Learning-by-Doing in Non-Homogeneous Tasks: An Empirical Study of Content Creator Performance on A Music Streaming Platform

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Learning-by-doing in non-homogeneous tasks: An empirical study of content creator performance on a music streaming platform

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ABSTRACT

With the development of high-speed internet and better mobile connections, online streaming platforms with user-generated videos are becoming popular. The success of these platforms relies on content creators who can effectively enhance user engagement (e.g., subscribing to a content creator's channel). As opposed to homogeneous production scenarios (e.g., assembling automobiles in a factory), creating user-generated videos is a more complex task in which learning might happen. In this study, we empirically test the effect of prior experience on content creators' performance. Furthermore, we examine the role of specialization in learning. We use a dataset from NetEase Cloud Music, one of the most popular music streaming platforms in China, with 21,549 content creators and 252,762 user-generated videos. The findings indicate that: (1) prior experience has a positive effect on creators' performance; (2) specialized experience across distinct video categories has a nonlinear effect on creators' performance. These results have implications for improving user engagement for online user-generated video streaming platforms.

1. Introduction

Content, these days, is the catchall term for all the media that we consume, both traditional and brand-generated (Gallagher, 2019). Every-one can be a content creator in the era of digitalization to post Tweets, Instagram, blogs, and music videos on miscellaneous types of social media platforms. Does learning-by-doing take place and how does it affect creators' performance? This study investigates the impact of learning-by-doing in non-homogeneous tasks on creators' performance in the context of a music streaming platform.

With the rising penetration of smartphones, digital platforms, and smart devices, the global online music streaming market will foresee a fast-growing tendency to maintain in the near future. According to a recent report published by Allied Market Research (Correa, 2021), it is projected to reach $24.71 billion by 2027 with a compound annual growth rate (CAGR) of 9.8 % from 2021 to 2027. Many people are streaming music on audio/media streaming services providers such as Spotify, Apple Music, and Amazon Music. Creators design and post the music or video, exhibiting their micro-storytelling to the board audience. Users who enjoy the content and want to know more about it will like the post or become a follower of the creator. The followers play multi-dimensional roles in the community, such as sponsors, co-creators of value, stakeholders, investors, and filters (Galuszka, 2015). The number of followers typically serves as a proxy of the creator's popularity and social influence (De Veirman et al., 2017; Hou et al., 2021; Hwang, 2015; Yoganarasimhan, 2012). Therefore, we implement the daily number of new followers as the measurement for the creator's performance in this work.

Indeed, a rapid growth of followers or fans cannot happen overnight. Before getting their name known, creators need great efforts to establish essential gears, obtain expertise in software and technology, study the preference of the audience, and develop a habit of creation. Intuitively, these might be achieved through learning-by-doing. Learning-by-doing refers to the fact that knowledge is growing in time (Arrow, 1962). At the same time, experience will enhance organization and individual learning and productivity (Yelle, 1979). Particularly, the process of music video creation is complex and contains both repetitive and non-repetitive tasks. To produce a music video, the creator has to go over several major steps including theme conceptualization, storyboarding and music selection, filming, and editing the videoo. While filming and editing the video involve much repetitive work that requires software proficiency (Bakkay et al., 2019; Cayari, 2014), theme

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conceptualization and storyboarding at the core of innovation exhibit a greater heterogeneity of roles (i.e., less repetition) across music videoos. For example, a content creator might learn to choose the music that best fits the theme of the videoo over less repetitive attempts in diverse music styles. A content creator might also learn to edit videoos more efficiently over repeated use of editing software. Therefore, the effect of learning-by-doing in music videoos, similar to movie production (Narayan & Kadiyali, 2016), is not constrained by homogeneous tasks but includes non-homogeneous tasks. Following the above logic, one would expect that prior experience will affect current and future productivity as a result of learning-by-doing. For instance, a content creator has three years of experiences in creating content on a music streaming platform. To show how leaning-by-doing affects their performance, we can investigate how their experiences from the past three years affect their current and future performance. Leaning-by-doing, therefore, is a cumulative time-invariant measure, in our context. Specifically, we define the learning variable as the number of videoos the creator produced at the beginning of the sample period. Such measure is similar to the cumulative experience that affects productivity in software development (e.g., Kang et al., 2017; Kim et al., 2012).

It is widely acknowledged that learning-by-doing can occur from both focused experiences at a specific task and diversified experiences in different tasks. Prior research defined these two types of exposures as task specialization and task variety, respectively (Argote, 2013; Narayanan et al., 2009; Newell & Rosenbloom, 1981). Similarly, videoo creators gain experiences from a combination of specialized tasks (i.e., editing videos in a specific category following similar steps) and diversified tasks (i.e., creating music videos of different themes and in different categories/genres), which triggers learning-by-doing. Some existing work on learning-by-doing in heterogeneous tasks evidences that specialized experiences enhance productivity in software development and maintenance environment (Boh et al., 2007; Narayanan et al., 2009). These findings are consistent with Adam Smith's championship of the division of labor, according to which firms have long viewed task specialization as a steppingstone to enhanced employee learning and productivity. On the other hand, exposure to task variety enables individuals to gain knowledge about the broader schema (Paas & Van Merriënboer, 1994) and can also help improve the workers' productivity (Staats & Gino, 2012). In the context of video creation, content creators can thus take two different strategies to accumulate experience: focusing on fewer video categories to gain experience on specific tasks or expanding to more categories to gain experience on various tasks. However, the role of task specialization in content creators' learning-by-doing process is still unexplored in the literature. Our study will contribute to the literature by corroborating the existing theory on learning-by-doing in heterogeneous tasks and examining the impact of task specialization in the context of content creation on music streaming platforms.

The overarching questions we are exploring in this work are: 1) Is there a causal relationship between creation experiences and the creator's performance? 2) How would such relationship be affected by factors associated with the creator's specialization and habits? To measure the creator's learning-by-doing status, we implement two learning variables to quantify the creator's achievements in both prior experience and specialization. Specifically, the experience variable indicates the number of videos produced by the creator, while the specification variable is a Herfindahl-Hirschman Index (HHI) (Narayanan et al., 2009) computed based on the number of categories as well as the number of videos produced by the creator. We develop a dynamic panel data model to estimate the effect of learning-by-doing on the daily growth of new followers. Our findings confirm the effect of learning in the context of video creation, and experienced creators who have produced more videos will have a higher growth rate of followers. More importantly, the effect of specialization exhibits an inverted U-shape pattern, meaning that the creator's performance is optimized at a moderate level of specialization.

The remainder of this paper is structured as follows: Section 2 discusses the related literature; Section 3 describes the data along with the econometrics model; Section 4 presents the empirical findings and robustness checks; Section 5 provides practical implications; Finally, Section 6 concludes with a discussion of the main findings and suggestions for future research.

2. Literature review

This work is related to a variety of disciplines across marketing, economics, and information systems. In order to help address our research questions, we discuss two of the most relevant streams of literature: 1) Follower behavior and growth in the social media community; 2) Impact of learning-by-doing on performance improvement.

2.1. Follower behavior and growth in social media community

Social media empower every-one in the community to post and repost, follow and be followed, respond and interact, which make the sharing and diffusion of content much faster than any traditional media. The economy of followers emerges as the aggregation power of social media; particularly, their role in bringing together the followers of one's profile can easily be harnessed by advertisers for the promotion of their brands and products (Jin & Phua, 2014). The number of followers, which reflects the content creator's network size and popularity, is frequently applied as a measurement of user's influence and social power.

The literature on followers' economy primarily focuses on followers' behavior in the context of product and information diffusion in marketing. A higher number of followers may result in a larger reach of the (commercial) message, and may thus leverage the power of this specific type of word-of-mouth at scale (De Veirman et al., 2017). Twitter celebrities with a higher number of followers will be perceived as more credible and have more social influence on other users' following intentions (Jin & Phua, 2014). Opinion leadership will be gained by those individuals who possess a higher number of followers and actively exchange information (Nisbet, 2006). The size of the followers is also found as a significant driver of the popularity of videos seeded by the YouTube video creator (Yoganarasimhan, 2012). All the aforementioned works apply the number of followers as the independent variable, while not much literature implements it as the dependent variable and examines the follower growth empirically. A recent study by Hou et al. (2021) examined the pattern of follower growth and found that the number of newly increased followers had a similar pattern that grew rapidly in the early stages and kept a relatively low and steady rate of increase rate later on. Moreover, online streaming and content creation have drawn increasing attention in recent years. Existing literature has extensively studied viewers' behavior, such as gifting (e.g., Guan et al., 2021; Li et al., 2021), engagement (e.g., Hilvert-Bruce et al., 2018), purchase intentions (e.g., Sun et al., 2019), and viewing (e.g., Zhao et al., 2021). Different from the above research, our focus is on the performance of streamers. Zhao et al. (2019) investigate how streamers' characteristics, namely personality traits, professionalism, and social affordance associated with the popularity of streamers. Although Zhao et al. (2019) have a similar focus to ours, i.e., the performance of streamers, they study viewers' motives or behavior. We, on the other hand, shift our attention to content creators and the content-generating process, which have not yet been fully studied in the literature. Particularly, we consider one major and commonly studied factor that affects productivity/performance in the context of learning-by-doing.

