Platform Categorization and Complement Performance:

Evidence from A Quasi-Natural Experiment on Mobile Apps

Shihao Zhou
School of Business
Nanjing University
16 Jinyin Street, Nanjing, Jiangsu, China 210093
E-mail: zhoush@nju.edu.cn

Yuchen Zhang
Freeman School of Business
Tulane University
7 McAlister Dr. New Orleans, LA 70123
E-mail: yzhang54@tulane.edu

Tony W. Tong
Leeds School of Business
University of Colorado Boulder
995 Regent Dr., Boulder, CO 80309
Tel.: (303) 492-0141
Email: tony.tong@colorado.edu

Zhilei Qiao
Collat School of Business
The University of Alabama at Birmingham
710 13th St. S., Birmingham, AL 35233
Email: qiaozl@uab.edu

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ABSTRACT

Managing complement heterogeneity has a salient impact on value creation in platform markets, but remains underexamined in the platform governance literature. Local homogenization (i.e., increasing complement homogeneity within a product category) can improve customer-complement matching efficiency, without weakening the network effect of the platform market. However, although local homogenization enables customers to better identify potentially fitted complements, the presence of more fitted complements makes customers more selective in making payments. By exploiting the removing of shopping apps from the lifestyle category on Apple's App store as an exogenous shock which increases local homogeneity of the lifestyle category, we find that local homogenization increases complements' new installs, but reduces revenue generation from each install. Since new installs and revenue are both important for digital complementors, this research illustrates a nuanced relationship between platform categorization and complement performance.

Keywords: platform categorization, complement homogenization, platform governance, matching efficiency, search frictions

INTRODUCTION

During the past decade, an increasing number of firms operate in platform markets, in which they function as complementors and offer complementary products or service to customers affiliated with the platform (Jacobides, Cennamo, & Gawer, 2018; McIntyre & Srinivasan, 2017). Both complementors and the owner of the hub platform enjoy a positive cross-side network externality, wherein the increase of complements spawns the participation of more customers, which in turn increases the demands for complements (Katz & Shapiro, 1985). The cross-side network effect is strengthened when complements are more heterogeneous and can address diverse customer demands (Cennamo & Santaló, 2013; Hagiu, 2009). However, recent studies show that complement heterogeneity can also lead to inefficiency in matching customers and complements, resulting in the loss of business opportunities (Halaburda, Piskorski, & Yıldırım, 2018). Thus, managing complement heterogeneity is a key challenge of the platform owner.

There is a burgeoning stream of literature on platform governance (see Chen, Tong, Tang, & Han, 2022 for a recent literature review), but the management of complement heterogeneity is a largely underexamined issue. We submit that, to obtain a balance between the cross-side network effect and the matching efficiency, the platform owner can pursue “local” complement homogeneity by offering limited and homogenous choices of complements. We call such strategy “local homogenization”. While extant research has discussed approaches to attract, control, and coordinate complements (Constantinides, Henfridsson, & Parker, 2018; Kretschmer, Leiponen, Schilling, & Vasudeva, 2020), little is known about how platform owners may implement local homogenization.

Our study views assigning complements into more specified product categories (hereafter "platform categorization") as a platform governance strategy of local homogenization. Prior studies indicated that complement competition for customers is localized within product categories (Barlow, Verhaal, & Angus, 2019; Li & Agarwal, 2017; Wen & Zhu, 2019). Nevertheless, they implicitly assumed that categories are given and static. We emphasize that the platform owner has the authority to purposefully categorize complements; and our study aims to evaluate the effectiveness of platform categorization by examining if and how platform categorization can boost complement performance, a key task of platform governance (Adner, 2017). We contextualize our analysis by focusing on digital complements (e.g., mobile apps, software, video games), as they are playing an increasingly crucial role in today's platform economy (Teece, 2018).

Platform categorization is an appealing platform governance strategy, as it can improve matching efficiency within the product category, without reducing the overall complement heterogeneity at the platform level. However, the relationship between platform categorization and complement performance can be nuanced. On one hand, platform categorization reduces search frictions, facilitates customers to identify more complements that potentially match with their demands, and therefore creates more business opportunities to complementors (Casadesus-Masanell & Hałaburda, 2014; Li & Netessine, 2020). We name this effect the *search effect*. On the other hand, when searching for complements becomes easier, customers tend to become more selective and fastidious in making payments, intensifying competition on the complementor side (Diehl & Poynor, 2010; Jung, Lim, Lee, & Kim, 2021). We name this effect the *selection effect*. The selection effect is detrimental to complement performance and could cancel out the search effect.

