Master's Thesis of Business Administration

Created with a Silver Spoon?
– Spillover Effects of Management Companies in the Vtuber Market –

'금수저' 인플루언서들의 소속사 기반 스필오버 효과: 브이튜버 시장을 중심으로

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Graduate School of Business
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Abstract

Increasing usage of social media has given subsequent birth to micro-celebrities, or social media influencers (SMIs). Despite the fact that SMIs function as key opinion-leaders in society and the market, little is known about what traits make an SMI popular in the first place. While SMIs are generally considered to gain popularity from rock-bottom through individual endeavors alone, we find an exceptional media sector consisting of virtual YouTubers (vtubers). A vtuber, unlike the usual human YouTuber, is an artificially created figure strictly managed by sponsoring companies from the beginning of his/her debut. Finding a similarity between sponsor-vtuber relationships and parent-child relationships within brand extensions, we ran a random effects model against 560 company-owned vtubers to check whether similar spillover effects can be observed in a social media context as well. Our research yielded positive results, suggesting the existence of persistent spillover effects based on parent-brand popularity. An additional time series analysis was conducted against the weekly changes in the size of management agency influence on their affiliated vtubers. An ARIMA(1,2,0) model demonstrates a high fit with our data, and we find that the model confirms a constantly decreasing size of influence along with the passage of time.

Keyword : spillover effect, virality, social media influencer (SMI)
Student Number : 2019-24640

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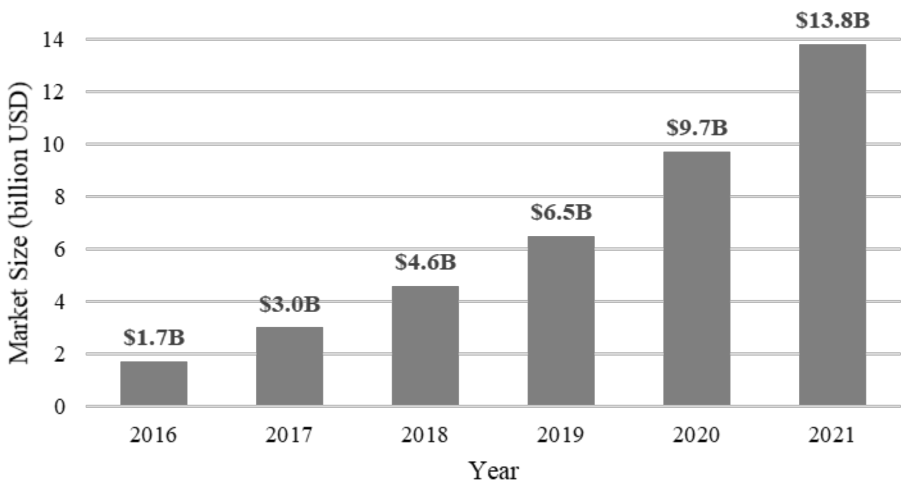
Chapter 1. Introduction

Social media has long since become an essential part of everyday life. Various social media platforms such as Twitter, Facebook, Instagram, and YouTube serve diverse purposes for both corporate and individual users, including information exchange, campaign/product promotion, and entertainment. The 2020 GlobalWebIndex survey found that "96% of US and UK consumers who followed influencers are engaging with them more or to the same extent as before the coronavirus outbreak," insinuating that the pandemic may have contributed to the growth of SMIs. Although there is no official published record so far, it is estimated that a top-tier YouTuber earns more than $20 million annually (Berg & Brown, 2020). Novel terms have been created to stratify SMIs into different groups (e.g., micro-influencers, nano-influencers, kidfluencers, virtual/computer-generated influencers) depending on their personal characteristics or levels of popularity.

Figure 1. Estimated Influencer Marketing Growth (YOY)



SMIs not only are lucrative models for the individuals themselves, but also serve as appealing resources for corporate bodies. Social media has taken on the role as a market channel for companies to advertise themselves or their products directly to their target consumers. The market for SMI advertising is expected to expand to $13.8 billion in 2021, and a 300% increase in corporate utilization of micro-influencers has been observed between 2016 and 2020. While large companies have nearly doubled the number of creators they activate per campaign since 2018, finding the appropriate influencers and avoiding influencer fraud is also one of the major challenges that they face (Influencer Marketing Hub, 2021).

A social media user's size of influence and success is generally determined through the number of other users he/she can reach through a post or upload. Within the YouTube platform, this is measured through the number of subscribers for each channel. A large fanbase ensures a stable number of views, which in turn promises greater profits for the creator, generally through inserted or direct advertisements included in his/her videos. A common tactic used by social media users is to focus on generating viral content in order to attract a large follower or subscriber base. Nevertheless, while many researchers have focused on individual content that enjoys virality on social media, there is little studied on a user/account-scale and what makes a social media figure inherently more appealing to other users. It is not uncommon to see specific challenges or keywords trending on social media, but not all creators benefit equally even as they tackle similar issues. This study aims to contribute to the body of research on social media popularity by focusing on individual YouTube channels and identifying channel-specific sources of popularity.

Vtubers, or virtual YouTubers, are a relatively novel form of YouTube creators. They are most different from regular YouTubers in that they are not actual human beings, but 2D/3D-rendered animation characters. Voice actors remotely control the characters behind the screen through motion-sensing technology, but never appear directly on any uploaded video. Since vtubers are virtual figures, they do not age or die. The voice actors are always substitutable because they are given little freedom in terms of their activities and are mainly instructed to behave based on each character's predesigned profile. This gives vtuber managing companies one huge advantage, which is that they gain, at least in theory, an everlasting source of profit. The vtuber industry officially kicked off from the debut of Kizuna Ai in October 2016. Once Kizuna Ai proved herself realistically capable of leading a huge fandom, other companies rapidly joined the competition with their own vtuber models. Current vtubers take on various occupations such as online game streamers, idol singers, cooks, weather forecasters, and even regional ambassadors.

While vtubers often benefit greatly from technological and financial support from the companies that own them, we have found that this strong and explicit relationship with the companies may influence vtuber accomplishments in more implicit ways: through spillover effects. Through this study, we attempt to address the following research question:

Do SMIs signed up with management agencies benefit from the popularity of their affiliated companies?

Chapter 2. Literature Review

2.1. Halo (Spillover) Effect

Janakiraman et al. (2009) defined the spillover effect as "when customers transfer their quality perceptions across brands from an existing brand to form the prior perception of quality of a new brand." In a more general sense, it refers to "the extent to which information provided in messages change beliefs about attributes that are not mentioned in the messages" (Ahluwalia, 2001). This concept has been expansively applied to include not only brand-to-brand affiliations, but brand-to-personnel affiliations and product-to-personnel affiliations as well.

The spillover effect is based on the accessibility-diagnosticity theory. This theory implies that “if people think information for brand X is accessible and diagnostic of brand Y (i.e., informative about), they will use perceptions of brand X's quality to infer quality of brand Y” (Feldman and Lynch, 1988). Halo effects, which are commonly used as corollaries of the spillover effect, generally refer to positive influence exchanges between different brands. Nevertheless, perverse halos—negative spillovers—have also been observed where negative online chatter about one brand’s product adversely affects the sales and images of competing products both within and across brands (Borah & Tellis, 2016).

2.1.1. Brand Extension Spillovers

On a brand-to-brand scale, spillover effects are commonly witnessed during brand extensions, where the vertical or categorical extension influences the brand image of its parent brand. Balachander and Ghose (2003) used scanner panel data on yogurt and detergent products to observe a reciprocal spillover effect between parent and child brand advertising. They found strong and consistent support of a positive spillover effect from advertising of a child on choice of a parent brand, but no significant effect in the reverse direction. Vertical extensions tend to affect brands in symmetrical ways (the brand is hurt by low-tier models just as much as it is boosted by high-tier models), and brand quality effects are more salient than variety effects, although the latter tends to be more noticeable if external brands are available for comparison (Palmeira et al., 2019). Spillover effects yield different outcomes depending on the industry, so high-end businesses such as luxury brands are encouraged to strategically avoid spillover effects when making line extensions to avoid unnecessary brand dilution (Boisvert & Ashill, 2018). A comprehensive research by Pina et al. (2013) took three elements into consideration: characteristics of the parent brand (luxury vs. non-luxury), extension type (goods vs. services), and country (Spain, U.K., and Italy). They observed that the fit between the parent brand and the extension were most influential on consumer evaluation, especially if the parent brand was associated with durable goods than services. The effect of brand image on extensions was weaker when the extension was in a different sector from its parent brand. Lane and Fatsoso (2016) studied the effect that advertisements have on spillover effects in the process of brand extensions. They stipulate that advertisements are capable of mediating spillover effects between low-fit extensions and their respective parent brands (Lane & Fatsoso, 2016). The size of this influence is large enough to even switch the initial valence (positivity or negativity) of the effects in the opposite direction.

2.1.2. Competition Spillovers

Promotional activities are closely related to inducing spillover effects between competing brands. An advertisement of a certain product can boost the sales of its complementary goods while diminishing sales of substitutable goods (Liu et al., 2017). Li and Lopez (2015) developed a model based on linear and constant elasticity of substitution (CES) advertising production functions to confirm that brand advertising has a strong and positive effect across brands belonging to the same company while competitor advertising yields negative effects. Sahni (2016) observed that advertisement intensity affected the degree of spillover effects and posited that while restaurants advertised with low frequency generated spillover benefits for their competitors, such effects gradually diminished along an increase of advertisement intensity and displayed more focused sales increases for the advertiser.