To the best of our knowledge, no extant empirical work studied the follower growth in the context of music streaming platforms and considered the impact of learning-by-doing. Our work will fill this gap and contribute to the literature investigating the follower growth on social media platforms. Despite the business value of followers in social networks, our understanding of how one can strategically gain followers is still understudied. For example, Guo et al. (2017) studied the factors that influence the follower growth of WeChat Official Accounts (WCOA) and found the users' motivation to participate and the high-quality information of WCOA contribute to the growth of followers. Church et al. (2021) empirically examined the follower growth on Pinterest and found broadcast media and social-earned media are positively associated with follower growth. Bredikhina et al. (2022) investigated athletes' follower growth on Instagram and found pre-existing followers and athletes' posting frequency are the key factors that boost follower growth. Our study advances follower growth literature by exploring the factors that impact the follower growth in a music streaming social network.

2.2. Impact of Learning-by-Doing on performance improvement

The basic idea behind the learning curve effect (or simply learning effect) is very straightforward—repeated experiences create a growing stock of knowledge and improve performances (Argote 2013). The main ingredient of a learning curve is the existence of the same elements between prior experiences and the current task (Ellis, 1965; Schunk, 2015). In this regard, learning effects are typically studied in the context of homogeneous production, where delivered products are identical, and the unit of the same experience is defined at the level of the products (Kang et al., 2017). Many researchers studied learning effects occurred in homogeneous task environments in the field of manufacturing and production processes (Adler & Clark, 1991; Cabral & Riordan, 1997; Deng et al., 2021; Freiesleben & Schwarz, 2006; Guo & Fan, 2017; Lapre et al., 2000; Levitt et al., 2013) and health care systems (Bavafa & Jónasson, 2021; David & Brachet, 2009; Epple et al., 1991; Huckman & Pisano, 2006; Stith, 2018). Different from the manufacturing process where workers repeat the same tasks, the creation of videos on music streaming platforms involves various ideas, technology, and formats, and thus belongs to heterogeneous tasks.

Task performance may improve not only as the cumulative experience on a particular task increases, but also over experiences of disparate tasks with sufficient overlap across tasks (Kang et al., 2017). A growing number of researchers study the learning-by-doing effect in heterogeneous tasks. Narayan and Kadiyali (2016) investigated whether and what kind of repeated interactions between movie production team members improve production success. Kim et al. (2012) empirically examined information technology knowledge workers' learning behavior and found that the learning effect occurs with experience. Boh et al. (2007) studied the impact of diversified experiences in the software development process on productivity improvement. Kang et al. (2017) examined learning effects in information system development and suggested that learning effects are likely to occur when past experiences and current task share more identical elements and when this similarity between past experiences and current task is cognitively easier to identify. As extant literature provides theoretical foundations for learning effects in non-homogeneous tasks, the impact of learning-by-doing on creators' performance on music streaming platforms still remains unclear and unexplored. Music video creation on music streaming platforms such as NetEase Cloud Music is characterized by choosing the right song, setting up the equipment, editing and finishing the video with software, and distributing the video onto the social media platform. The creation process resembles the software development and information system development in the aforementioned literature, which are depicted in the way of diversified tasks and experiences. This paper will contribute to the existential theorization of learning-by-doing in heterogeneous tasks and create new managerial insights for music streaming platforms.

When performing heterogeneous tasks, individuals can achieve learning-by-doing during exposures to both task specialization and task variety (Narayanan et al., 2009). Some existing literature noted that exposure to specialized tasks could enhance learning as a task becomes more routine and automated for an individual who has greater focused experiences on that task (Argote, 2013; Boh et al., 2007; Narayanan et al., 2009; Schilling et al., 2003). Concurrently, researchers also indicated that exposure to task variety could lead to implicit learning, which will enhance productivity as well (Graydon & Griffin, 1996; Paas & Van Merriënboer, 1994; Reber, 1989; Schilling et al., 2003; Zhu & Simon, 1987). Not so much work was done to examine how exposure to specialization and variety jointly drive employee productivity. Narayanan et al.'s (2009) finding identified that specialization enhances productivity, while exposure to variety has a non-linear influence on productivity. However, their work was focused on software development and maintenance tasks. Whether the impact of task specialization and variety follow the same pattern in the context of content creation has not been discussed in the literature yet. To extend the literature, we include a specialization/variation variable in our model, which is generated through Herfindahl-Hirschman Index, to further discuss the relationship between creators' performance and learning-by-doing.

3. Data and methods

We obtain data from the data-driven research challenge by INFORMS Revenue Management and Pricing Section (Zhang et al., 2022). The dataset contains creators' data from NetEase Cloud Music, one of China's largest music streaming platforms. According to a recent report (Aswad, 2019), it provided free music streaming services to 800 million users in 2019, with a valuation of around 9 billion dollars. Similar to video streaming social media platforms such as TikTok and YouTube, NetEase Cloud Music app allows content creators to produce their own short videos with specific music. The audience can then watch the videos and interact with creators through actions such as liking, commenting on and sharing videos or following creators' channels. In practice, user-generated content (UGC) may attract immense attention in a short period of time (i.e., going viral) and thus lead to a rapid growth of followers. To alleviate the concern on going viral, we follow Han et al. (2020) and identify creators as outliers who have experienced a spike in follower growth if (1) there are more than 5000 existing followers, and (2) the monthly growth rate of new followers is above two standard deviations of the mean. We exclude the outliers from the dataset. The final dataset contains 21,537 content creators and 252,697 short videos, from November 1, 2019, to November 30, 2019, on a daily basis.

3.1. Measures

In many previous studies, longitudinal panel data were collected, and thus the learning variable was defined as a dynamic measure that accumulates over time (KC et al., 2013; Kim et al., 2012). Accordingly, a longitudinal model such as feasible generalized least squares (FGLS) with autoregressive within-subject covariance structure was used to deliver estimates of the learning effect. However, the dataset in our study is quite different from those of previous studies in that a large number of cross-sectional units were collected along with relatively fewer periods (also known as large N small T panel data). Therefore, we adjust our empirical specification to a dynamic panel and estimate coefficients using system generalized method of moments (system GMM) model as it generates better results for large N small T panel data (Roodman, 2020). Furthermore, we define learning as a cumulative time-invariant measure (i.e., the number of videos the creator produced at the beginning of the sample period) for two reasons: 1) In our context, the performance measure in the sample period is marginal as compared to the beginning; for instance, new followers in the sample period takes$<$3 % of the cumulative followers at the beginning. This is consistent with Crosby et al. (2018), in which authors empirically examined the follower growth of artists on Facebook, Instagram, and Twitter after a major music poll in Australia — "Triple J Hottest 100." In specific, they have found a monthly follower growth of 3 % on average for artists who are nominated to the poll; 2) the performance measure in the sample period, as time series, is stationary, as the panel unitroot test in Table 1a indicated. These make the learning effect more salient among cross-sectional units as compared to time series units.

3.1.1. Dependent variable

Our study was motivated by a desire to understand learning by content creators. We set the unit of analysis at the individual level. To measure creators' performance, we use the number of new followers a creator gets each day during the sample period. Specifically, the number of new followers the creator i gets in day t is denoted by y_{it}. Note that y_{it} is a contemporaneous variable which describes the growth of followers in a day.

