2.138*** | 43599.9*** | -0.02*** |
| Std_Dev | 0.099 | 3182.443 | 0.0026 |

Table D4: **Comparison of Treated and Control Groups: Pre- and Post-matching.**

| | Pre-matching | | | Post-matching | | |
|---|---|---|---|---|---|---|
| | Treated (1) | Control (2) | Diff (3) | Treated (4) | Control (5) | Diff (6) |
| log(Followers) | 14.41 | 14.08 | 0.33*** | 13.94 | 14.08 | -0.14 |
| log(Advertisement_price) | 10.43 | 10.09 | 0.35*** | 9.95 | 10.09 | -0.14 |
| Number of posts | 10.04 | 12.65 | -2.61*** | 10.89 | 12.65 | -1.76 |

Note: The statistical significance of the differences is based on a two-sample t-test.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D5: **Effects of Multihoming (Robustness Check).**

| **VARIABLES** | (1) log (Followers) | (2) log (Likes) | (3) Number of advertisement | (4) Number of posts | (5) Within-creator topic similarity | (6) Cross-platform content similarity |
|---|---|---|---|---|---|---|
| *Multihoming* | 0.189*** | 0.149** | 0.225** | 2.265*** | -0.00187 | 0.0198*** |
| | (0.0476) | (0.0712) | (0.0883) | (0.452) | (0.0104) | (0.00392) |
| Constant | 13.17*** | 10.38*** | 0.573*** | 6.448*** | 0.499*** | 0.813*** |
| | (0.0159) | (0.0239) | (0.0246) | (0.126) | (0.00351) | (0.00132) |
| Individual fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,247 | 11,034 | 14,084 | 14,084 | 10,938 | 10,983 |
| R-squared | 0.915 | 0.639 | 0.586 | 0.601 | 0.725 | 0.532 |

Note: Robust standard errors are clustered at the creator level in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D6: **Impact of Multihoming on Creator Outcomes - RedNote.**

| VARIABLES | (1) log(Likes) | (2) Number of posts | (3) Within-creator topic similarity |
|---|---|---|---|
| *Multihoming* | 0.565*** | 3.605*** | -0.061*** |
| | (0.101) | (0.692) | (0.016) |
| Constant | 7.193*** | 4.734*** | 0.539*** |
| | (0.068) | (0.413) | (0.011) |
| Individual fixed effect | Yes | Yes | Yes |
| Month fixed effect | Yes | Yes | Yes |
| Observations | 4,440 | 6,090 | 4,411 |

Note: Robust standard errors are clustered at the creator level in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D7: **Effect of RedNote Policy on Engagement of Non-multihomed Creators.**

| VARIABLES | (1) log(Likes) |
|---|---|
| *Multihoming_policy* | 0.0664 |
| | (0.0984) |
| Constant | 10.59*** |
| | (0.0708) |
| Individual fixed effect | Yes |
| Month fixed effect | Yes |
| Observations | 2,022 |
| R-squared | 0.748 |

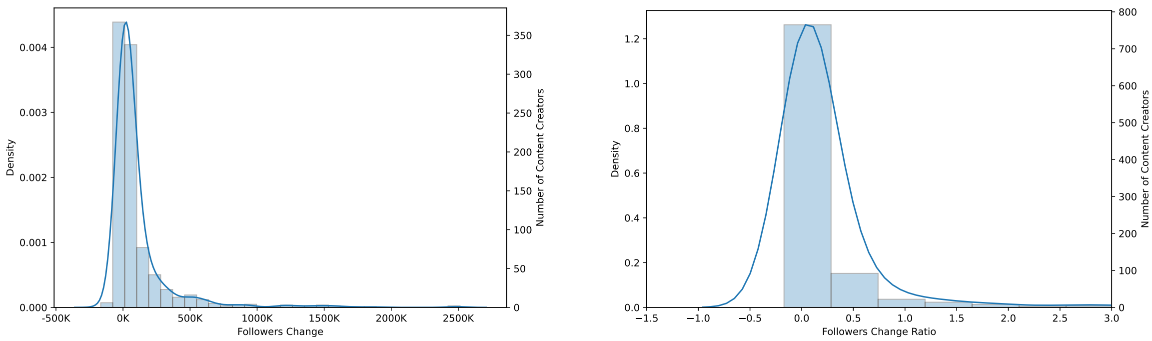
Note: Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D8: **Moderating Effects: Multihoming Percentage.**

| VARIABLES | (1) log(Followers) | (2) log(Likes) |
|---|---|---|
| Multihoming | 0.195*** | 0.180* |
| | (0.0706) | (0.0986) |
| *Multihoming*Cross-posting ratio* | 0.180*** | 0.310* |
| | (0.0638) | (0.178) |
| Constant | 13.17*** | 10.42*** |
| | (0.0275) | (0.0404) |
| Individual fixed effect | Yes | Yes |
| Month fixed effect | Yes | Yes |
| Observations | 7,019 | 7,626 |
| R-squared | 0.922 | 0.674 |