2.1.3. eWOM / Consumer Perception Spillovers

The scale of spillover effects can be amplified or moderated depending on consumer perceptions of the product or associated brand. Bowden et al. (2017) discovered that the valence of online brand community (OBC) engagement is positively correlated with the degree of consumer brand engagement. A comparative experiment on consumers with different degrees of brand engagement showed that compared to low-commitment subjects,

Table 1. Literature on Spillover Effects (Spillover Context x Measured Variables)

		focal product price	product features	product category	industry	own advertisement	parent-/child-brand advertisement	competitor advertisement	competitor performance	media citation	brand image	brand loyalty	negative corporate events	key brand developments	brand extension direction (low vs. high)	perceived fit of extension	consumer professionalism	consumer engagement	country
Brand Extension Spillover	Balachander & Ghose (2003)	O	O			O	O					O							
	Pina et al. (2013)			O	O						O					O			O
	Lane & Fatsoso (2016)						O									O	O		
	Boisvert & Ashill (2018)					O									O				
	Palmeira et al. (2019)														O				
Competitive Spillover	Li & Lopez (2015)	O	O			O													
	Borah & Tellis (2016)					O				O			O	O					O
	Sahni (2016)		O			O													
	Liu et al. (2017)							O	O										
eWOM / Consumer Perception Spillover	Ahluwalia (2001)										O	O							
	Nottorf & Funk (2013)			O	O	O													
	Bowden et al. (2017)							O										O	
	Chae et al. (2017)			O					O										
	Sanchez et al. (2020)	O				O													
	Fan et al. (2020)												O					O	
	Hsiao et al. (2020)																	O	

high-commitment subjects showed a lower magnitude of attitude change toward negative information and a higher magnitude of change toward positive information about the brand (Ahluwalia, 2001). Simple brand exposure through paid search advertising also contributes to spillovers from generic search activities to brand-related awareness and corresponding activities, though the sizes of the effect differ depending on the industry (Nottorf & Funk, 2013).

Spillover effects can also result from external forces, such as third-party endorsements (e.g. celebrity presentations) and word-of-mouth (WOM) influences. Seeded WOM campaigns have found to generate spillover effects on the brand- and category-level beyond the promotion of the focal product (Chae et al., 2017). Diagnostic electronic WOM can potentially even have a stronger effect on the sales of competitive brands than actual advertisements by creating more product-specific buzz which negatively affects competing products, whereas typical advertisements would benefit competitors by simulating category-related WOM (Sanchez et al., 2020).

Sometimes spillover effects are not necessarily limited to the market because of the existence of brands closely affiliated with, or run by, specific countries. It has been studied that the presence of large national brands has a positive spillover effect on the popularity and product sales of private labels in fashion social media (Hsiao et al., 2020). Depending on the pre-established national image, the impact of a product failure such as a product recall can reach beyond individual brands to entire countries (Fan et al., 2020).

2.2. Microcelebrities

Celebrities are often incorporated as an important part of marketing strategies for raising consumer interest. They are also referred to as "human brands," or famous people whose marketing and communication efforts are professionally managed (Thomson, 2016). The majority of celebrity research have focused on the effect that celebrities have on the products they advertise or star in, while very few investigate what fundamentally generates celebrity fame. Numerous studies focusing on the role of celebrities as endorsers suggest that such use of celebrities can substantially enhance advertising effectiveness and financial success based on various success measures such as advertising efficiency, product sales, and firm value (Mowen & Brown, 1981; Misra & Beatty, 1990; Petty, Cacioppo, & Schumann, 1983; Agrawal & Kamakura, 1995). Other literature predominantly attest to a positive relationship between celebrity power and the performance of entertainment products (De Vany & Walls, 2004; Hamlen, 1991; Schmidt-Stölting et al., 2011, Hennig-Thurau et al., 2013).

Little has been studied about the antecedents and dynamics of human brand equities or the reciprocal effects exerted on celebrities by products or endorsements that they endorse. Only a few scholars have taken attitudinal brand value measures into account, including the strength of consumer-celebrity relationships (Thomson, 2006), stars' longitudinal favorability ratings (Luo et al., 2010), or the perceived credibility/likeability of celebrity endorsers (Tripp et al., 1994).

Khamis et al. (2017) defined microcelebrity as "a set of practices that courts attention through insights into its practitioners' private lives, and a sense of realness that renders their narratives, their branding, both accessible and intimate." In other words, microcelebrities are popular figures who, unlike traditional celebrities who are mostly inaccessible beyond the screen, impose a much more familiar image as an ordinary person and intimately communicate with their fans through various social media routes.

SMIs are typical examples of microcelebrities. They are users who have highly established credibility for a specific industry (Hearn & Schoenhoff, 2016; Doyle, 2008) and generally have connections with large audiences with whom they share mutual trust and support based on their authenticity and position (Lou & Yuan, 2019). Influence is defined as "the act or power of producing an effect without apparent exertion of force or direct exercise of command" or "the power or capacity of causing an effect in indirect or intangible ways" (Merriam-Webster Dictionary). Influence is generally measured through the propagation of content through platforms such as Twitter (Aswani et al., 2017a; Bakshy et al., 2011; Cha et., 2010), Facebook (Aswani et al., 2017b; Cavalli et al., 2011), and GitHub (Bana and Arora, 2018). Hence, we may link influence back to the concept of social media virality/popularity.

Influencers are also viewed as third-party endorsers who divert audience attitude through various social media platforms (Freberg et al., 2010). Literature highlights that the SMI community plays the role as the market's "opinion leaders" who exercise significant power over brand perceptions (Childers et al., 2018) and strongly influence consumers' attitudes and behaviors (Godey et al., 2016). SMIs' market power is exerted usually via word of mouth (Moldovan et al., 2017) based on their superior status, social prestige, personal appeal or expertise (Lin et al. 2018; Xiong et al., 2018).

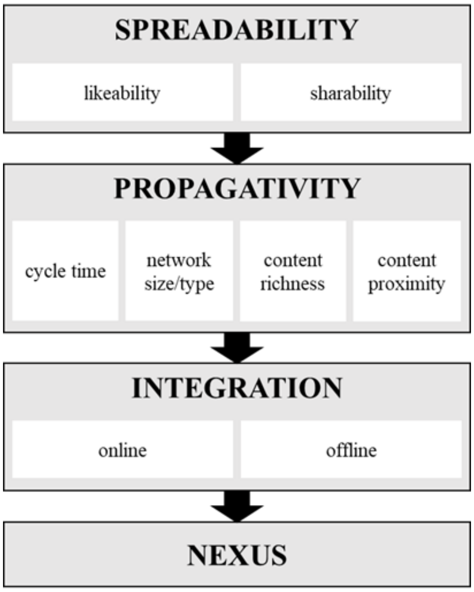
While all users enjoy a certain amount of influence on social media (Bakshy et al., 2011), various methods have been developed to identify particularly powerful SMIs, such as network centrality methods (Carrington et al., 2005; Gómez et al., 2012). Li et al. (2011) developed an artificial neural network-based marketing influential value model for measuring blogger influences in the blogosphere. Cha et al. (2010) utilized the number of followers, the number of retweets, and the number of mentions as proxies for analyzing user influence on Twitter. Wu and Hofman Jake (2011) took a different approach by moving its focus toward the flow of information among different category users instead of individual user rankings. A combined model of a PageRank-based algorithm and the temporal attributes of network nodes and edges were also used to identify trendsetters for a given topic (Saez-Trumper & Comarela, 2012). Liu et al. (2015) developed a product review domain-aware (PRDA) approach to identify influencers and categorize them into three types (i.e., emerging influencers, holding influencers, and vanishing influencers), based on dimensions of trust, domain, and time. Arora et al. (2019) identified engagement, outreach, sentiment, and growth as key components of the influencer index.

While the majority of studies in the stream of SMI research focus on influencer identification, little attention is given to developing predictive models for influencers. Existent literature is heavily limited to identifying already powerful and stable influencers in a temporal snapshot of a dynamic social network. If not void of predictive power, analytical models place an exclusive emphasis on the flow of distributed content rather than the individual characteristics of the users. Moreover, spillover effects in SMI popularity in particular have not been addressed, possibly due to the relatively small population of creators who have any affiliated sponsors. Management companies for human SMIs generally adopt the strategy of scouting already-popular figures instead of investing in promising figures at an early stage, which limits the number of SMIs who manage to receive an opportunity to sign up with a sponsor. This study aims to examine the existence of microcelebrities' management companies as a unique characteristic that exerts external influence on their affiliated SMIs.

2.3. Popularity/Virality on the Social Media

2.3.1. SPIN Framework

Figure 2. SPIN Framework



Virality is defined as "a rapid, large-scale increase in adoption that is driven largely, if not exclusively, by peer-to-peer spreading" (Goel, 2016). This term is often used as a synonym for popularity but with user network characteristics involved, since most social media platforms allow unique forms of information replication and propagation through sharing, retweeting, or regramming. SPIN is a conceptual framework designed to explain causal elements of virality on social media (Mills, 2012). The acronym SPIN is derived from four different phases of virality development (spreadability, propagativity, integration, and nexus). Each phase is based on consumers' personal factors, media type, integration of multiple media platforms, and the reinforcement of messaging, respectively.

Most research investigating social media virality fall within the SPIN framework. Proxies measuring the actual content' s virality generally fall within the likeability and content richness range. Those measuring network characteristics are associated with the network size/type and integration phases. Consumer characteristics generally fall within the spreadability phase. Additional factors involving creator characteristics and affiliated brand image have been studied as well.

2.3.2. Content

As one may intuitively assume, social media content characteristics are important determinants of virality. Content usefulness (Pousttchi & Wiedemann, 2007), emotional appeal (Berger and Milkman, 2009; Heimbach & Hinz, 2016) and content length (Quesenberry & Coolsen, 2019) were found to play a significant role in obtaining social media popularity. Goel et al. (2016) observed that emotional valence and content novelty, or degree of surprisingness, also contribute to virality on Twitter. Tellis et al. (2019) additionally identified emotional valence, length, and informativeness as significant factors influencing online ad virality across multiple social platforms including Facebook, Google+, and Twitter. Contrary to other works, however, they found informativeness to have a negative association. Hoffman et al. (2020) observed that emotional valence and story development were key factors of social media virality when it came to social campaigns. Meanwhile, Qiu et al. (2017) developed an experimental model using empirical data and concluded that content quality may not necessarily be a significant contributor to popularity, indicating a tradeoff between users' discriminative power and information diversity. They also identified an inverted U-shaped relationship between content informativeness and popularity.

2.3.3. Network Characteristics

Because the concept of virality usually involves peer-to-peer propagation, the volume of social media virality has been studied to be closely related with network structures. Researchers have observed social networks with an emphasis on social connections surrounding the content' s origin or general platform structures and sizes (Bampo et al., 2008; Ko et al., 2008; Liu et al., 2012). Khan and Vong (2014) suggested the importance of offline/online social capital (e.g. fan base and fame) in determining the ultimate virality of news articles in social media. Goel et al. (2016) divided network structures into broadcasts and viral diffusion and studied that the ultimate degree of virality is mainly determined by the influence of the former rather than the latter.