3.1.2. Independent variables

The primary learning-related variable exp_i proxies the creator i's experience using the number of videos the creator produced at the beginning of the sample period. Creators on NetEase Music can produce videos of various genres and content categories (e.g., gaming, movie, and concert). Some creators focus their videos on a single or few categories, while some others create videos of diverse categories. Therefore, it is interesting to examine the impact of specialization on learning. In the dataset, each video is tagged with a content ID that represents its category/genre, allowing us to construct a measure for the degree of the creator's exposure to various types of video-creating tasks. We consider genres because they reflect internal aspects of videoos. Similar research in the game domain has shown that game genres present a rich collection of information describing gameplay, such as action, strategy, or casual, and are closely associated with consumers' personality and psychological characteristics (Potard et al., 2020; Von Der Heiden et al., 2019). In our sample, genres are captured by 122 unique categories such as gaming, concert, movie, and entertainment. The approach is similar to that taken in Sheu et al. (2017), where consumers' internal personal cognition was evaluated through sensory, feel, think, act, and relate experiences in the games. We do not use the number of distinct categories of videoos as the measure of specialization because it does not capture the depth of exposure. Two creators who have produced the same number of videoos of the same number of distinct categories could have very different experience portfolios. For example, let's consider a creator who has produced ten videoos in total, with five under category A and five under category B. In contrast, let's consider another creator with the same number of total videoos who has one videoo under category A and nine videos under category B. Each creator has equal exposure to variety in terms of the number of categories/genres, but varying depths of exposure to each element of variety. To address this issue, we adopt the Herfindahl-Hirschman-Index (HHI; Salvador et al., 2021), which has been widely used to measure market concentration in economics. The index varies between $1/N$ and 1, where N is the number of firms in the market. When the market share is evenly distributed across firms, $HHI = 1/N$. If the market is dominated by a single firm, $HHI = 1$. Let N_i be the total number of videos produced by creator i and D_{ik} be the number of videos produced by creator i in category k. Then, the HHI of creator i is $HHI_i = \sum_{\forall k}\left(\frac{D_{ik}}{N_i}\right)^2$. A high value of HHI indicates that the creator produces videos with a limited number of categories with specialized experiences in one or a couple of video categories. In contrast, for low values of HHI, the creator is less specialized and has diverse experience producing various categories of videoos. It is important to notice that exp_i and HHI_i measure experience and specialization at the beginning of the sample period and do not change over time.

Table 1a
Panel Unit Root Test.

	Statistic	p-value
Inverse chi-squared	18,700	0.0000
Inverse normal	−109.02	0.0000
Inverse logit	−159.27	0.0000
Modified inverse chi-squared	259.13	0.0000
Fisher-type unit root test based on Phillips-Perron tests		
Ho: All panels contain unit roots		
H1: At least one panel is stationary		

3.1.3. Control variables

We include two types of control variables: time-varying and time-invariant. Time-varying variables consist of lagged aggregations of audience-video interactions such as: $comment_{it-1}$, the total number of comments the creator i received from posted videos on day $t-1$; $share_{it-1}$, the total number of times users share creator i's videos to friends on day $t-1$; $like_{it-1}$, the total number of likes creator i received from posted videos on day $t-1$; $check\_profile_{it-1}$, the total number users who checked creator i's profile on day $t-1$. These user actions are typically considered as indicators of message content diffusion on social networks (De Vries et al., 2012; Hoang et al., 2016) and have been included in modeling the growth of followers in recent literature (Hou et al., 2021). The time-invariant variables consist of the creators' characteristics including: $gender_i$, the gender of the creator; $activity_i$, the activity intensity level of creator i , ranging from 0 to 10, as measured by the amount of time and frequency creator i engages with the music app at the beginning of the sample period, the smaller this value, the less active the user; $registered_i$, the number of months creator i has registered till the beginning of the sample period; $followers_i$, the total number of followers of creator i at the beginning of the sample period. Creator's activity level and follower number can effectively indicate the creator's professionalism /career stage, given the literature evidence that professionalism is associated with both activeness and popularity (Chai et al., 2013; Seo, 2016; Zhao et al., 2021). Popular streamers create tremendous business values for social media influencer investors, as they have a high potential to create persuasive advertisements and endorsements for firms by promoting their products and services (Zhao et al., 2021). Therefore, the inclusion of the number of followers can also reflect the sponsorship of creators.

We use a log transform of the dependent variable and a log transform of the primary learning variable. We also employ log transforms of control variables, when appropriate. We do not use a log transform of HHI because its value is constrained between 0 and 1 with a specific meaning. Table 1b shows the summary statistics of the data.

3.2. Model specification

In this section, we develop a dynamic panel data model to examine the effect of learning on the growth of new followers y_{it}. The standard form of the learning curve is formulated as $y = ax^b$, where y measures performance, x proxies prior experience, and b is the learning rate. Taking a natural log transformation on both sides and adding covariates, we use the following model specification:

$$Lny_{it} = \alpha + \gamma Lny_{it-1} + \beta Z_i + \delta X_{it-1} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where vector Z_i contains the time-invariant learning-related

Table 1b
Descriptive Statistics.

Variable	Mean	SD	Min	Max
Ln y	0.0562	0.2655	0	5.8377
Ln exp	1.0444	0.6315	0.6931	5.4424
HHI	0.7709	0.3360	0.0082	1
Ln comment	0.0607	0.2548	0	4.7706
Ln share	0.0873	0.3405	0	5.6767
Ln check_profile	0.1189	0.4286	0	7.8099
Ln like	0.3412	0.7776	0	7.7384
gender	0.4849	0.4997	0	1
activity	7.0775	1.6933	0	10
Ln registered	3.2871	0.6231	0.6931	6.4118
Ln followers	3.4357	2.155	0	19.2576

variables exp_i and HHI_i, and time-invariant control variables, such as $gender_i$, $activity_i$, $registered_i$, and $followers_i$; vector X_{it-1} contains the time-varying creator-user interaction variables including $comment_{it-1}$, $share_{it-1}$, $like_{it-1}$, and $check\_profile_{it-1}$, ; μ_i is individual-specific effects; λ_t is time dummy variables that proxy time-varying factors influencing the creators' performance, such as the breaking news and trending topics during the sample period; finally, ε_{it} is idiosyncratic error terms. We demonstrate the temporal relationship between time-invariant and time-varying covariates in Fig. 1. In Equation (1), control variables X_{it} are lagged because there is much overlapping information embedded in X_{it} and Lny_{it}. For example, the crowd of new followers of creator i in day t (Lny_{it}) is very likely to include the audiences who have commented on, shared, and liked the videos produced by the creator, which is illustrated in our assumption that $E[\varepsilon_{is}X_{it}] \neq 0$ if $s \leq t$. In other words, X_{it-1} is considered in Equation (1) because it is strictly exogenous to ε_{it} in the sense that information in the past is uncorrelated to the disturbance in the future.

The main concern on the endogeneity lies in the fact that creator's prior experience exp_i, included in Z_i, may be correlated with ε_{it} in Equation (1), resulting in $EZ_i\varepsilon_{it} \neq 0$. We show that ΔLny_{it-2}, or more generally ΔLny_p, $p \leq t-2$ can be good instrumental variables (variables that are correlated with endogenous variables but uncorrelated with the idiosyncratic errors) for Z_i. Specifically, it can be proven that the effect of the unobserved fixed effect μ_i on Lny_{it} is constant for all periods in Equation (1) (Appendix). We thus can decompose Lny_{it} into a time-invariant creator-specific term $a\mu_i$ and a time-varying function of covariates $f_t(Z_i^{'}, I_t)$ independent of μ_i, where a is a constant, $Z_i^{'}$ is the part in Z_i that is independent of μ_i, $f_t(.)$ is a time-varying function, and I_t is a vector of covariates that contains information up to period t. We then write ΔLny_{it-2} as $\Delta Lny_{it-2} = Lny_{it-2} - Lny_{it-3} = f_{t-2}(Z_i^{'}, I_{t-2}) - f_{t-3}(Z_i^{'}, I_{t-3})$. Accordingly, $E\Delta Lny_{it-2}\varepsilon_{it} = E\left[f_{t-2}(Z_i^{'}, I_{t-2}) - f_{t-3}(Z_i^{'}, I_{t-3})\right]\varepsilon_{it} = 0$ because information from the past is uncorrelated with shock in the future, and $E\Delta y_{it-2}Z_i = E\left[f_{t-2}(Z_i^{'}, I_{t-2}) - f_{t-3}(Z_i^{'}, I_{t-3})\right]Z_i \neq 0$ because $Z_i^{'}$ is a part of Z_i, ensuring that ΔLny_{it-2} are good instrumental variables for Z_i. Therefore, the system GMM addresses the endogeneity issues in a way similar to the instrumental variables of two-stage least squares (2SLS). However, it's worth noting that system GMM is easier to implement than 2SLS because the former can use lagged covariates as instrumental variables while it is usually difficult to find proper instrumental variables for the latter.