We tease apart the tension between the search effect and the selection effect by examining two complement performance outcomes: *new installs* and *revenue generation from each installed customer*. Differentiating the two performance outcomes is sensible in our research context for two reasons. First, digital complementors often interact with customers in a two-staged mode in which customers' initial consumption of the complement (i.e., install a trial version for free) precedes consumer payments (i.e., for add-ons and upgraded service) (Liu, Au, & Choi, 2014; Tidhar & Eisenhardt, 2020). New installs and revenue generation are both important, because they correspond to the first and the second stages of the interaction, respectively. Second, the two performance outcomes have independent implications to complementors. On one hand, revenue generation directly contributes to the complementor's bottom line. On the other hand, even when some of the installed customers do not make any payments, acquiring more installs is still valuable, because the increase of installed base contributes to the complement's long-term performance by strengthening the complementor's own network externality (Shapiro & Varian, 1998) and diffusing positive word-of-mouth (Jiang & Sarkar, 2009).

We propose that the impact of platform categorization on new installs and revenue generation from each customer can be explained by the search effect and the selection effect, respectively. First, since installing a digital product is oftentimes cost free for both the complementor and the customer (Liu et al., 2014), complementors are relaxed from fierce competition for new installs. We thus hypothesize that platform categorization will increase complements' new installs, as the search effect tends to outweigh the selection effect at this point. However, when customers install more homogeneous complements on local devices (e.g., laptops and smartphones), they may sequentially be more selective and fastidious in making payments, as complement competition on the device layer of the platform is escalated (Yoo, Henfridsson, & Lyytinen, 2010). As a result, experiencing a platform categorization can make complements generate less revenue from each installed customer.

To test our theory, we exploit a quasi-natural experiment provided by the removing of shopping mobile apps from the lifestyle category on Apple's App store, which homogenizes the lifestyle category. Results of our difference-in-differences (DD) analysis yield strong support for our propositions. We conduct a variety of additional analyses (e.g., using alternative research designs and measures) to check the robustness of empirical results. Furthermore, as supplementary analyses, we examine how our findings are contingent on the mobile app's business model (which shapes the way app publishers interact with customers) and product ranking (which affects an app's likelihood of appearing in customers' search outcomes). We also test and discuss how platform categorization influenced the app's total revenue.

Our study makes three major contributions. First, our research expands the platform governance literature (Rietveld & Schilling, 2021; Wareham, Fox, & Giner, 2014) by proposing platform categorization as a platform governance strategy and evaluating its effectiveness. While product categorizing in markets is generally viewed as a socio-cognitive process (Cattani, Porac, & Thomas, 2017), we highlight that platform owners can categorize complements purposefully to coordinate the interaction between complements and customers. We also directly tested how platform categorization affects complement performance, answering the call for research to examine the economic outcomes of platform governance (Chen et al., 2022).

Second, our findings help to resolve the inconsistent findings regarding the relationship between complement heterogeneity and value creation in platform markets (Clements & Ohashi, 2005; Boudreau, 2012; Halaburda et al., 2018). We propose that a platform can balance the benefits (e.g., the cross-side network effect) and the costs (e.g., matching inefficiency) of complement heterogeneity by implementing a strategy of local homogenization. Our theory also explains why local homogenization only enhances complements' new installs, but does not lead to more revenue immediately.

Finally, our research sheds light on the antecedents of complement performance (e.g., Claussen, Kretschmer, & Mayrhofer, 2013; Kapoor & Agarwal, 2017) and contributes to a better understanding of how digital complementors interact with customers and compete with peers. Our study implies that complements with different visibility (e.g., rankings) and business models may benefit from platform categorization differently. These findings offer insights on how complementors can better position themselves in platform markets.

THEORY AND HYPOTHESIS DEVELOPMENT

Platform governance and local homogenization

A platform market is one in which the platform owner offers a hub platform catering to complementors (sellers) and customers. To facilitate value creation and appropriation within the platform market, the platform owner aims to orchestrate the activities of platform participants, motivating participations, coordinating participants' interactions, and setting boundaries of participants' behaviors (Chen et al., 2022; Kretschmer et al., 2020). As complementors, customers, and the hub platform are often interdependent with each other, well-functioning platform governance strategies should promote activities that create collective value that can be shared by all platform participants (Wareham et al., 2014).