2.3.4. Consumer Characteristics

Hoffman et al. (2020) focused on consumer motivation and information processing abilities' effects on content sharing activities based on the Elaboration Likelihood Model (ELM). Other studies have focused on various social, behavioral, and motivational characteristics of the content viewers (Jalilvand and Samiei, 2012; Camarero and San Jose ́, 2011; Bampo et al., 2008; Cheung et al., 2008; Wojnicki and Godes, 2008; Hennig-Thurau et al., 2004). The influential users hypothesis was used to examine the effect of influencer involvement in content sharing on its resulting virality (Iyengar et al., 2011; Marcus and Perez, 2007; Subramani and Rajagopalan, 2003).

2.3.5. Creator Characteristics

Although the SPIN framework encompasses elements about social media content and its consumers, it does not consider specific elements regarding the creators. Nevertheless, recent students have shown that creator characteristics may be significantly related with social media virality. While Khan and Vong (2014) observed that author reputation was insignificant to a news article' s popularity, Goel et al. (2016) observed that news articles are more easily propagated when the author is famous and

Table 2. Literature on Social Media Virality/Popularity

	Content									Network Characteristics				Consumer Characteristics			Creator Characteristics			
	usefulness	quality	emotional appeal	length	emotional valence	novelty	informativeness	story development	attractiveness	social connections of source	platform structure	platform size	offline/online social capital	motivation	information processing ability	influencer effects	reputation	gender	company size	brand price
Alloca (2011)																O				
Bampo et al. (2008)										O	O	O		O						
Berger & Milkman (2009)			O																	
Camarero & San Jose (2011)														O						
Cheung et al. (2008)														O						
Gladwell (2002)																				
Goel et al. (2016)					O	O					O						O	O		
Heimbach & Hinz (2016)			O																	
Hennig-Thurau et al. (2004)														O						
Hoffman et al. (2020)					O			O						O	O					
Iyengar et al. (2011)																O				
Jalilvand & Samiei (2012)														O						
Khan & Vong (2014)													O				O			
Ko et al. (2008)										O	O	O								
Liu et al. (2012)										O	O	O								
Marcus & Perez (2007)																O				
Pancer & Poole (2016)		O																		
Porter & Golan (2007)									O											
Pousttchi & Wiedemann (2007)	O																			
Quesenberry & Coolsen (2019)				O															O	
Qiu et al. (2017)		O					O													
Subramani & Rajagopalan (2003)																O				
Tellis et al. (2019)				O	O		O													O
Wojnicki & Godes (2008)														O						

additionally stated that greater virality was achieved when the author was female. Other research focused on product advertisement propagation. Quesenberry and Coolsen' s (2019) analysis of 155 viral ad videos revealed that the size of the companies releasing the videos were positively correlated with video virality. In a similar fashion, Tellis et al.

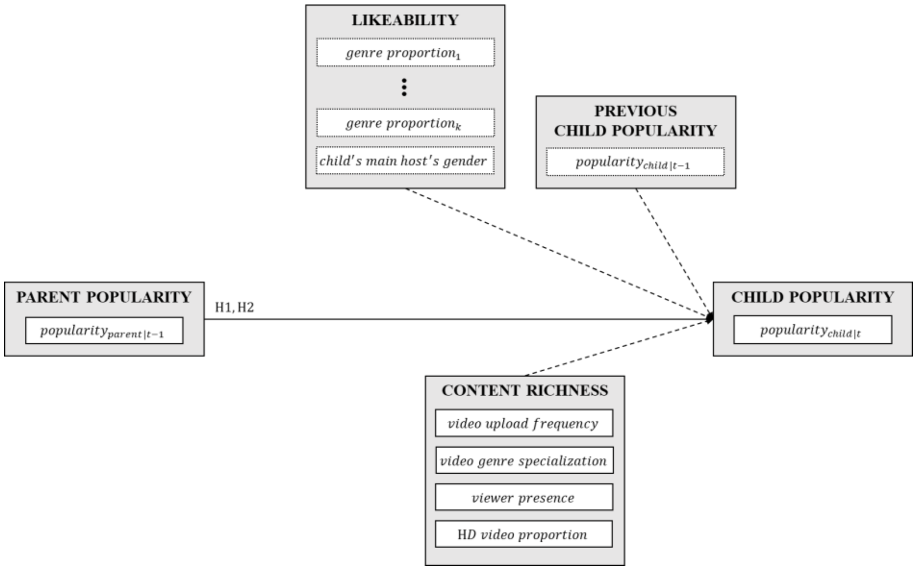
(2019) stated that associated brand price was also a significant contributing factor to promoting video sharing behavior across multiple social media platforms.

Chapter 3. Research Model and Hypotheses

3.1. Research Model

Taking the SPIN framework into consideration, we assume that management companies affect three different elements leading to popularity: likeability, content richness, and network size/type. The other elements—sharability, cycle time, content proximity, online/offline integration—are either unaffectable consumer traits or systematically identical on the YouTube platform for all creators.

Figure 4. Research Model



While the main objective is to observe the influence that parent popularity has on subsequent child popularity, we include additional variables within our model to control for additional effects on the observed variable.

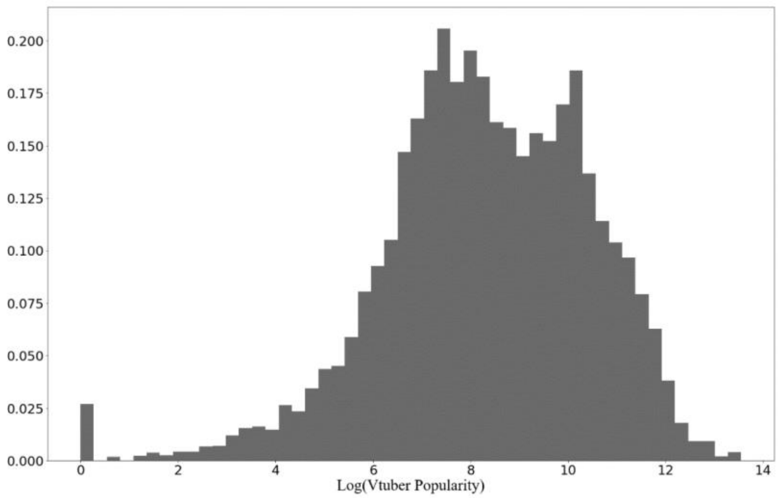
3.2. Variables

The research model is expressed through the following equation.

$$\begin{aligned}\log(CP_{it}+1) = {} & \beta_1 * \log\left(PP_{i(t-1)}+1\right) + \beta_2 * \log(Fq_{it}) + \beta_3 * S_{it} + \beta_4 * VP_{it} \\ & + \beta_5 * HDP_{it} + \beta_6 * GP_{1it} + \cdots + \beta_{19} * GP_{14it} \\ & + \beta_{20} * \log\left(CP_{i(t-1)}+1\right) + \delta_1 * M_i + \delta_2 * F_i + \epsilon\end{aligned}$$

CP_{it} and PP_{it} each denote the cumulative popularity of child i and its parent by the end of week t. These are measured by calculating the cumulative number of subscribers obtained by vtuber i and its affiliated managing company. Those companies which do not run separate YouTube channels were treated as having no subscribers, since this variable represents the scale of influence each company exerts to the YouTube audience. CP_{it} was log transformed to be closer to a normal distribution. Accordingly, PP_{it} and Fq_{it} were also log transformed to suffice an approximately linear relationship with the dependent variable.

Figure 5. Vtuber Popularity Distribution



Based on previous research on social media virality, we add control variables that account for content richness, likeability, and network size/type factors. including vtubers' gender and video genre concentration. In addition, we consider vtubers' degrees of popularities (numbers of subscribers) obtained the week prior to the time frame of interest.

Content richness control variables include $\boldsymbol{Fq_{it}}$, $\boldsymbol{S_{it}}$, $\boldsymbol{VP_{it}}$, and $\boldsymbol{HDP_{it}}$. $\boldsymbol{Fq_{it}}$ refers to the average number of weekly video uploads by vtuber *i* by the end of week *t*. $\boldsymbol{S_{it}}$ is calculated by adding the proportions of each channel's two most prominently focused genres. This variable is meant to measure the strength of a vtuber's identity. While some creators cover more diverse subject matters in their videos, some are strictly dedicated to one or two specific genres. We assume that the stronger an identity is, the easier it is to attract a greater number of viewers who steadily remain steady fans (i.e., subscribers). $\boldsymbol{VP_{it}}$ refers to the level of viewer presence presented by channel *i*. Viewer presence is measured by the proportion of videos that support 3D technology. 3D view is often a common proxy used to measure media richness (Lu et al., 2014) because a "3D view of spaces enhances users' viewing experience of a space much like when they are physically in the space because they can explore it realistically from a variety of angles" (Ganapathy et al., 2004) and provide viewers the sensation of "being there" in a scene (Li et al., 2002). $\boldsymbol{HDP_{it}}$ represents channel *i*'s proportion of high-definition videos among the entire list of uploads until week *t*.

Likeability variables were measured through individual genre concentration levels and creator genders. YouTube requires creators to classify their uploaded videos into one of 15 different categories. We considered the possibility that viewer subscription volumes may be affected by absolute differences in the fandom size of each genre (Wu & Hofman Jake, 2011). Thus, we included genre proportions of each vtuber channel as a control variable to level out any fundamental differences in viewer preferences for each genre category. $GP_{1it}, \cdots, GP_{14it}$ refer to 14 different video genres pre-defined by YouTube. The specific genres include Autos & Vehicles, Comedy, Education, Film & Animation, Gaming, Howto & Style, Music, News & Politics, Nonprofits & Activism, People & Blogs, Pets & Animals, Science & Technology, Sports, and Travel & Events. The Entertainment genre was treated as a base case to avoid multicollinearity issues.

M_i and F_i are dummy variables indicating the inclusion/exclusion of male and female figures among the channel hosts. These variables were defined separately to be able to incorporate multi-creator channels run by mix-gender groups and vtubers who are gender-neutral or intentionally conceal their sexual identities.