In addition to finding instrumental variables for the endogenous learning variable exp_i, we now discuss the inclusion of unobserved effects λ_t and μ_i. We include the time-specific effect λ_t because unobserved time-varying variables such as breaking news and trending topics may have non-negligible effects on the number of new followers. For example, Cha et al. (2010) found that trackers of trending topics tend to be the most followed users on Twitter. In our study, we model λ_t as a time-specific shock without autocorrelation and assume $E\lambda_t X_{is} = E\lambda_t Lny_{is} = 0$, if $s < t$ because breaking news tomorrow has no effect on learning and performance variables today. We then consider two other types of unobservables that may lead to endogeneity: 1) Creator-specific variables, such as creator's capability; 2) other learning variables that we do not observe (e.g., knowledge gained). Since the 30-day sample period is relatively short, we argue that we should expect marginal changes in these unobservables, making time-invariant μ_i an appropriate proxy. As a result, there is a correlation between μ_i and X_{it-1}, between μ_i and Lny_{it-1} as well as between μ_i and Z_i. Failing to address these endogenous issues may lead to biased estimates of learning effects. The difficulty of estimating coefficients in Equation (1) lies in the fact that Z_i is time-invariant. Therefore, the fixed-effects model cannot be used because Z_i will be absorbed by μ_i after the within transformation. Following Yoganarasimhan (2012), we take advantage of the dynamic panel data structure and use lagged dependent variables as well as lagged independent variables as instruments to derive an estimate of Z_i. Taken together, the use of λ_t and μ_i as proxies for unobservables in this study is sufficient.

The identification strategy is to explore instruments and then construct moment conditions for system GMM model (Roodman, 2020). As in Yoganarasimhan's (2012) study, we assume $E[\varepsilon_{is}X_{it}] \neq 0$ if $s \leq t$, $E[\varepsilon_{is}Lny_{it}] \neq 0$ if $s \leq t$, and heteroskedastic error terms. To find proper instruments for endogenous variables Z_i, X_{it-1}, and Lny_{it-1}, we first explore the first-differenced equations:

$$\Delta Lny_{it} = \gamma\Delta Lny_{it-1} + \delta\Delta X_{it-1} + \Delta\lambda_t + \Delta\varepsilon_{it} \tag{2}$$

In the above Equation, the vector of time-invariant variables Z_i has been eliminated. However, the endogenous issue remains because:

$$E[\Delta\varepsilon_{it}\Delta X_{it-1}] = E[\varepsilon_{it}X_{it-1}] - E[\varepsilon_{it}X_{it-2}] - E[\varepsilon_{it-1}X_{it-1}] + E[\varepsilon_{it-1}X_{it-2}] \neq 0$$

$$E[\Delta\varepsilon_{it}\Delta y_{it-1}] = E[\varepsilon_{it}y_{it-1}] - E[\varepsilon_{it}y_{it-2}] - E[\varepsilon_{it-1}y_{it-1}] + E[\varepsilon_{it-1}y_{it-2}] \neq 0$$

To develop moment conditions, we use X_{ip} and Lny_{ip} (for $p \leq t-2$) as instruments (also known as IV-style instruments) since they are correlated with ΔX_{it-1} and ΔLny_{it-1}, but uncorrelated with $\Delta\varepsilon_{it}$. Therefore, we specify the following moment conditions for Equation (2):

$$E[X_{ip}(\Delta\varepsilon_{it} + \Delta\lambda_t)] = 0 \quad where \quad p \leq t-2 \tag{2a}$$

$$E[Lny_{ip}(\Delta\varepsilon_{it} + \Delta\lambda_t)] = 0 \quad where \quad p \leq t-2 \tag{2b}$$

To estimate the learning effects, we also explore moment conditions for level Equation (1). It can be shown that ΔX_{ip} (for $p \leq t-2$) is correlated with Z_i, X_{it-1} and Lny_{it-1}, but uncorrelated with $(\mu_i + \varepsilon_{it} + \lambda_t)$. Similarly, ΔLny_{ip} (for $p \leq t-2$) is correlated with X_{it-1} and Lny_{it-1} but uncorrelated with $(\mu_i + \varepsilon_{it} + \lambda_t)$. Therefore, we use ΔX_{ip} and ΔLny_{ip} (for $p \leq t-2$) as instruments (also known as GMM-style instruments) and set the following moment conditions:

$$E[\Delta X_{ip}(\mu_i + \varepsilon_{it} + \lambda_t)] = 0 \quad where \quad p \leq t-2 \tag{1a}$$

$$E[\Delta Lny_{ip}(\mu_i + \varepsilon_{it} + \lambda_t)] = 0 \quad where \quad p \leq t-2 \tag{1b}$$

Taken together, we combine moment conditions (1a), (1b), (2a), and (2b) and use system GMM for estimation. We provide detailed proof of moment conditions in the Appendix. We use STATA package xtabond2 (Roodman, 2020) to carry out the analysis.

4. Results

Table 2 shows the correlations among variables in our analysis. The baseline correlations provide initial insights into the effect of experience and specialization on creators' performance. The number of new followers has a positive correlation with the creator's prior experience. In other words, the more videos a creator has produced, the more followers

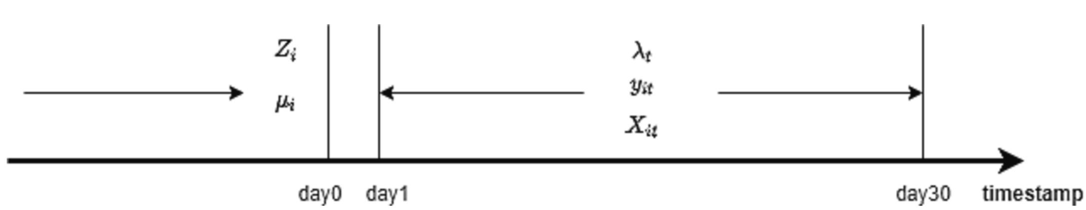

Fig. 1. Temporal relationship of variables.

Table 2
Correlation Matrix.

Variable	*Ln y*	*Ln* exp	*HHI*	*Ln comment*	*Ln share*	*Ln like*	*gender*	*activity*	*Ln registered*	*Ln followers*
Ln y	1									
Ln exp	0.3696	1								
HHI	−0.1985	−0.4006	1							
Ln comment	0.4697	0.3427	−0.2065	1						
Ln share	0.5477	0.3980	−0.2255	0.5707	1					
Ln check_profile	0.5884	0.3968	−0.2366	0.5688	0.6372	1				
gender	−0.0028	0.0406	−0.0410	−0.0122	0.0058	0.0098	1			
activity	0.0236	0.0714	−0.0949	0.0283	0.0375	0.0173	0.1364	1		
Ln registered	0.0055	0.0645	−0.0653	0.0014	0.0062	0.0117	0.1650	0.6335	1	
Ln followers	0.2636	0.3203	−0.3703	0.2059	0.2553	0.3190	0.1048	0.1592	0.2368	1
Ln like	0.5724	0.4162	−0.3015	0.6243	0.7063	0.7213	−0.0270	0.0181	−0.0119	0.3438

they can get in the future. We also notice that audience-video interactions are positively correlated with the growth of followers.

Table 3 illustrates our findings. We start from the baseline model 1, which does not contain learning-related variables, and make gradual expansion to the full model 6 by adding one variable at a time. Model 1 has controls only. The positive and significant coefficient of the lagged dependent variable suggests a positive autocorrelation in the growth of followers. The positive signs of audience-video interaction variables suggest creators who receive more likes and have more videos shared by the audience attract more followers in the future. Model 2 examines the effect of prior experience on creator's performance. Consistent with prior research (Kim et al., 2012; Narayanan et al., 2009), results show that prior experience has a positive effect on individuals' performance. Experienced creators with more videos in the channel are inclined to have a higher growth rate of followers. Model 3 examines the effect of specialization on the creator's performance. A positive and significant coefficient indicates focused experience is associated with better performance. Model 4 includes both learning-related variables. The results show the same effects of prior experience and specialization. Model 5 adds the quadratic term for *HHI*. The coefficients of the linear and quadratic terms for *HHI* are significantly positive and negative, respectively. This indicates a diminishing effect of focused experiences on the growth of followers. In other words, reducing the variety of video categories improves the creator's performance, but too little variety may hurt productivity. The signs and significance of the estimated coefficients we present in Table 3 are generally stable across models. We report the results of various specification tests in Table 3. A key assumption of the system GMM model is that error terms are not serially

Table 3
Coefficient Estimates and Standard Errors of sys-GMM.