Note: Robust standard errors are clustered at the creator level in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

# E Additional Figures




(a) Number of Follower Changes

(b) Ratio of Follower Changes

Figure E1: **Distributions of Follower Changes.**

Notes: The left y-axis reports density and the right y-axis reports the number of creators.

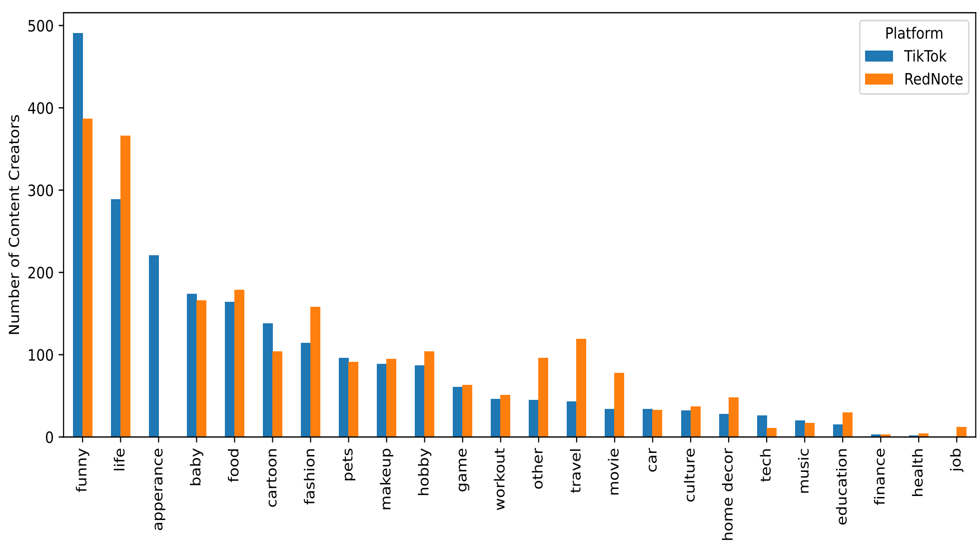



Figure E2: **Categories of Content Creators.**

Notes: We manually reviewed and matched these tag systems across the two platforms, identifying 22 common content types, along with one unique category on TikTok ("appearance") and one unique category on RedNote ("job"). Among the 1,583 content creators in our dataset, the category distributions appear highly similar between the two platforms. This similarity suggests that creators often maintain consistent content themes across platforms.

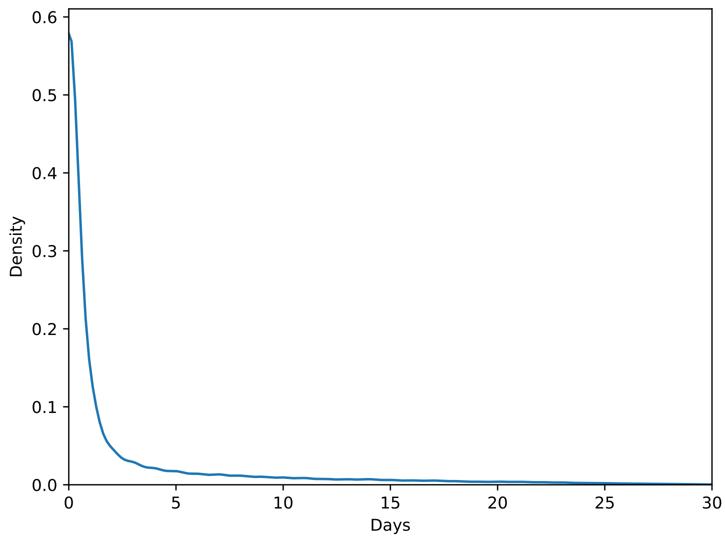



Figure E3: **Time Differences between Cross-posted Posts on Two Platforms.**


Figure E4: **Screenshot of a RedNote Account.**