Managing complement heterogeneity on the platform (e.g., homogenization or heterogenization) is an important but largely underexamined issue of platform governance. Complement heterogeneity increases as the platform owner introduces more differentiated complements on the platform. In a platform market, both complementors and customers realize more value from participating in a platform when the number of participants on the other side of the platform increases. This effect is described as the *cross-side network effect* and viewed as a primary value creation mechanism in platform ecosystems (Katz & Shapiro 1985; Parker & Van Alstyne, 2005; Schilling, 2002). If complements on the platform are more heterogeneous (i.e., differentiated from each other), the platform becomes more appealing to customers with diverse demands, enhancing the cross-side network effect (Boudreau, 2012; Brynjolfsson, Hu, & Smith, 2003; Cennamo & Santaló, 2013; Clements & Ohashi, 2005; Hagiu, 2009).

Although complement heterogeneity contributes to the cross-side network effect, it increases the customer's difficulties of searching and identifying complements that match her demands. We name such effect the *search effect*. Complement heterogeneity creates search frictions, because as both the number of options (complement group size) and the information about options (degree of heterogeneity) increase, customers tend to process a smaller fraction of the overall information regarding the options (Iyengar & Lepper, 2000). In addition, complement heterogeneity may dilute the "dominant" among assortments. In the absence of a dominate subject, customers suffer from information overload (Chernev, 2006), and become inefficient in searching for complements. Along the same line, researchers found that implementing complement homogenization (e.g., offer limited and more homogeneous choices) leads to more matches on the platform (Cullen & Farronato, 2021; Li & Netessine, 2020), enhancing value creation in the platform market and bringing benefits to all the platform participants.

To balance the benefits (e.g., the cross-side network effect) and costs (e.g., the search inefficiency) of complement heterogeneity, the platform owner can initiate a strategy of *local homogenization* by offering limited and homogeneous choices of complements to a specific group of customers. Doing so would improve local search efficiency. At the same time, the platform owner can continue to foster global heterogeneity (i.e., attract numerous heterogenous complements on the platform), promoting the cross-side network effect.

However, while complement homogenization can increase the number of potential matches between customers and complementors by mitigating information overload and search frictions, the number of final transactions between customers and complementors may not be sequentially increased. This is because when facing more choices that seem to be equally close to her preferences, the customer tends to have higher expectations about the quality of the ideal product and accordingly has lower confidence in making the final decision of purchase (Chernev, 2003; Diehl & Poynor, 2010). As a result, customers will be more selective and fastidious in choosing complements to transact, deferring or even eliminating transactions (Jung et al., 2021). We name this effect the *selection effect*.

Taking all the three effects into account, we find that while the platform owner seems to be able to resolve the tension between the network effect and the search inefficiency by implementing local homogenization, local homogenization can trigger a new tension between the search efficiency and the motivation of making choices. Thus, the effectiveness of local homogenization as a platform governance strategy remains a puzzle. Our study aims to comprehend how local homogenization affects complement performance. Boosting complement performance is a key task of platform governance, as the platform market's survival and development heavily rely on the extent to which the platform owner can stimulate complementors' engagement into the value creation activities (Adner, 2017; Kapoor, 2018).

Customer-complementor interactions and digital complement performance

To understand what affects complement performance, we first discuss how the customer and the complementor interact on the digital platform. The previous literature (e.g., Chernev, 2006; Cullen & Farronato, 2021; Halaburda et al., 2018) viewed customer-complementor interaction as a one-time only process, i.e., the matching and the transaction are tightly corresponded and occur synchronously. For example, an Uber user will be matched with a taxi driver, and buy service from this driver only in a particular transaction. Differing from the previous literature, we contend that the interaction between a digital complementor and a customer is often *two-staged* (see also, Liu et al., 2014). In the first stage, the customer searches for complements that can potentially address her demand from large assortments available on the platform, and installs the trial versions of these complements, usually for free. Then, in the second stage, the customer evaluates the installed complements further and pay some of the complementors for advanced features and functionality (e.g., lives or gems in a video game, additional filters in a photo app, access of premium contents). In the two-staged interaction mode, identifying a potential match and completing a transaction are separated activities.