	Dependent Variable: Lny_{it}				
Variable	(1)	(2)	(3)	(4)	(5)
$Ln\ y_{it-1}$	0.2880***	0.2788***	0.2546***	0.1207	0.2098***
	(0.0525)	(0.0617)	(0.0690)	(0.0987)	(0.0669)
exp_i		0.0063***	0.0082***	0.0058***	0.0039***
		(0.0013)	(0.0018)	(0.0022)	(0.0013)
HHI_i			0.2280***		0.5921***
			(0.0504)		(0.1385)
HHI_i^2				−0.2149***	−0.4365***
				(0.0664)	(0.1349)
$Ln\ comment_{it-1}$	−0.0596	−0.0854*	−0.0638	0.0561	0.0574**
	(0.0522)	(0.0513)	(0.0607)	(0.0615)	(0.0243)
$Ln\ share_{it-1}$	0.0675**	0.0501	0.0560*	0.1434***	0.0865***
	(0.0304)	(0.0306)	(0.0339)	(0.0317)	(0.0188)
$Ln\ like_{it-1}$	0.0938**	0.1067**	0.1182**	−0.0211	0.0641**
	(0.0411)	(0.0488)	(0.0483)	(0.0342)	(0.0266)
$Ln\ check\_profile_{it-1}$	0.1316***	0.1417***	0.1415***	0.2746***	0.1487***
	(0.0203)	(0.0384)	(0.0415)	(0.0830)	(0.0580)
$gender_i$	0.0768	0.0538	0.0841	−0.0631	−0.0506
	(0.0851)	(0.0890)	(0.0767)	(0.736)	(0.0559)
$activity_i$	−0.0547***	−0.0634***	−0.0594***	−0.0962***	−0.0414***
	(0.0133)	(0.0108)	(0.0136)	(0.0366)	(0.0059)
$Ln\ registered_i$	0.2112**	0.2125**	0.2431***	−0.1757***	0.1866***
	(0.0908)	(0.0911)	(0.0801)	(0.0255)	(0.0218)
$Ln\ followers_i$	0.0087	−0.0231	−0.0180	−0.0336***	0.0024
	(0.0257)	(0.0186)	(0.0199)	(0.0116)	(0.0113)
Time Dummies	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes
Hansen J-test of overidentifying restrictions (P-value)					
	0.390	0.400	0.385	0.310	0.390
Difference-in-Hansen J-test (P-value)					
	0.450	0.420	0.420	0.430	0.410
Arellano and Bond AR(2) test (P-value)					
	0.196	0.367	0.698	0.421	0.873
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
Number of Observations	452,480	452, 480	452, 480	452, 480	452, 480
Number of Groups	21,537	21,537	21,537	21,537	21,537

Notes. Robust standard errors are shown in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

correlated. If the autocorrelation exists, the instruments in (1a), (1b), (2a), and (2b) will no longer be valid. For example, if $E[\varepsilon_{is}\varepsilon_{it}] \neq 0 \forall i \neq j$, the instrument $\Delta y_{it-2} = y_{it-2} - y_{it-3}$ in (1b) is not valid because it contains ε_{it-2}, which is correlated with ε_{it} due to autocorrelation. Therefore, we report the results of Arellano-Bond serial correlation test. The large p-values indicate that the null hypothesis of no serial correlation is not rejected. We use Hansen's J statistic to test if the instruments as a group are valid for both level and differenced equations. An insignificant statistic for the J-test indicates that the GMM-style instruments for level Equation (1) are valid. An insignificant statistic for the difference-in-J-test indicates that the IV-style instruments for differenced Equation (2) are valid.

To confirm the inverted U-shape relationship between the creators' specialization level and their performance, we have calculated the extreme point of the curve and the slopes on the boundaries (Lind and Mehlum, 2010). If the inverted U-shape does exist, we would expect 1) the optimal value of HHI that achieves the best performance should fall into the range $[0,1]$, and 2) the slope at $HHI = 0$ and $HHI = 1$ should be positive and negative, respectively. As Table 4 shows, the 95 % Fieller interval of the extreme point $[0.5955, 0.9634]$ is within the normal range of HHI values. Meanwhile, the slopes on the boundaries are significantly positive and negative, indicating that creators will benefit from extending/reducing the variety of video categories when fewer/excessive categories are presented in their creations. According to our estimate of the extreme point, creators can obtain the best growth rate of followers when $HHI = 0.6783$. Fig. 2 illustrates the estimated relationship, the Fieller interval for the turning point and the slope at each endpoint. We see a hump-shaped relationship with the extreme point larger than the midpoint of the range of *HHI*. Intuitively, for very low values of *HHI*, the creator has a shallow exposure to a range of distinct video categories and suffers from a lack of experience in each of the focal category. In this case, creator's strategy of focusing on fewer categories and increasing the intensity of exposure to a more limited set of categories will lead to a higher growth rate of followers. In contrast, for very high values of *HHI*, the creator is overly specialized in one or a couple of categories. In this case, adding variety to the creator's experience portfolio and ensuring that the creator gains some depth of experience in diverse categories will lead to better performance.

We also perform a robustness check to assess how our findings hold up under alternative model specifications and alternative performance measures. Due to the hierarchical structure of the dataset, we conduct a series of multi-level mixed-effect regressions to examine the effects of experience and specialization on learning. In these regressions, we treat the music videos from the same creator as a random sample from a larger population and model the between-video variability as a random effect that has an impact on both intercept and slope. We consider the effect of learning on the number of likes creators received and measure creator i's performance using the aggregate of new likes received from video j during the sample period, denoted by $like_{ij} = \sum_{t=1}^{t=30} like_{ijt}$. We thus fit the following model

$$like_{ij} = \beta_0 + (\beta_1 + u_{1i})exp_i + \beta_2 HHI + \beta_3 HHI^2 + \gamma X + u_{0i} + \varepsilon_{ij} \tag{3}$$

where vector X contains the creator level control variables such as $gender_i$, $activity_i$, and $registered_i$. The estimates of coefficients are presented in Table 5. We center our discussion on model 5, which includes all variables. Experience is positively correlated to the number of likes received in the sample period. The positive and negative coefficient on specialization and its quadratic term indicates an inverted U-shape relationship. Extending the variety of video categories to a moderate level is associated with better performance, but this effect reverses when adding too much variety, which suggests that diverse experience is not entirely beneficial to content creators. In Table 6, we use $share_{it}$, the total number of times users share creator i's videos to friends on day t, to measure the performance of creator i on day t. The coefficients of learning variables are similar to those in Table 3, which confirms the learning effect and a curve-linear effect of specialization. These findings are consistent with our prior findings in the main results.

Table 4
Fieller U-shape Test.

Fieller U-shape test	
Extreme point	0.6783
95 % Fieller interval	[0.5955, 0.9634]
Slope at $HHI = 0$	0.5921***
Slope at $HHI = 1$	−0.2808**
Overall test of presence of inverted U-shape (P-value)	0.0199
Ho: Monotone or U-shape	
H1: Inverted U-shape	

5. Practical implications

In practice, using HHI may limit our model's capacity to provide actionable insights to creators. Therefore, we interpret the results in terms of the strategies creators can take. We start from a simple numerical example. Suppose there are only two categories A and B involved in a creator's video production process, then an allocation of 80 % in category A and 20 % in category B will lead to $HHI = 0.8^2 + 0.2^2 = 0.68$. In other words, the creator will benefit most if s/he can put 80 % of efforts in creating videos of a main category. We can also generalize this finding when more categories are considered. Taking into account the variations among creators, we denote by random variables $X_1, X_2, \cdots, X_K$ creators' video category allocation in the presence of K categories where $X_1 + X_2 + \cdots + X_K = 1$. We then use a Dirichlet distribution $Dir(\alpha_1, \alpha_2, \cdots, \alpha_K)$ to describe the strategy regarding the variety of video categories. For example, if creators evenly distribute efforts to all categories, then $\alpha_1 = \alpha_2 = \cdots = \alpha_K = \frac{\theta}{K}$ and the expected value of proportion in each category is $\frac{\alpha_i}{\sum_{i=1}^{K}\alpha_i} = \frac{1}{K}$. Similarly, creators can also focus on a main category i by increasing the value of the corresponding parameter α_i and decreasing the value of other parameters. Therefore, we can compare the performance of different strategies using simulation and calculating the probability that $HHI = \sum_{i=1}^{K} X_i^2$ falls into the optimal Fieller interval $[0.5955, 0.9634]$. A higher probability is desired for a superior strategy. We conduct an array of simulations for the main category strategy with corresponding proportions ranging from 55 % to 95 % and the number of categories from $K = 5$ to $K = 100$. We also compare the main category strategy to the benchmark that has the same proportion in each category. Fig. 3 presents the simulation results. It can be shown that the benchmark with equal proportions in all categories can barely give rise to an optimal *HHI*. We can also see that focusing on the main category significantly increases the probability that *HHI* remains optimal as compared to the benchmark. A proportion between 75 % and 85 % on the main category leads to the highest probability of achieving the best performance. To summarize, introducing a variety of categories to creators' profiles may have beneficial effects on the growth of followers, but only at a moderate level. Our findings suggest a simple yet effective strategy that helps creators achieve the best growth rate of followers when extending variety, that is, maintaining the main category that comprises 75 % to 85 % of the videos in the profile.