3.3. Hypotheses

Within a spillover effect context, a sponsor-creator relationship assumes a form similar to that of a parent-child relationship in a brand extension. There is a clear hierarchical relationship between the two entities, and a single company has the authority to decide whether or not to expand its pool of affiliated creators, each with a different concept and target viewer group just like any corporate brand extension. It is reasonable to expect to observe spillover effects from the management companies to their affiliate vtubers, since it is common for vtubers to explicitly reveal their management agencies through directly mentioning the company name in their videos or, more commonly, including the company emblem in their YouTube banners. Many sponsors such as Nijisanji and Honeystrap run their own company channels where they constantly interact with the viewers through updated videos of their vtubers and upcoming company-wide events. Since the target consumer group for vtubers centers around YouTube users, we may assume that the degree of spillover effects will differ depending on potential viewers' familiarity with the vtuber management companies. Thus, companies that possess a greater number of subscribers for their corporate YouTube channels are prone to enjoy greater spillover effects than those which do not. Based on such logic, we test the following hypothesis:

H1: Greater popularities of parent-brands will have a positive effect on the popularity of their respective child-brands.

In addition, we assume that there will be a difference between the influence of parent-brands along with the passage of time. The longer a vtuber continues his/her activities and the more solid his/her fandom base becomes, the more independent he/she is likely to become from the influences of the management agency. Based on this assumption, we propose the following hypothesis:

H2: A parent-brand's influences on its child-brand's popularity will decrease as time elapses.

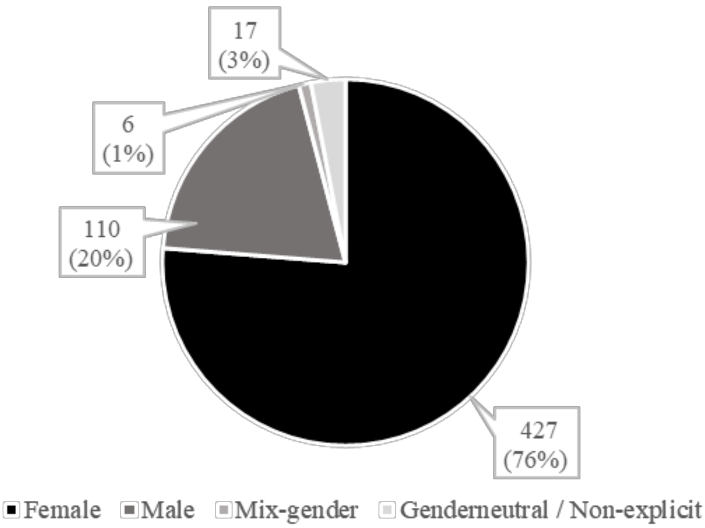
Chapter 4. Data Analysis and Methodology

4.1. Data Description

A list of the top 2,000 active vtubers based on their number of subscribers were retrieved from UserLocal, a Japanese vtuber ranking site exclusively used for keeping daily records of vtubers' uploading schedules, numbers of views, and subscriber volumes. 463 channels which had been active for less than one year were eliminated from the initial list. Finally, we trimmed down the dataset to consist of 560 vtubers managed by external sponsors. Within our dataset, 427 vtubers are female individuals or female-only groups;

110 vtubers are male individuals or male-only groups; 6 vtubers are mix-gender groups; the remaining 17 vtubers are either gender-neutral or non-explicit about their sexual orientation (e.g. using mechanically generated / autotuned voices).

Figure 3. Vtuber Gender Distribution



YouTube channel and video data were collected using the YouTube Data API. Video data (e.g. upload date, length, 3D/HD support options, genre) were merged with channel data (e.g. gender, debut date, company affiliation) to organize a panel database for all 560 vtubers. Channel subscription records for both vtubers and management companies were collected from socialBlade.

On average, each vtuber uploaded approximately 2.2 videos every week. The mean length of one video was 57.8 minutes, mainly because creators uploaded a mixture of short edited videos (5-15 minutes long) and raw versions of their live streams (50~120 minutes). Very few channels extensively support 3D functions, while the average vtuber uploaded high-definition videos for 93.9% of his/her contents. The majority of vtubers show a high degree of genre specialization, with approximately 94.1% of their videos concentrated on less than three genres.

Table 3. Vtuber Data Summary

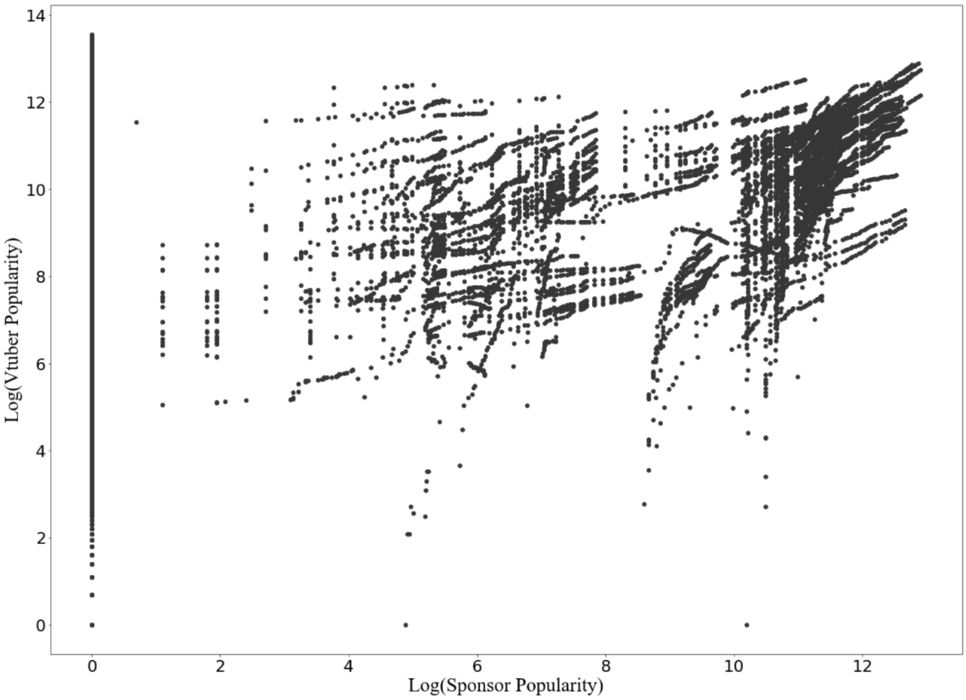
	Mean	*Std*	*Min*	*Max*
Upload frequency (videos per week)	2.2137	2.8792	0.0192	25.4231
Avg. video length (sec)	3470.8240	2976.9793	16.0000	16387.5000
3D proportion (%)	0.0150	0.2699	0.0000	5.8824
HD proportion (%)	93.8944	16.8381	0.0000	100.0000
Specialization (%)	94.1085	9.6530	40.9091	100.0000

4.2. Research Methodology

4.2.1. Panel Regression

Based on a balanced panel dataset, a panel regression model was implemented to analyze the relationship between a vtuber' s popularity and its sponsor' s popularity observed throughout 52 weeks after the creator' s debut.

Figure 6. Log(Sponsor Popularity) × Log(Vtuber Popularity)



We observe a closely linear relationship between management agency popularity and vtuber popularity. No multicollinearity was observed in the original database based on the variance inflation factors.

While testing for the assumptions of conducting an OLS regression on the panel data, the Breusch-Pagan test returned a significantly small p-value (< 0.01), showing signs of heteroskedasticity. The Durbin-Watson test also produced a value of 0.8214, indicating significant negative autocorrelation. Thus we rejected As the model contains non-time-variant variables (e.g. vtuber gender, agency affiliation status), we implemented a random effects model. In order to observe the changes in variable parameters, the model was evaluated for each week's cumulative dataset, with only data corresponding to the first week run against a simple OLS model.

4.2.2. Time Series Analysis

In order to observe chronological changes in the degree of sponsor influence on vtuber popularity, we conducted a time series analysis by fitting an ARIMA model on the regression coefficients obtained through the panel regression process.

Once the model significance was statistically validated, the model was then used to predict future trends in the last 13 weeks (25% of the entire dataset) of the observation period based on data obtained through the first 39 weeks of a vtuber's activity.

Chapter 5. Results

Panel regression analysis results indicated that management companies' YouTube channel popularities were constantly statistically significant ($p < 0.01$) with a positive effect on affiliated vtubers' popularities, supporting H1. During the first week after a vtuber's debut, the correlation coefficient indicates that every 1% increase in the company's channel subscription links to a 0.27% increase in the vtuber's popularity. The parameters decrease to a 0.03% influence by the end of a year's worth of activity.

Table 4. Random Model Effects Parameters (weeks 1–52)

R-squared **:** 0.9024

	Parameter	**Std. Err.**
Constant	1.1321	0.0561
Male	**0.0920*****	0.0209
Female	**0.1700*****	0.0201
Agency_popularity	**0.0374*****	0.0010
Upload frequency	**0.1376*****	0.0036
3D proportion	**0.0329****	0.0137
HD proportion	**0.0018*****	0.0002
Autos & Vehicles	**-0.0045*****	0.0007
Comedy	**0.0028*****	0.0004
Education	0.0006	0.0007
Film & Animation	**0.0030*****	0.0002
Gaming	**-0.0017*****	0.0001
Howto & Style	**0.0020*****	0.0005
Music	**0.0025*****	0.0002
News & Politics	**-0.0024****	0.0010
Nonprofits & Activism	**-0.0623*****	0.0176
People & Blogs	**0.0013*****	0.0001
Pets & Animals	**-0.0071*****	0.0008
Science & Technology	-0.0004	0.0004
Sports	-0.0003	0.0015
Travel & Events	-0.0025	0.0022
Specialization	**0.0033*****	0.0005
Previous popularity	**0.7893*****	0.0019

Symbols: ($p < 0.10$), ($p < 0.05$)**, ($p < 0.01$)****

On a chronological scale, weekly analyses indicate a constantly steady decline in parent brand influence. No instances of significant changes in company status (e.g. social scandals, bankruptcy) were observed for any management agency during the observation period, so we may reasonably assume that no additional spillover effects from management companies have been neglected in the observation. There is a noticeably steeper drop in company influence on vtubers during the first two months post-debut. The general form of this tendency is in line with Borah and Tellis's

(2016) findings regarding the perverse halo effects of negative chatter in online communities.