The practice of offering a product for free and collecting fees for advanced features in follow-ups is called freemium, a business model that is widely adopted by digital product publishers (Boudreau, Jeppesen, & Miric, 2021; Rietveld, 2018; Tidhar & Eisenhardt, 2020). For example, in 2021, 97% of the mobile apps in the Google Play app store were available for free. Digital complementors find the freemium strategy viable because digital resources have two unique features. First, digital resources are highly scalable (Adner, Puranam, & Zhu, 2019; Giustiziero, Kretschmer, Somaya, & Wu, 2021), enabling the complementor to deliver a trial version of its product for free to massive customers. Second, digital products often have modularized product architectures and are ready to version (Gawer, 2014; Schilling, 2000). To be sure, not all complementors interact with customers in a two-stage mode. For example, some complements only have a paid version, and others do not collect fees at all (Boudreau & Jeppesen, 2015). While we do not specifically discuss these cases in theory and hypothesis development, we consider complementors' business models in a supplementary analysis (Panel A, Table 6).

We further submit that, corresponding to the two stages of customer-complementor interaction, complementors pursue two performance outcomes: *the number of new installs* and *revenue generation from each installed customer*.[1] Management scholars traditionally focus on revenue generation, as it directly contributes to financial performance (c.f., Greve & Gaba,

[1] We focus on revenue generation from each customer instead of total revenue. This is primarily because a complement's total revenue is affected by both revenue generation from each install and the number of installs. Thus, we believe our theory development can be more precise if we just focus on revenue generation from each customer. Instead, we discuss total revenue in a supplementary analysis (Panel B, Table 6).

2017). However, we argue that acquiring new installs has at least three unique strategic implications to complementors. First, many digital complements exhibit a direct network effect, wherein customers are better off using the same products as other customers (Casadesus-Masanell & Hałaburda, 2014). Even if some installed customers do not pay for the complement, making them just use the product can strengthen the direct network effect, reinforcing the complement's market position (Shankar & Bayus, 2003). Second, even in the absence of the direct network effect, acquiring new installs can still diffuse the complement's word-of-mouth and bring a variety of benefits to the complementor such as exerting peer pressure and social influence to potential customers (Jiang & Sarkar, 2009). Finally, many digital complementors join a platform to fulfill the individual product developer's personal interests and pursue non-sales achievements such as a good reputation. Individual product developers also value the increase of new installs, which signals their capabilities of product development (Boudreau & Jeppesen, 2015).

Examining how local homogenization affects the two complement performance outcomes is meaningful in two regards. First, since acquiring new installs and generating revenue have independent implications to the complementor, examining them separately helps us to better evaluate the effectiveness of local homogenization as a platform governance strategy. Second, as we will elaborate below, the two stages of interaction (i.e., initial matching and follow-up transaction) correspond to the search effect and the selection effect respectively. Therefore, examining two performance outcomes separately facilitates us to tease apart the tension inherent in local homogenization.

The impact of platform categorization on complement performance

We have explicated that the value of local homogenization lies in its positive impact on the search and matching efficiency in the platform market. The majority of prior studies viewed matching on platforms as a technological issue and proposed that the improvement of matching efficiency counts on information technologies such as search algorithms and recommendation engines (e.g., Brynjolfsson et al., 2003; Kanoria & Saban, 2021; Li & Netessine, 2020). Differing from prior studies, our research notes that customers' search for complements and competition between complements are both localized within product categories (Barlow et al., 2019; Li & Agarwal, 2017; Raj, 2021; Wen & Zhu, 2019), and proposes that the platform owner can implement local homogenization by categorizing complements on the platform.

We define platform categorization as a platform owner's initiative of assigning complements into a specified product category with a clear dominate subject. To execute categorization, the platform owner can create new product categories or split existing categories to make them more specified and focused.[2] Platform categorization will generally result in a reduction of complements and an increased degree of complement homogeneity within the category, imposing significant influence on interactions between customers and complementors.[3] For example, looking at the top app chart was listed as one of the most common approaches of finding apps (Lim et al., 2015). Categorization can homogenize the

[2] A platform owner can also combine categories when multiple categories share one dominate subject. Combining categories cannot be directly interpreted using our theory (e.g., after the combination, the new category may still have one focused dominate subject, but includes more, rather than less, complements). Thus, our study does not consider combining categories and we encourage future research to examine this phenomenon further.

[3] In practice, reducing the number of complements and increasing complement homogeneity often come along with each other (see also, Boudreau, 2012; Iyengar & Lepper, 2000). While we did not differentiate them in our theory, we try to tease them apart in a supplementary analysis (Panel B, Table 6).

complements ranked in the top chart and increase the (remaining) apps' ranking (if some apps are moved out in the categorization process). To evaluate the effectiveness of platform categorization, we investigate its impacts on two complement performance outcomes. More specifically, we develop arguments by exploring how platform categorization influences the tension between the search effect and the selection effect.