6. Conclusion

To the best of our knowledge, this study is the first empirical investigation of the learning-by-doing effects in the context of content creation on a music streaming platform. We found evidence that creators achieve benefits from their prior experiences in producing videoos. Experienced creators who have produced more videos will have a higher growth rate of followers. We also explore the impact of specialization on learning. Our findings show that specialized experience across distinct

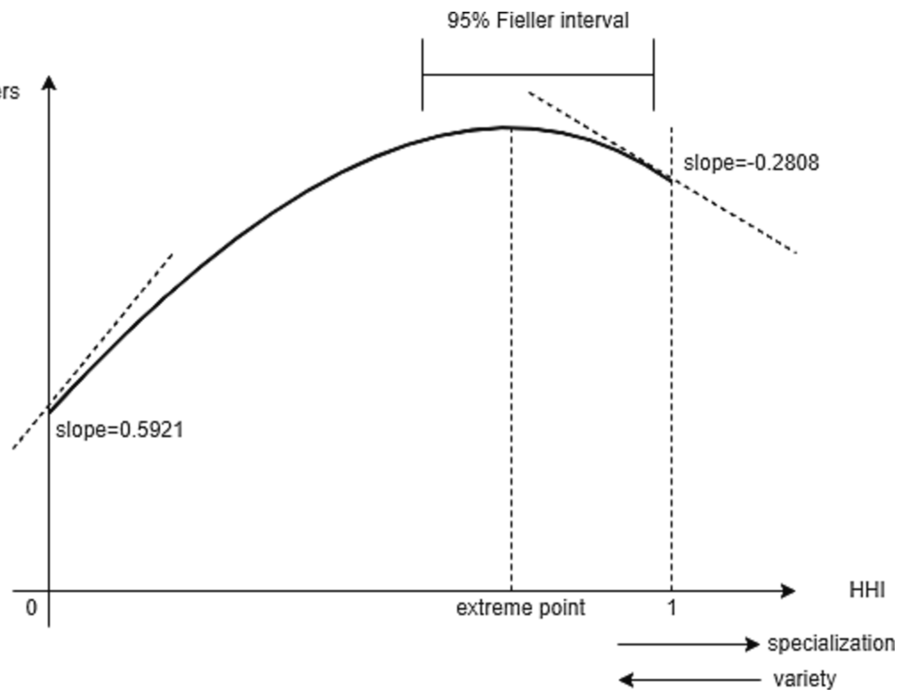

Fig. 2. Inverted U-Shape Curve.

Table 5
Coefficient Estimates and Standard Errors of Mixed-effect model Alternative Measure.

Variable	Dependent Variable: $Lnlike_T$ (1)	(2)	(3)	(4)	(5)
exp_i		0.1426***	0.0888***	0.0835***	0.0888***
		(0.0111)	(0.0156)	(0.0154)	(0.0155)
HHI_i			0.1551***		0.3121***
			(0.0316)		(0.1422)
HHI_i^2				−0.1395***	−0.3824***
				(0.0252)	(0.1135)
$gender_i$	−0.1529***	−0.1604***	−0.1591***	−0.1592***	−0.1597***
	(0.0156)	(0.0155)	(0.0155)	(0.0155)	(0.0155)
$activity_i$	−0.0103*	−0.0159***	−0.0172***	−0.0175***	−0.0174***
	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)
$Ln\ registered_i$	−0.0973***	−0.0980***	−0.0966***	−0.0963***	−0.0962***
	(0.0157)	(0.0155)	(0.0156)	(0.0156)	(0.0156)
intercept	1.3261***	1.2124***	1.3939***	1.3786***	1.3027***
	(0.0397)	(0.0404)	(0.0548)	(0.0504)	(0.0610)
Random Effects Parameters					
$\widehat{\sigma_{u1}}$	0.1263	0.1071	0.1083	0.1070	0.1048
$\widehat{\sigma_{u0}}$	0.5571	0.5594	0.5591	0.5595	0.5599
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
Number of Observations	57,073	57,073	57,073	57,073	57,073
Number of Groups	22,894	22,894	22,894	22,894	22,894

Notes. Standard errors are shown in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

video categories has a non-linear effect on creators' performances. Both creators with overly specialized experience in a few categories and creators with overly diverse experience in a range of categories will have a lower growth rate of followers compared to creators with balanced experience of the specialized and diverse tasks.

In addition to contributing to an empirically grounded study of learning in emerging music streaming platforms, our study has several implications for managerial practice. First, our findings highlight the need for content creators on streaming platforms to proactively maintain a profile that properly balances specialization and diversification of video categories. While there is no surprise that extending creators' experience portfolios with new video categories has a non-linear effect on performance, the optimum level of specialization is still unclear. To what extent, from 0 % to 100 %, should content creators on streaming platforms span their video categories? Our study fills the gap by providing an actionable index that helps content creators obtain a higher growth rate of followers, which is a key measure of success in social networks (Mozas-Moral et al., 2016). The results suggest content creators may focus on the main category that comprises 75 % to 85 % of the videos in the profile. Second, our findings also shed light on the strategies of streaming platforms that rely on user-created content. Maintaining a large number of active users is crucial to the success of these platforms, and the key to engaging users is the productivity of content creators. The platform can make policies to encourage overly

Table 6
Coefficient Estimates and Standard Errors of sys-GMM with Alternative Measure.

	Dependent Variable: $Lnshare_{it}$				
Variable	(1)	(2)	(3)	(4)	(5)
$Ln\ share_{it-1}$	0.2127***	0.6027***	0.0812	−0.0145	0.2452***
	(0.0733)	(0.0109)	(0.0954)	(0.0875)	(0.0419)
exp_i		0.0120***	0.0170*	0.0268***	0.0123***
		(0.0015)	(0.0111)	(0.0059)	(0.0037)
HHI_i			0.2784**		1.4461***
			(0.1176)		(0.2059)
HHI_i^2			.	−0.5119***	−1.4211***
				(0.1260)	(0.1947)
$Ln\ like_{it-1}$	0.3111***	0.1130***	0.2565***	0.4186***	0.2516***
	(0.0535)	(0.0140)	(0.0915)	(0.0772)	(0.0185)
$Ln\ check\_profile_{it-1}$	0.0069	0.0247**	0.5866***	−0.0421	−0.0546
	(0.0578)	(0.0105)	(0.0602)	(0.0664)	(0.0396)
$Ln\ comment_{it-1}$	−0.3022***	−0.0264	−0.3799***	−0.3305***	−0.0233
	(0.0585)	(0.0187)	(0.1067)	(0.0889)	(0.0999)
$gender_i$	0.1788**	0.0663***	0.1547	0.0901	−0.2818***
	(0.0838)	(0.0149)	(0.3010)	(0.1998)	(0.0998)
$activity_i$	−0.0692	0.0653***	−0.1714	−0.1231	0.2006***
	(0.0688)	(0.0062)	(0.1347)	(0.1346)	(0.0194)
$Ln\ registered_i$	−0.2414***	−0.1667***	0.1049	−0.2510*	−0.5234***
	(0.0277)	(0.0131)	(0.2249)	(0.1324)	(0.0422)
$Ln\ followers_i$	0.0726***	−0.0325***	−0.616	−0.1170	−0.0196
	(0.0104)	(0.0019)	(0.0620)	(0.0409)	(0.0235)
Time Dummies	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes
Hansen J-test of overidentifying restrictions (P-value)					
	0.405	0.370	0.430	0.380	0.470
Difference-in-Hansen J-test (P-value)					
	0.420	0.470	0.500	0.450	0.520
Arellano and Bond AR(2) test (P-value)					
	0.092	0.839	0.667	0.486	0.098
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
Number of Observations	452,480	452,480	452,480	452,480	452,480
Number of Groups	21,537	21,537	21,537	21,537	21,537

Notes. Robust standard errors are shown in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

specialized/diverse creators to optimize their experience portfolios.

For future research, one can take advantage of the rich information in the NetEase dataset and explore the multifaceted effect of learning-by-doing. For example, the dataset contains detailed information on the watch time an app user interacts with the videoo. Therefore, survival analysis can be used to examine the effects of learning on user engagement in addition to the growth rate of followers.