Figure 7. Influence of 1% Increase in Parent Brand Popularity on Child Brand Popularity

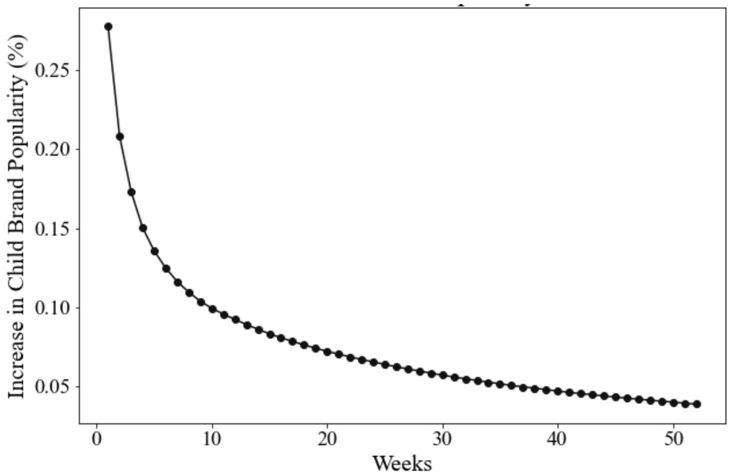


Figure 8. Parent Brand Influence on Child Brand Popularity (Box−Cox Transformation)

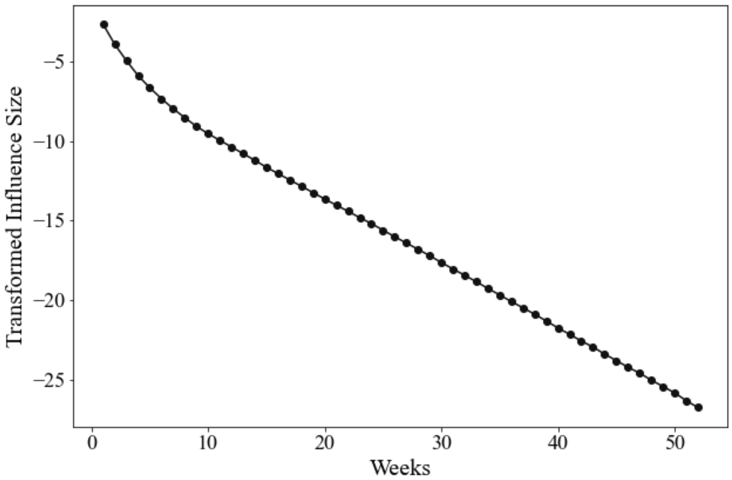


Figure 7 illustrates the chronological change in percentage increase of a vtuber’ s popularity for every 1% increase in his/her affiliated management company’ s popularity. The augmented Dickey−Fuller test returns a test value of −1.8335 with a p−value

(0.3640) significantly greater than 0.05, indicating a non−stationary dataset. The popularity influencing factors are box−cox transformed to control for data variance with an optimal lambda value of −1.0335. The transformed values are graphed in Figure 8.

Figure 9. Residual Plots for Units ARIMA (0,2,0) with Constant

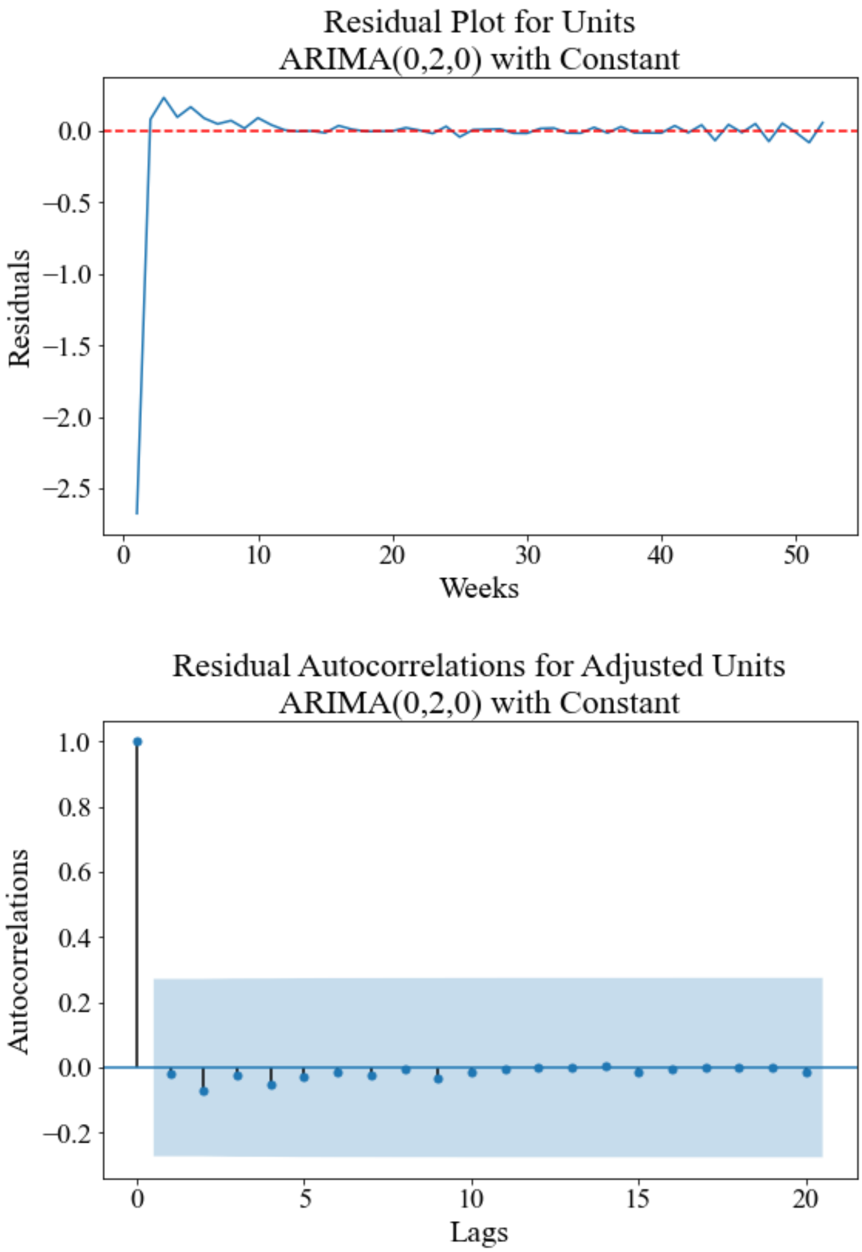


Figure 10. ACF & PACF Plots for Units ARIMA (0,0,0) with Constant

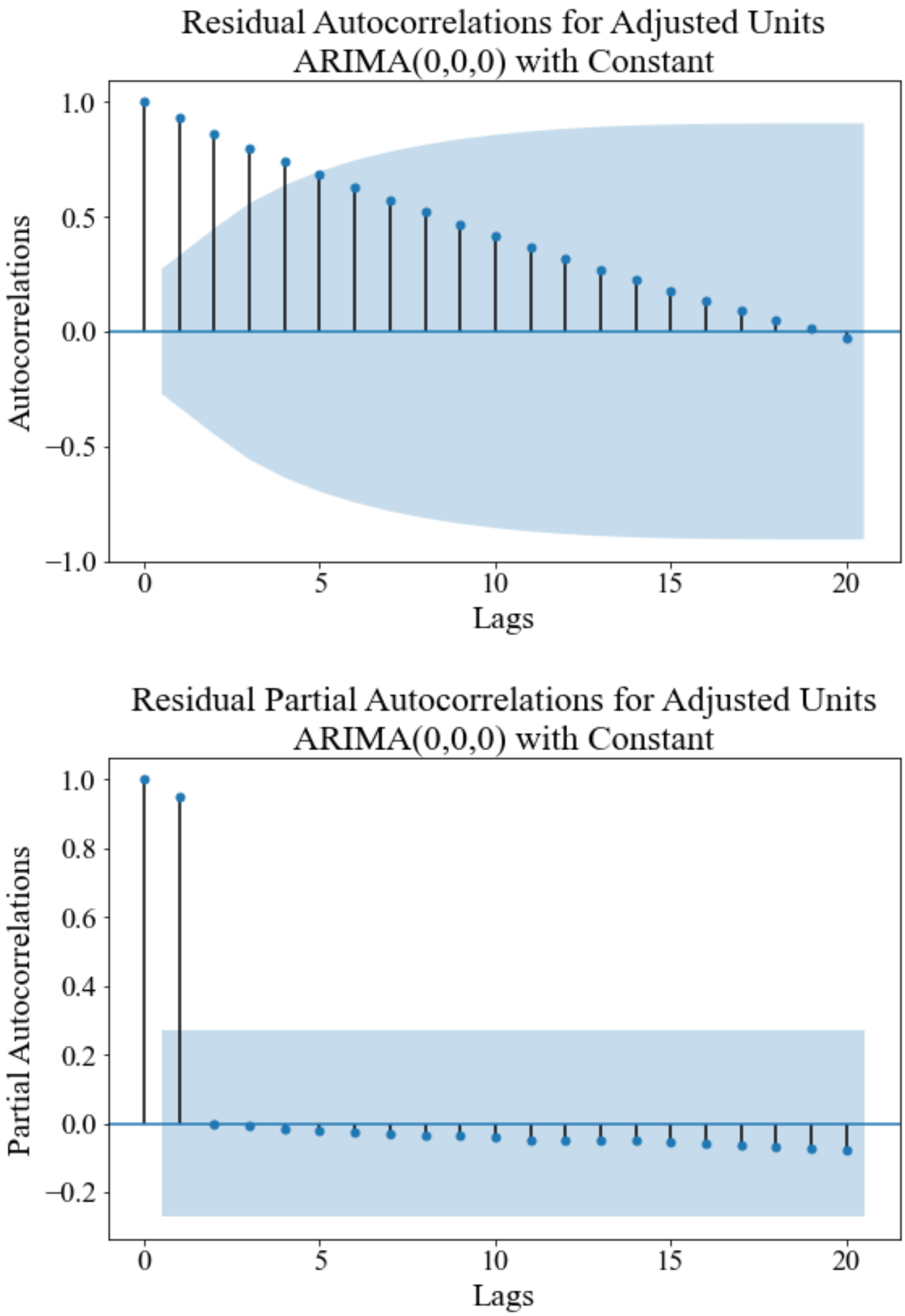
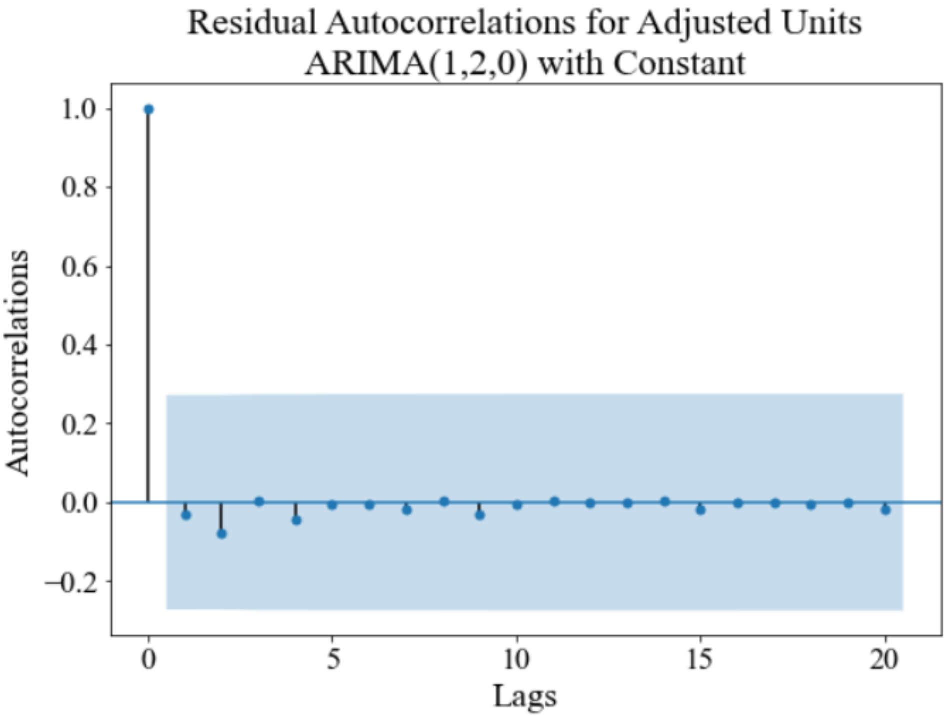