To begin with, we examine the relationship between platform categorization and our first dependent variable, i.e., the number of new installs. First, we argue that platform categorization can increase new installs by improving customers' search efficiency. The process of searching is essentially about processing complement information. Customers make sense of the attributes of a complement by assessing the category label associated with the complement (Chakravarti & Janiszewski, 2003; Pontikes, 2012). Through platform categorization, the category has a clearer category label (i.e., dominate subject), making customers evaluate complements more effectively and reducing the likelihood of missing potentially fitted complements (Mogilner, Rudnick, & Iyengar, 2008). As a result of the improvement of search efficiency, customers would be able to identify more fitted complements and will on average install more complements. Therefore, platform categorization can significantly mitigate search frictions, and increase the number of new installs of complementors in the category.

On the other hand, we argue that the selection effect is unlikely to affect new installs. The selection effect emerges when the presence of more seemingly fitted complements makes the customer more selective and delays the final decision of purchase. The underlying mechanism is that when assortments get larger, making the best choice among assortments is inclined to be perceived as more challenging (Diehl & Poynor, 2010). However, it is reasonable to predict that such concern will be relieved if the customers' choice is non-exclusive and free of charge. On digital platforms, installations are often non-exclusive and free of charge (Boudreau et al., 2021; Rietveld, 2018). (As mentioned earlier, we will consider the complementor's business model in supplementary analyses.) Thus, customers are usually not selective in installing complements, as the opportunity cost of installing a "wrong" complement is trivial. Hence, the relationship between platform categorization and complements' new install performance is more likely to be explained by the search effect, rather than the selection effect.

Some may note that although local homogenization is not likely to affect the overall cross-side network effect of the platform market, the network effect can sometimes be localized within a product category. This is because introducing valuable complements into a category can create a spillover effect to other complements in the category (Li & Agarwal, 2017; Raj, 2021). If customers value complement heterogeneity, removing heterogeneous complements from a category will weaken the spillover effect. Nevertheless, in our research context (the mobile app industry), the majority (i.e., around 80%) of complement search has a clear goal (Lim et al., 2015). It means that even though customers may value complement heterogeneity in general, most of them do not value heterogeneity in the process of product search. Thus, while platform categorization may weaken the localized cross-side network effect, the cost it brings tends to be smaller than the benefits it brings through the improvement of search efficiency. This discussion leads to the following hypothesis:

Hypothesis 1 (H1). *An increase in the homogeneity of a platform category will increase the new installs of a complement in the category.*

Next, we investigate how platform categorization influences revenue generation from each installed customer, which corresponds to the second stage of customer-complementor interaction. A critical difference between the first stage of interaction (i.e., search for and install complements) and the second stage of interaction (i.e., pay for the complements) is that they often take place at different places. Specifically, many digital technologies have a layered architecture in which product components are interconnected through multiple interfaces (Yoo et al., 2010). For example, operating system platforms such as the iOS system are developed with an architecture that has a service layer (e.g., App store, download center) in which the customers can access and search for all the complements, and a device layer (e.g., start menu on the smartphone) in which customers can retrieve and use their installed complements. The second stage of customer-complementor interaction primarily takes place in the device layer, even though some transactions may be made at the service layer. For example, app users need to use the apps on their smartphones, and make purchase decisions based on experiences of using (Liu et al., 2014). Therefore, platform categorization influences revenue generation from each customer by shaping the way customers and complementors interact in the device layer, rather than in the service layer.

The discussion above indicates that the search effect becomes largely irrelevant in explaining the impact of platform categorization on revenue generation. The search problem is much more salient in the service layer than in the device layer, as the number of complements in the service layer is usually much larger than the number of complements in the device layer

(Lim et al., 2015). Thereby, the platform owner will implement categorization in the service layer. It means that platform categorization will not affect customers' search efficiency in the device layer. For the same reason, platform categorization also does not affect the network effect in the device layer.

On the contrary to the search effect, platform categorization will make the selection effect more salient in predicting revenue generation performance. As far as platform categorization reduces search frictions at the service layer and facilitates identifications of potentially fitted complements, the customer will generally install more complements on her local device. From the customer's perspective, installing more complements will make her more selective and delay the decision of purchase (Jung et al., 2021). From the complementor's perspective, when more complements are installed on a local device, the complementor faces more intense competition in the device layer, resulting in a congestion problem (Belleflamme & Peitz, 2019). Taken together, platform categorization is detrimental to a complementor's performance on a local device, which reflects in the amount of revenue the complementor can generate from the customer (who owns the device). We, therefore, hypothesize the following:

Hypothesis 2 (H2). *An increase in the homogeneity of a platform category will decrease the revenue generation from each customer of a complement in the category.*

In Table 1 and 2, we summarize the key arguments of our theory and hypotheses. As per previous discussions, we will explore contingent factors (e.g., the complementor's business model) and other performance outcomes (e.g., total revenue) in supplementary analyses.