CRediT authorship contribution statement

Yang Li: Conceptualization, Methodology, Software. **Yanni Ping:** Writing – original draft. **Yuyun Zhong:** Investigation. **Ram Misra:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

We discuss the assumptions of our system GMM estimator and provide detailed proofs of moment conditions. We modify and extend the proofs by Yoganarasimhan (2012) to include a time-specific term λ_t. First, we make the following assumptions regarding the model.

A1. $E\varepsilon_{it} = E\mu_i = 0$ and.$E\varepsilon_{it}\mu_i = 0 \forall i, t$

- We follow the fixed-effect specification in panel data.

A2. $E\varepsilon_{it}\varepsilon_{is} = \sigma_i^2$ if $s = t$, and 0 otherwise.$\forall i, s, t$

- Idiosyncratic errors are assumed to be serially uncorrelated and heteroskedastic across creators.

A3. $E\mu_i\mu_j = \sigma_\mu^2$ if $i = j$, and 0 otherwise.$\forall i, j$

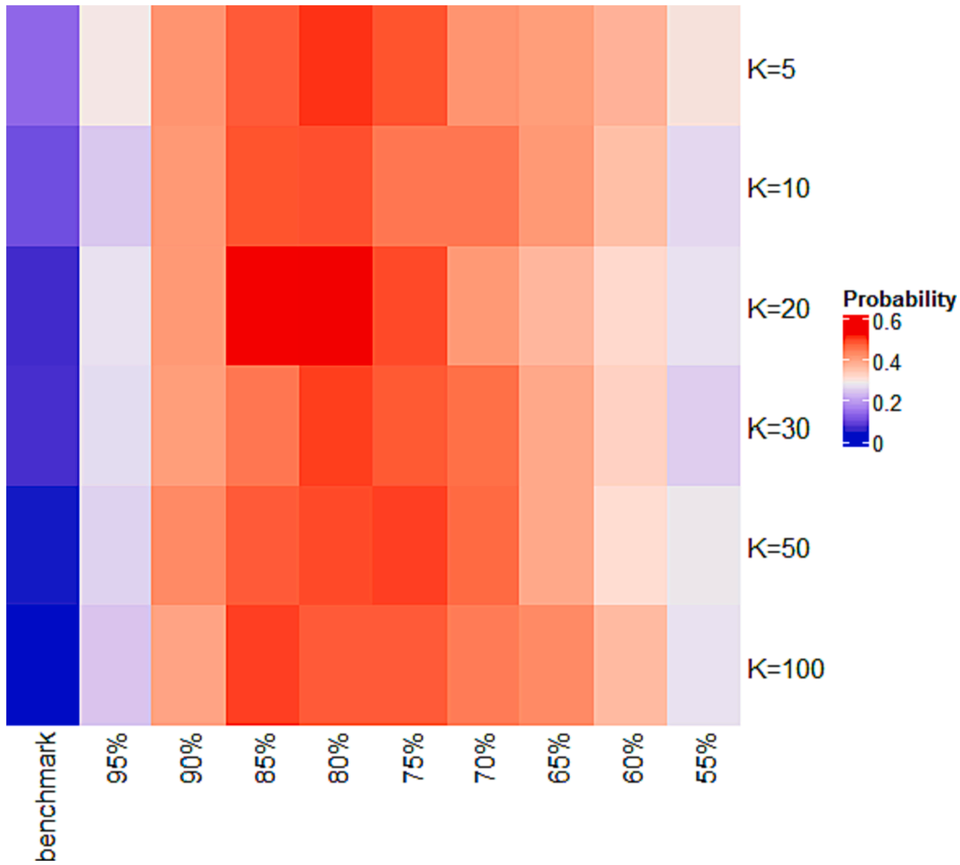

Fig. 3. Simulation of Category Strategies.

- We assume that there is no spatial correlation between cross-sectional units. Therefore, unobserved creator-specific effects from different users are uncorrelated.

A4. $EX_{it}\varepsilon_{is} \neq 0$ if $t \geq s$, and 0 otherwise.$\forall s, t$

- Idiosyncratic errors in the future are interpreted as unexpected shocks and thus are assumed to be uncorrelated with creators' performance in the past.

A5..$EX_{it}\mu_i \neq 0 \forall i, t$

- There may exist unobserved creator-specific effects that impact time-varying control variables. For example, creators who can produce high-quality videos are also likely to receive more comments and likes.

A6. $EZ_i\mu_i \neq 0$ and.$EZ_i\varepsilon_{it} \neq 0 \forall i$

- We also allow unobserved creator-specific effects that confound the learning effect and treat Z_i as an endogenous variable. For example, creators who have received sponsorship will have more resources and are more likely to attract new followers by producing high-quality videos.

A7. $E\lambda_t = 0$ and.$E\varepsilon_{is}\lambda_t = 0 \forall i, s, t$

- We assume a time-specific effect that is uncorrelated with idiosyncratic errors.

A8. $EX_{is}\lambda_t \neq 0$ if $s > t$, and 0 otherwise.$\forall s, t$

- The time-specific effect in the future is assumed to be uncorrelated with the time-varying control variables from the past. For example, breaking news or trending topics in the future have no impact on the number of comments and likes the creator has previously received.

A9. $E\lambda_t\lambda_s = \sigma_\lambda^2$ if $s = t$, and 0 otherwise.$\forall s, t$

- Similar to idiosyncratic errors, time-specific effects are assumed to be serially uncorrelated.

A10..$E\mu_i\lambda_t = 0 \forall i, t$

- Since μ_i proxies the creator-specific unobservables before the sample period, we assume that time-specific effects in the future, i.e., shocks, are uncorrelated with these unobservables.

A11..$EZ_i\lambda_t = 0\forall i, t$

- We investigate the effect of learning across creators and define the learning variable before the sample period. Therefore, breaking news and trending topics are not correlated with learning in the past.

A12. We assume the time-varying control variables X_{it} and time-invariant learning variable Z_i are linearly correlated with μ_i so that the creator-specific effect can be diminished by taking the first difference. Therefore, we can disentangle the effect of μ_i and rewrite the covariates as.
$X_{it} = \theta_X X'_{it} + \kappa_X\mu_i + \eta_{it}$ A12.1.
And.
$Z_i = \theta_Z Z'_i + \kappa_Z\mu_i + \xi_i$ A12.2.
where X'_{it} and Z'_i is uncorrelated with X_{it} and Z_i, respectively. Random shocks are denoted by η_{it} and ξ_i such that $E\eta_{it}\mu_i = E\xi_i\mu_i = 0$.
A13. Initial conditions assumption: Since Equation (1) holds when $t \geq 2$. We assume Lny_{i1} can be expressed as

$$Lny_{i1} = \alpha + \frac{1+\delta\kappa_X+\gamma\beta\kappa_Z}{1-\gamma}\mu_i + \beta Z_i + \lambda_1 + \varepsilon_{i1}$$

We now show that the effect of μ_i on Lny_{it} is constant for all periods $t \geq 1$.

Lemma 1. *The effect of the unobserved fixed effect μ_i on Lny_{it} is constant for all periods and is equal to $\mu_0 = \frac{1+\delta\kappa_X+\beta\kappa_Z}{1-\gamma}$. Furthermore, Lny_{it} can be decomposed to a time-invariant term $\mu_0\mu_i$, and a time-varying term $f_t(Z'_i, I_t)$, where $f_t(.)$ is a time-varying function and I_t is a vector of covariates that contains information up to period t such that $E\mu_i f_t(Z'_i, I_t) = 0$.*

Proof: We prove Lemma 1 using mathematical induction.
1 We first show that Lemma 1 holds when $t = 1$. By substituting for Z_i in assumption A13, we can express Lny_{i1} as:

$$Lny_{i1} = \alpha + \frac{1+\delta\kappa_X+\gamma\beta\kappa_Z}{1-\gamma}\mu_i + \beta\theta_Z Z'_i + \beta\kappa_Z\mu_i + \beta\xi_i + \lambda_1 + \varepsilon_{i1}$$

$$= \alpha + \frac{1+\delta\kappa_X+\beta\kappa_Z}{1-\gamma}\mu_i + \beta\theta_Z Z'_i + \beta\xi_i + \lambda_1 + \varepsilon_{i1}$$