Figure 11. Residual ACF Plot for Adjusted Units ARIMA (1,2,0) with Constant



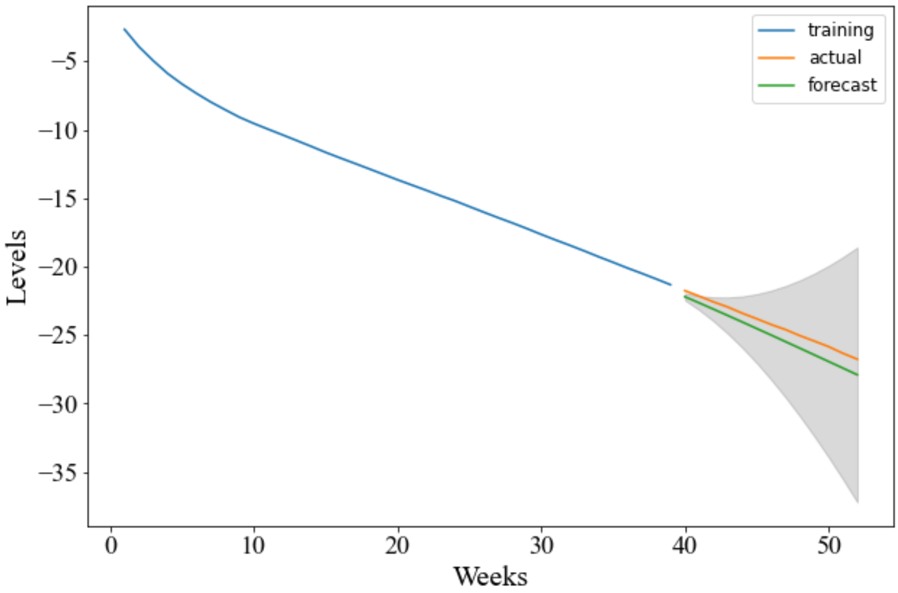
ACF graphs for lag−1 and lag−2 residual autocorrelations (Figure 8) indicated that a second−order difference was required to eliminate any additional non−stationarity. While ACF values decreased at a relatively gradual pace with autocorrelations remaining statistically significant for a number of lags, PACF values displayed a sharp spike only at lag 1 (Figure 9), meaning that all the higher−order autocorrelations are effectively explained by the lag−1 autocorrelation. Hence, we implement an ARIMA (1, 2, 0) model with a constant to fit the data. We find that both the constant and AR(1) parameters yield statistical significance.

Table 5. ARIMA (1, 2, 0) Model Results

```
                               SARIMAX Results
==============================================================================
Dep. Variable:      Agency_popularity   No. Observations:                   52
Model:                 ARIMA(1, 2, 0)   Log Likelihood                  76.579
Date:                Mon, 31 May 2021   AIC                           -147.158
Time:                        04:51:10   BIC                           -141.422
Sample:                             0   HQIC                          -144.973
                                 - 52
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       3.079e-09   3.64e-10      8.454      0.000    2.37e-09    3.79e-09
ar.L1          0.4172      0.139      3.009      0.003       0.145       0.689
sigma2         0.0027      0.000      6.167      0.000       0.002       0.004
===================================================================================
Ljung-Box (Q):                       27.36   Jarque-Bera (JB):                36.29
Prob(Q):                              0.94   Prob(JB):                         0.00
Heteroskedasticity (H):               0.76   Skew:                             1.19
Prob(H) (two-sided):                  0.58   Kurtosis:                         6.43
===================================================================================
```

We first fit the model against the entire dataset. The model returns a MAPE value of 0.0224, meaning it shows approximately 97.6% accuracy against the base dataset.

Figure 12. Forecasts vs. Actual Levels



To check for robustness, we then divided the dataset into a training set and testing set with a 75:25 ratio. A forecast against the test set yielded highly accurate results with a MAPE value of 0.0323. The graph also indicates that the forecasted values were closely estimated to the actual values in terms of both predicted valence and levels.

Table 5. Hypothesis Validation Results

H1	*Greater popularities of parent-brands will have a positive effect on the popularity of their respective child-brands.*	✔
H2	*A parent-brand's influences on its child-brand's popularity will decrease as time elapses.*	✔

All content richness variables were statistically significant. HD video proportions and specialization levels were both positively correlated with vtuber popularity all throughout our observation period. Upload frequencies did not have a significant effect during the first three weeks, but displayed a positive correlation with vtuber subscription volumes soon after. No creators uploaded 3D-support videos during the first 16 weeks after their debut, and the proportion of 3D videos did not have a statistical significance for another 16 weeks. Significant positive correlations were observed beginning from week 33 and persisted until the end of week 52.

Additional findings include that creator gender serves as a significant factor for attracting initial subscribers. Both the inclusions of male and female figures were positively correlated with greater vtuber popularity with a greater coefficient for females than males. This is in line with Goel et al. (2016)'s findings that news articles written by female authors were more likely to receive public attention than those written by men. In addition, by separating the male and female dummy variables to include a more diverse range of sexual variations, our research finds that it is more beneficial in general for vtubers to be explicit about their genders rather than keeping them ambiguous.

Higher focus on Autos & Vehicles, Gaming, News & Politics, and Pets & Animals genres appeared to have a negative effect on channel subscription growth. On the other hand, uploading more videos in the Comedy, Film & Animation, Howto & Style, Music, Nonprofits & Activism, and People & Blogs genres were positively associated with greater subscription volumes. This result implies that the latter group enjoys a greater fandom base compared to the former. The biggest correlation was with the Nonprofits & Activism genre, with 1% increase in proportion associated with a 5.6% growth in popularity.

Chapter 6. Dicussion

6.1. Research Implications

6.1.1. Academic Implications

This research contributes to the stream of research on spillover effects on brand extensions by examining chronological changes in spillover effect sizes in a brand extension-like situation. Borah and Tellis (2016) have observed the duration of perverse halo effects caused by competitors' negative performance and have concluded on a wear-in period of 1 day and a wear-out period of 6 days. On the contrary, we observe year-long persistent, albeit diminishing, influences from parent brands to their child brands. These results are contradictory to Balachander and Ghose's (2003) findings that parent advertisements are not significantly influential for child companies. Further investigation will be necessary to explain the differences in examination results.

In addition, this paper takes an atypical stance by addressing the issue of social media popularity on a creator level (in lieu of content level). While social media virality and popularity have been the center of interest, external influences have rarely been highlighted. Our research suggests that additional implicit advantages can be expected through corporate affiliation other than direct resource investment or marketing support.

6.1.2. Implications for Practice

Our research results provide managerial implications for corporations and organizations who are facing problems locating appropriate SMIs for their marketing campaigns. Our findings suggest that companies may want to consider investing in creating in-house influencers. While many companies already run their own social media channels, their functions are often limited to uploading official advertisement videos rather than directly communicating with the viewers. Considering that vtubers are often appointed as advertisement models or even official marketing ambassadors for companies hoping to overcome the inherent limit their own channels have toward attracting potential consumers, it may be a good option for companies to expand their social media activities by opening sub-channels which are more viewer-intimate. Our study implies that corporate bodies have an upper hand in gaining social media popularity once they do make attempts to reach out to their consumers.

6.2. Limitations and Future Research

While this research suggests a base model for measuring the influence of parent brands on child brands, it has room for improvement. The degree of agency popularity outside of YouTube could not be accurately reflected in the model due to difficulties in locating other platforms utilized for company activity updates. Although using YouTube popularity as a proxy for corporate influence served its purpose well for measuring the amount of power that a management agency possesses against its most direct target audience, incorporating additional data on non-YouTube platform influence through measuring Twitter followers or

Facebook friends may provide a clearer standard of comparison between the effects if intra- and inter-platform spillover effects.

A recent phenomenon found in the vtuber market is vtuber "graduation," or separation from its former management agency. Several successful vtubers (e.g. Kizuna Ai) have begun announcing their independence from their affiliated companies to become full-fledged independent creators. Although there are very few example cases of this phenomenon, we expect to find novel insights by analyzing spillover effects that occur within an unstudied framework: former allies.

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Abstract

소셜미디어의 확산은 마이크로셀레브리티와 소셜미디어 인플루언서(SMI)의 등장을 초래했다. 이미 사회적, 경제적으로 SMI들이 오피니언 리더로서 큰 영향력을 행사하고 있음에도 불구하고 이들이 정확히 어떤 근본적 요인으로 인해 대중적 인기를 얻게 되었는지에 대해 알려진 바는 많지 않다. 많은 경우에 SMI들이 순수하게 자력으로만 팬덤을 구축하는 것으로 간주되는 것에 반해, 필자들은 버츄얼 유튜버(vtuber) 업계로부터 예외적인 상황을 목격했다. 일반적인 인간 유튜버와 달리, vtuber는 데뷔 이전부터 소속사로부터 엄격하게 관리당하고 통제 받는 가상의 디지털 캐릭터들이다. 본 연구에서는 소속사 대 vtuber의 관계가 브랜드 확장 상태의 모브랜드 대 신규 브랜드의 관계와 유사하다는 점에 착안하여, 후자의 경우에 관찰되는 스필오버 효과가 전자에서도 발현되는지 검증하기 위해 소속사와 계약을 맺고 있는 총 560 명의 vtuber에 대해 임의효과 모형을 적용시킨다. 그 결과, 소속사의 영향력이 vtuber의 인기에 대해 긍정적 스필오버 효과가 있음이 확인되었다. 또, 주차별 스필오버 효과 크기의 변화에 대한 시계열 분석을 통해 추세를 예측하는 데 적합한 모형으로 ARIMA(1,2,0) 모델을 특정해내어 시간이 지남에 따라 스필오버 효과가 감소하는 경향성을 지님을 검증했다.

Appendices

A. VIF Analysis Results

Features	VIF Factor
Constant	204.236417
Male	4.640979
Female	4.617225
Agency_popularity	1.387453
Upload frequency	1.410519
3D proportion	1.010093
HD proportion	1.082626
Autos & Vehicles	1.019646
Comedy	1.072979
Education	1.031839
Film & Animation	1.140601
Gaming	1.357152
Howto & Style	1.038654
Music	1.157516
News & Politics	1.006233
Nonprofits & Activism	1.009255
People & Blogs	1.266154
Pets & Animals	1.037742
Science & Technology	1.084405
Sports	1.023067
Travel & Events	1.028223
Specialization	1.094229
Previous popularity	1.325756

B. Random Effects Model Parameters

	Week												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Constant	3.7027	2.3321	1.9820	1.7993	1.7758	1.6976	1.6542	1.6293	1.5997	1.5594	1.5602	1.5373	1.5118
Male	0.2489	0.2301	0.2447	0.2404	0.2337	0.2241*	0.2173**	0.2085**	0.2020**	0.1962**	0.1900**	0.1841***	0.1811***
Female	0.8326*	0.6935**	0.6299***	0.5824***	0.5511***	0.5231***	0.5029***	0.4797***	0.4596***	0.4413***	0.4235***	0.4077***	0.3945***
Agency_popularity	0.2724***	0.2064***	0.1715***	0.1487***	0.1335***	0.1226***	0.1139***	0.1072***	0.1015***	0.0971***	0.0934***	0.0899***	0.0868***
Upload frequency	0.2878**	0.3486***	0.3560***	0.3494***	0.3454***	0.3365***	0.3257***	0.3142***	0.3048***	0.2948***	0.2852***	0.2765***	0.2679***
3D proportion	-	-	-	-	-	-	-	-	-	-	-	-	-
HD proportion	0.0066*	0.0051**	0.0044***	0.0041***	0.0039***	0.0038***	0.0037***	0.0036***	0.0035***	0.0035***	0.0035***	0.0034***	0.0034***
Autos & Vehicles	-0.0320**	-0.0269***	-0.0235***	-0.0209***	-0.0190***	-0.0177***	-0.0163***	-0.0150***	-0.0141***	-0.0133***	-0.0127***	-0.0121***	-0.0116***
Comedy	-0.0055	-0.0050	-0.0032	-0.0026	-0.0016	-0.0008	-0.0002	0.0002	0.0005	0.0008	0.0012	0.0016	0.0018
Education	0.0046	0.0025	0.0018	0.0014	0.0011	0.0010	0.0006	0.0006	0.0006	0.0006	0.0003	0.0001	-5.016e-05
Film & Animation	0.0014	0.0029	0.0036*	0.0037**	0.0038***	0.0037***	0.0037***	0.0036***	0.0037***	0.0037***	0.0038***	0.0038***	0.0038***
Gaming	-0.0051*	-0.0051***	-0.0048***	-0.0045***	-0.0043***	-0.0041***	-0.0041***	-0.0040***	-0.0039***	-0.0038***	-0.0037***	-0.0037***	-0.0036***
Howto & Style	0.0020	-0.0006	-0.0014	-0.0013	-0.0011	-0.0009	-0.0007	-0.0005	-0.0003	-0.0001	3.566e-05	0.0002	0.0003
Music	0.0017	0.0005	0.0006	0.0007	0.0013	0.0018	0.0020*	0.0022**	0.0024***	0.0026***	0.0027***	0.0028***	0.0028***
News & Politics	-0.1001**	-0.0560***	-0.0298**	-0.0239**	-0.0210***	-0.0191***	-0.0164***	-0.0142***	-0.0123***	-0.0110***	-0.0101***	-0.0094***	-0.0088***
Nonprofits & Activism	-	-	-	-	-	-	-	-	-	-	0.3275	0.3286	0.3336
People & Blogs	-0.0031	-0.0025	-0.0016	-0.0011	-0.0006	-0.0002	8.235e-05	0.0003	0.0005	0.0006	0.0007	0.0008*	0.0009**
Pets & Animals	-0.0060	-0.0074	-0.0091	-0.0098	-0.0103*	-0.0107**	-0.0106**	-0.0107***	-0.0105***	-0.0102***	-0.0100***	-0.0096***	-0.0094***
Science & Technology	-0.0044	5.619e-05	0.0005	0.0007	0.0010	0.0012	0.0012	0.0010	0.0008	0.0007	0.0006	0.0005	0.0004
Sports	-0.0179	-0.0181	-0.0155	-0.0139*	-0.0124*	-0.0112**	-0.0102**	-0.0096**	-0.0090**	-0.0085**	-0.0079**	-0.0074**	-0.0064**
Travel & Events	-	-	-	-0.0148	-0.0091	-0.0068	-0.0057	-0.0044	-0.0032	-0.0024	-0.0020	-0.0016	-0.0015
Specialization	-0.0044	0.0095	0.0116	0.0124**	0.0114**	0.0111***	0.0107***	0.0102***	0.0099***	0.0096***	0.0090***	0.0087***	0.0085***
Previous popularity	-	0.3424***	0.3955***	0.4358***	0.4670***	0.4933***	0.5149***	0.5340***	0.5509***	0.5657***	0.5786***	0.5907***	0.6019***
R-squared	0.2210	0.4182	0.5088	0.5695	0.6129	0.6464	0.6724	0.6942	0.7127	0.7284	0.7423	0.7545	0.7653

	Week												
	14	15	16	17	18	19	20	21	22	23	24	25	26
Constant	1.4922	1.4702	1.4497	1.4252	1.4023	1.3791	1.3585	1.3421	1.3319	1.3300	1.3300	1.3244	1.3184
Male	0.1765***	0.1714***	0.1676***	0.1631***	0.1591***	0.1556***	0.1522***	0.1486***	0.1457***	0.1416***	0.1375***	0.1342***	0.1305***
Female	0.3811***	0.3686***	0.3578***	0.3474***	0.3380***	0.3295***	0.3216***	0.3139***	0.3052***	0.2975***	0.2900***	0.2828***	0.2760***
Agency_popularity	0.0839***	0.0811***	0.0786***	0.0763***	0.0742***	0.0722***	0.0702***	0.0684***	0.0668***	0.0651***	0.0636***	0.0621***	0.0606***
Upload frequency	0.2599***	0.2531***	0.2460***	0.2392***	0.2330***	0.2271***	0.2217***	0.2166***	0.2119***	0.2074***	0.2032***	0.1993***	0.1955***
3D proportion	-	-	-	0.0497	0.0477	0.0460	0.0445	0.0431	0.0427	0.0422	0.0412	0.0402	0.0393
HD proportion	0.0033***	0.0033***	0.0032***	0.0032***	0.0032***	0.0031***	0.0030***	0.0030***	0.0029***	0.0029***	0.0028***	0.0028***	0.0027***
Autos & Vehicles	-0.0112***	-0.0108***	-0.0104***	-0.0101***	-0.0098***	-0.0094***	-0.0091***	-0.0088***	-0.0085***	-0.0083***	-0.0080***	-0.0078***	-0.0076***
Comedy	0.0020	0.0022*	0.0023**	0.0024**	0.0025**	0.0027***	0.0028***	0.0029***	0.0030***	0.0030***	0.0031***	0.0031***	0.0031***
Education	-0.0002	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005
Film & Animation	0.0037***	0.0037***	0.0037***	0.0037***	0.0037***	0.0037***	0.0036***	0.0036***	0.0036***	0.0036***	0.0035***	0.0035***	0.0035***
Gaming	-0.0035***	-0.0035***	-0.0034***	-0.0033***	-0.0032***	-0.0031***	-0.0031***	-0.0030***	-0.0029***	-0.0028***	-0.0028***	-0.0027***	-0.0027***
Howto & Style	0.0004	0.0006	0.0008	0.0009	0.0010	0.0010	0.0011	0.0012	0.0012	0.0013	0.0013	0.0013	0.0014
Music	0.0028***	0.0029***	0.0029***	0.0029***	0.0029***	0.0029***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***
News & Politics	-0.0083***	-0.0079***	-0.0075***	-0.0072***	-0.0069***	-0.0066***	-0.0063***	-0.0061***	-0.0059***	-0.0057***	-0.0055***	-0.0053***	-0.0051***
Nonprofits & Activism	0.3354	0.3386	0.3386	0.3387	0.3379	0.3363	0.3354	0.3341	-0.0644	-0.0877	-0.0944	-0.0956*	-0.0953**
People & Blogs	0.0009**	0.0010***	0.0010***	0.0010***	0.0011***	0.0011***	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***	0.0013***	0.0013***
Pets & Animals	-0.0091***	-0.0089***	-0.0087***	-0.0084***	-0.0080***	-0.0077***	-0.0075***	-0.0073***	-0.0071***	-0.0069***	-0.0069***	-0.0068***	-0.0067***
Science & Technology	0.0002	0.0001	3.101e-05	-4.974e-05	0.0001	-0.0002	-0.0002	-0.0002	-0.0003	-0.0003	-0.0003	-0.0003	-0.0004
Sports	-0.0054*	-0.0044*	-0.0036	-0.0030	-0.0025	-0.0020	-0.0016	-0.0015	-0.0014	-0.0014	-0.0013	-0.0013	-0.0012
Travel & Events	-0.0012	-0.0010	-0.0009	-0.0009	-0.0008	-0.0009	-0.0008	-0.0009	-0.0010	-0.0013	-0.0015	-0.0017	-0.0017
Specialization	0.0082***	0.0080***	0.0078***	0.0077***	0.0075***	0.0074***	0.0072***	0.0071***	0.0069***	0.0066***	0.0063***	0.0061***	0.0059***
Previous popularity	0.6123***	0.6220***	0.6310***	0.6394***	0.6475***	0.6552***	0.6625***	0.6695***	0.6762***	0.6825***	0.6885***	0.6942***	0.6996***
R-squared	0.7749	0.7836	0.7915	0.7987	0.8054	0.8115	0.8173	0.8226	0.8277	0.8324	0.8368	0.8410	0.8449