From assumptions A1, A10, and A12, we know ε_{i1}, λ_1, Z'_i, and ξ_i are uncorrelated with μ_i. Therefore, Lny_{i1} can be decomposed to a linear term of μ_i, and a term independent of μ_i. Let $\mu_0 = \frac{1+\delta\kappa_X+\beta\kappa_Z}{1-\gamma}$ and $f_1(Z'_i, I_1) = \beta\theta_Z Z'_i + \beta\xi_i + \lambda_1 + \varepsilon_{i1}$. We can thus get $Lny_{i1} = \alpha + \mu_0\mu_i + f_1(Z'_i, I_1)$ with $E\mu_i f_1(Z'_i, I_1) = 0$.
2 We now show that Lemma 1 holds when $t = 2$. By substituting for Lny_{i1}, Z_i, and X_{i1} in Equation (1), we can express Lny_{i2} as:

$$Lny_{i2} = \alpha + \gamma Lny_{i1} + \beta Z_i + \delta X_{i1} + \mu_i + \lambda_2 + \varepsilon_{i2}$$

$$= (1+\gamma)\alpha + \frac{1+\delta\kappa_X+\beta\kappa_Z}{1-\gamma}\mu_i + (1+\gamma)\beta\theta_Z Z'_i + \delta\theta_X X'_{i1} + (1+\gamma)\beta\xi_i + \delta\eta_{i1} + \gamma\lambda_1 + \lambda_2 + \gamma\varepsilon_{i1} + \varepsilon_{i2}$$

As before, ε_{i1}, ε_{i2}, λ_1, λ_2, X'_{i1}, Z'_i, η_{i1} and ξ_i are uncorrelated with μ_i because of assumptions A1, A10, and A12. Therefore, the coefficient of μ_i is $\mu_0 = \frac{1+\delta\kappa_X+\beta\kappa_Z}{1-\gamma}$. Let $f_2(Z'_i, I_2) = (1+\gamma)\beta\theta_Z Z'_i + \delta\theta_X X'_{i1} + (1+\gamma)\beta\xi_i + \gamma\lambda_1 + \lambda_2 + \gamma\varepsilon_{i1} + \varepsilon_{i2}$, we then get $Lny_{i2} = (1+\gamma)\alpha + \mu_0\mu_i + f_2(Z'_i, I_2)$ with $E\mu_i f_2(Z'_i, I_2) = 0$.
3 We then assume Lemma 1 holds when $t = K$ and prove it when $t = K+1$. Accordingly, Lny_{iK} can be expressed as:

$$Lny_{iK} = C_K + \mu_0\mu_i + f_K(Z'_i, I_K)$$

Where C_K is a constant and $E\mu_i f_K(Z'_i, I_K) = 0$.
We then consider Lny_{iK+1} in Equation (1) and substitute for Lny_{iK}, Z_i, and X_{iK}

$$Lny_{iK+1} = \alpha + \gamma Lny_{iK} + \beta Z_i + \delta X_{iK} + \mu_i + \lambda_{K+1} + \varepsilon_{iK+1}$$

$$= \alpha + \gamma C_K + \gamma\mu_0\mu_i + \gamma f_K(Z'_i, I_K) + \beta Z_i + \delta X_{iK} + \mu_i + \lambda_{K+1} + \varepsilon_{iK+1}$$

$$= \alpha + \gamma C_K + \gamma\mu_0\mu_i + \gamma f_K(Z'_i, I_K) + \beta\theta_Z Z'_i + \beta\kappa_Z\mu_i + \beta\xi_i + \delta\theta_X X'_{iK} + \delta\kappa_X\mu_i$$

$$+ \delta\eta_{iK} + \mu_i + \lambda_{K+1} + \varepsilon_{iK+1}$$

$$= \alpha + \gamma C_K + \mu_0\mu_i + \gamma f_K(Z'_i, I_K) + \beta\theta_Z Z'_i + \beta\xi_i + \delta\theta_X X'_{iK} + \delta\eta_{iK} + \lambda_{K+1} + \varepsilon_{iK+1}$$

From assumptions A1, A10, and A12, we know ε_{iK+1}, λ_{K+1}, Z'_i, X'_{iK}, η_{iK} and ξ_i are uncorrelated with μ_i. Let $f_{K+1}(Z'_i, I_{K+1}) = \gamma f_K(Z'_i, I_K) + \beta\theta_Z Z'_i + \beta\xi_i + \delta\theta_X X'_{iK} + \delta\eta_{iK} + \lambda_{K+1} + \varepsilon_{iK+1}$ and $C_{K+1} = \alpha + \gamma C_K$, we can get $E\mu_i f_{K+1}(Z'_i, I_{K+1}) = 0$ and $Lny_{iK+1} = C_{K+1} + \mu_0\mu_i + f_{K+1}(Z'_i, I_{K+1})$. Since Lemma 1 holds when $t = K+1$, we conclude that Lemma 1 holds for all periods. ■.
We can now prove the moment conditions for Equation1 in proposition 1.

Proposition 1. $EX_{ip}(\Delta\varepsilon_{it} + \Delta\lambda_t) = 0$ and $ELny_{ip}(\Delta\varepsilon_{it} + \Delta\lambda_t) = 0$ *when* $p \leq t-2$.

Proof: We start with $EX_{ip}(\Delta\varepsilon_{it} + \Delta\lambda_t) = 0$. From assumption A4, we show that $X_{ip}(p \leq t-2)$ is uncorrelated with ε_{it} and ε_{it-1}. Accordingly,

$EX_{ip}\Delta\varepsilon_{it} = 0$. From assumption A8, we know $X_{ip}(p \le t-2)$ is uncorrelated with λ_t and λ_{t-1}. Thus, we get $EX_{ip}\Delta\lambda_t = 0$. Therefore, $EX_{ip}(\Delta\varepsilon_{it} + \Delta\lambda_t) = 0$. To prove $ELny_{ip}(\Delta\varepsilon_{it} + \Delta\lambda_t) = 0$, we use Lemma 1 and express Lny_{ip} as $C_p + \mu_0\mu_i + f_p(Z'_i, I_P)$. From assumptions A1 and A10, $E\mu_i\Delta\varepsilon_{it} = 0$ and $E\mu_i\Delta\lambda_t = 0$. Since $f_p(Z'_i, I_P)$ contains information up to period $t-2$, it is unlikely that $f_p(Z'_i, I_P)$ is correlated with future time-specific shocks and random shocks, indicating $Ef_p(Z'_i, I_P)\Delta\varepsilon_{it} = Ef_p(Z'_i, I_P)\Delta\lambda_t = 0$. Therefore, $ELny_{ip}(\Delta\varepsilon_{it} + \Delta\lambda_t) = 0$. ■.

We then prove the moment conditions for Equation (2) in proposition 2.

Proposition 2. $E[\Delta X_{ip}(\mu_i + \varepsilon_{it} + \lambda_t)] = 0$ and $E[\Delta Lny_{ip}(\mu_i + \varepsilon_{it} + \lambda_t)] = 0$ *when* $p \le t-2$.

Proof: We start with $E[\Delta X_{ip}(\mu_i + \varepsilon_{it} + \lambda_t)] = 0$. Recall that ΔX_{it} is formulated as linearly correlated with μ_i, we can then diminish μ_i by taking the first difference. From assumption A12, we have $\Delta X_{ip} = \theta_X X'_{ip} - \theta_X X'_{ip-1} + \eta_{ip} - \eta_{ip-1}$ and thus $E\Delta X_{ip}\mu_i = 0$ because X'_{ip} and X'_{ip-1} are terms that are uncorrelated with μ_i and $E\eta_{it}\mu_i = 0$. From assumptions A4 and A8, we have $E\Delta X_{ip}\varepsilon_{it} = 0$ and $E\Delta X_{ip}\lambda_t = 0$ in the sense that future shocks are uncorrelated with the creator's performance in the past. Therefore, $E[\Delta X_{ip}(\mu_i + \varepsilon_{it} + \lambda_t)] = 0$. We then prove $E[\Delta Lny_{ip}(\mu_i + \varepsilon_{it} + \lambda_t)] = 0$. Using Lemma 1, we express ΔLny_{ip} as $\Delta C_p + \Delta f_p(Z'_i, I_P)$. Since ΔC_p is a constant, we prove $E[\Delta f_p(Z'_i, I_P)(\mu_i + \varepsilon_{it} + \lambda_t)] = 0$ instead. We have $E\Delta Lny_{ip}\mu_i = 0$ because Z'_i is uncorrelated with μ_i. Similar to the proof in proposition 1, $\Delta f_p(Z'_i, I_P)$ contains information up to period $t-2$ and it is unlikely that $\Delta f_p(Z'_i, I_P)$ is correlated with future time-specific shocks and random shocks, indicating $E\Delta f_p(Z'_i, I_P)\varepsilon_{it} = E\Delta f_p(Z'_i, I_P)\lambda_t = 0$. Taken together, $E[\Delta Lny_{ip}(\mu_i + \varepsilon_{it} + \lambda_t)] = 0$.■.

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