	Week												
	27	28	29	30	31	32	33	34	35	36	37	38	39
Constant	1.3239	1.3190	1.3117	1.3030	1.2953	1.2886	1.2808	1.2733	1.2608	1.2573	1.2495	1.2437	1.2370
Male	0.1267***	0.1226***	0.1193***	0.1169***	0.1148***	0.1126***	0.1106***	0.1088***	0.1063***	0.1045***	0.1027***	0.1014***	0.0998***
Female	0.2696***	0.2624***	0.2561***	0.2508***	0.2456***	0.2406***	0.2356***	0.2310***	0.2262***	0.2215***	0.2171***	0.2128***	0.2087***
Agency_popularity	0.0592***	0.0580***	0.0567***	0.0555***	0.0543***	0.0532***	0.0521***	0.0510***	0.0500***	0.0491***	0.0481***	0.0472***	0.0464***
Upload frequency	0.1910***	0.1874***	0.1840***	0.1808***	0.1778***	0.1749***	0.1721***	0.1695***	0.1670***	0.1647***	0.1624***	0.1602***	0.1581***
3D proportion	0.0382	0.0373	0.0366	0.0360	0.0353	0.0346	0.0349*	0.0350*	0.0351*	0.0352*	0.0354*	0.0353**	0.0352**
HD proportion	0.0027***	0.0027***	0.0026***	0.0026***	0.0025***	0.0025***	0.0025***	0.0024***	0.0024***	0.0024***	0.0023***	0.0023***	0.0022***
Autos & Vehicles	-0.0074***	-0.0072***	-0.0070***	-0.0068***	-0.0067***	-0.0065***	-0.0064***	-0.0062***	-0.0061***	-0.0060***	-0.0059***	-0.0058***	-0.0057***
Comedy	0.0031***	0.0031***	0.0031***	0.0031***	0.0031***	0.0031***	0.0031***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***
Education	-0.0006	-0.0005	-0.0005	-0.0002	-4.806e-05	3.98e-05	0.0001	0.0002	0.0002	0.0003	0.0003	0.0003	0.0004
Film & Animation	0.0034***	0.0034***	0.0034***	0.0033***	0.0033***	0.0033***	0.0033***	0.0032***	0.0032***	0.0032***	0.0031***	0.0031***	0.0031***
Gaming	-0.0026***	-0.0025***	-0.0025***	-0.0024***	-0.0024***	-0.0023***	-0.0023***	-0.0022***	-0.0022***	-0.0021***	-0.0021***	-0.0021***	-0.0020***
Howto & Style	0.0014	0.0014*	0.0014*	0.0015*	0.0015*	0.0016**	0.0016**	0.0016**	0.0017**	0.0017**	0.0017**	0.0017***	0.0018***
Music	0.0030***	0.0030***	0.0030***	0.0029***	0.0029***	0.0029***	0.0029***	0.0029***	0.0028***	0.0028***	0.0028***	0.0027***	0.0027***
News & Politics	-0.0050***	-0.0048***	-0.0047***	-0.0046***	-0.0044***	-0.0043***	-0.0042***	-0.0041***	-0.0040***	-0.0039***	-0.0039***	-0.0038***	-0.0037***
Nonprofits & Activism	-0.0958**	-0.0957***	-0.0950***	-0.0943***	-0.0941***	-0.0923***	-0.0914***	-0.0907***	-0.0902***	-0.0891***	-0.0857***	-0.0839***	-0.0818***
People & Blogs	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***
Pets & Animals	-0.0066***	-0.0069***	-0.0070***	-0.0070***	-0.0071***	-0.0071***	-0.0072***	-0.0072***	-0.0072***	-0.0073***	-0.0073***	-0.0073***	-0.0073***
Science & Technology	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0005	-0.0005	-0.0005	-0.0006	-0.0006	-0.0006	-0.0005	-0.0005
Sports	-0.0012	-0.0011	-0.0011	-0.0010	-0.0009	-0.0009	-0.0008	-0.0008	-0.0007	-0.0007	-0.0007	-0.0007	-0.0006
Travel & Events	-0.0017	-0.0018	-0.0018	-0.0022	-0.0025	-0.0028	-0.0029	-0.0030	-0.0029	-0.0029	-0.0029	-0.0029	-0.0028
Specialization	0.0056***	0.0054***	0.0052***	0.0051***	0.0049***	0.0048***	0.0047***	0.0046***	0.0045***	0.0043***	0.0043***	0.0042***	0.0041***
Previous popularity	0.7046***	0.7097***	0.7146***	0.7192***	0.7237***	0.7280***	0.7321***	0.7361***	0.7399***	0.7435***	0.7470***	0.7505***	0.7538***
R-squared	0.8481	0.8515	0.8549	0.8581	0.8612	0.8641	0.8669	0.8695	0.8719	0.8743	0.8766	0.8788	0.8810

	Week												
	40	41	42	43	44	45	46	47	48	49	50	51	52
Constant	1.2286	1.2189	1.2113	1.2020	1.1926	1.1866	1.1792	1.1723	1.1657	1.1583	1.1502	1.1416	1.1321
Male	0.0986***	0.0976***	0.0956***	0.0945***	0.0935***	0.0936***	0.0928***	0.0921***	0.0917***	0.0919***	0.0923***	0.0922***	0.0920***
Female	0.2047***	0.2008***	0.1972***	0.1938***	0.1905***	0.1874***	0.1845***	0.1815***	0.1788***	0.1764***	0.1746***	0.1723***	0.1700***
Agency_popularity	0.0455***	0.0447***	0.0440***	0.0432***	0.0425***	0.0418***	0.0411***	0.0405***	0.0398***	0.0392***	0.0386***	0.0380***	0.0374***
Upload frequency	0.1562***	0.1543***	0.1526***	0.1509***	0.1493***	0.1477***	0.1462***	0.1447***	0.1432***	0.1417***	0.1403***	0.1390***	0.1376***
3D proportion	0.0351**	0.0350**	0.0348**	0.0346**	0.0344**	0.0343**	0.0341**	0.0339**	0.0336**	0.0335**	0.0333**	0.0331**	0.0329**
HD proportion	0.0022***	0.0022***	0.0021***	0.0021***	0.0021***	0.0020***	0.0020***	0.0020***	0.0019***	0.0019***	0.0019***	0.0018***	0.0018***
Autos & Vehicles	-0.0055***	-0.0054***	-0.0053***	-0.0052***	-0.0051***	-0.0050***	-0.0050***	-0.0049***	-0.0048***	-0.0047***	-0.0046***	-0.0046***	-0.0045***
Comedy	0.0029***	0.0029***	0.0029***	0.0029***	0.0029***	0.0028***	0.0028***	0.0028***	0.0028***	0.0028***	0.0028***	0.0028***	0.0028***
Education	0.0004	0.0004	0.0004	0.0005	0.0005	0.0005	0.0005	0.0005	0.0006	0.0006	0.0006	0.0006	0.0006
Film & Animation	0.0031***	0.0031***	0.0031***	0.0031***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***	0.0030***
Gaming	-0.0020***	-0.0020***	-0.0019***	-0.0019***	-0.0019***	-0.0019***	-0.0018***	-0.0018***	-0.0018***	-0.0018***	-0.0017***	-0.0017***	-0.0017***
Howto & Style	0.0018***	0.0018***	0.0018***	0.0018***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0020***	0.0020***	0.0020***	0.0020***
Music	0.0027***	0.0027***	0.0027***	0.0026***	0.0026***	0.0026***	0.0026***	0.0026***	0.0025***	0.0025***	0.0025***	0.0025***	0.0025***
News & Politics	-0.0036***	-0.0035***	-0.0035***	-0.0034***	-0.0032***	-0.0031***	-0.0030***	-0.0029***	-0.0028**	-0.0027**	-0.0026**	-0.0025**	-0.0024**
Nonprofits & Activism	-0.0806***	-0.0795***	-0.0779***	-0.0762***	-0.0745***	-0.0726***	-0.0710***	-0.0695***	-0.0680***	-0.0665***	-0.0649***	-0.0636***	-0.0623***
People & Blogs	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0013***	0.0013***	0.0013***	0.0013***
Pets & Animals	-0.0073***	-0.0073***	-0.0073***	-0.0073***	-0.0073***	-0.0073***	-0.0073***	-0.0072***	-0.0072***	-0.0072***	-0.0072***	-0.0072***	-0.0071***
Science & Technology	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0004	-0.0004
Sports	-0.0006	-0.0006	-0.0005	-0.0005	-0.0005	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0003	-0.0003	-0.0003
Travel & Events	-0.0028	-0.0028	-0.0027	-0.0027	-0.0026	-0.0026	-0.0026	-0.0025	-0.0025	-0.0025	-0.0025	-0.0025	-0.0025
Specialization	0.0040***	0.0039***	0.0038***	0.0038***	0.0037***	-0.0037***	0.0036***	0.0035***	0.0035***	0.0034***	0.0034***	0.0033***	0.0033***
Previous popularity	0.7570***	0.7601***	0.7632***	0.7662***	0.7692***	0.7717***	0.7744***	0.7770***	0.7795***	0.7820***	0.7845***	0.7869***	0.7893***
R-squared	0.8830	0.8850	0.8866	0.8885	0.8903	0.8918	0.8935	0.8951	0.8967	0.8982	0.8996	0.9011	0.9024