Insert TABLE 1 and 2 here

METHODOLOGY

Research design and identification strategy

The empirical context of the study was the mobile app industry, which has grown exponentially over the past decade and is one of the most popular markets for digital products. In 2021, global consumers spent 85.1 billion US dollars on the App Stores, climbing 17.7% from 72.3 billion US dollars in 2020 (Sensor Tower, 2021). The mobile app industry is also a typical platform market, dominated by two major platforms (i.e., Apple's iOS system and Google's Android system). Thus, the mobile app industry was widely used in prior studies as the empirical context of studying platform governance (e.g., Wen & Zhu, 2019; Zhang, Li, & Tong, 2021).

To test our hypotheses, we make use of a quasi-natural experiment on Apple's App store where the platform owner removed shopping apps from the lifestyle category. The categorization led to a new shopping category and a more homogenized lifestyle category. The focus of our research is the lifestyle category. From Apple's perspective, splitting the lifestyle and the shopping categories was reasonable because shopping was becoming an independent subject of app consumption. On Google's Google Play App store, lifestyle and shopping apps were assigned in different categories before 2015. In addition, by creating a new shopping category, Apple attempted to promote its e-commerce business and the Apple Pay service, which was released in 2014 (Rao, 2015). Thus, focusing on the lifestyle apps instead of shopping apps enables us to observe the effect of platform categorization, rather than app promotion.

Compared to similar events, removing shopping apps from the lifestyle category provides a better empirical setting to test platform categorization. To split the lifestyle category, Apple made an announcement on October 26th, 2015, and implemented the recategorization on November 4th, 2015. The whole process took a very short time (12 days) and was basically unexpected by app publishers (Rao, 2015). In contrast, Google implemented a platform recategorization in 2016. The announcement was made 60 days before the changes were reflected to users (Sinha, 2016), making it difficult to resolve the identification problem. Moreover, our observation period (July 15th, 2015 to February 28th, 2016) is nonoverlapping with the time in which Apple and Google hold the developer conferences (Apple: June, 2015; Google: May, 2015). It further strengthens our identification strategy as platform governance rules or changes were often released on these conferences.

We used the empirical setting to compare the performance of lifestyle apps on the iOS platform (treatment group) with that of "shock-immune" lifestyle apps on the Android platform (control group) before and after the platform (re)categorization. This difference-in-differences (DD) approach helps reduce endogeneity and identify causal effects (Angrist & Pischke, 2009). Extant research suggests that iOS apps and Android apps are comparable (Kapoor & Agarwal, 2017; Zhang et al., 2021). Moreover, we found that while at least 7% of the lifestyle apps on the iOS platform moved to the shopping category after the shock, only 0.13% of the lifestyle apps on the Android platform made the same move, showing that the shock we identified had nearly no impact on the control group. [4] In the robustness checks, we also used alternative control groups to further verify our results (Table 5).

[4] We tracked the Top 1500 apps in both lifestyle and shopping categories on a daily basis. Thus, it is highly likely we underestimate the percentage of moved apps, as many shopping apps were not listed in the Top 1500 lifestyle app chart. However, since we used the same approach to track both iOS and Android apps, our conclusion that the shock did not affect the control group still hold.

Sample construction

We collect sample apps in the two mobile app platform ecosystems from Apptopia , one of the leading analytics firms in the mobile app industry. The analytics firm collects and archives raw app information related to all mobile apps developed for the iOS and Android platforms. Its data are broadly used by app consumers, financial analysts, and marketing analysts (Chen et al., 2021). Our data set comprises detailed mobile apps information for the period from July 15th, 2015 (15 weeks before the date when the categorization plan was announced) to February 28th, 2016 (15 weeks after the categorization was implemented) on both iOS App Store and Google Play Store that were available from the analyst firm. Note that in order to strengthen our identification, we excluded the observations that appear from the announcement date (October 26th, 2015) to the release date of the new shopping category (November 4th, 2015).

We collect apps listed in the Top 1500 Grossing chart during the observation period. During the observation period, we collected the data required to calculate the variables used in our analyses for each app appearing at least once during our observation period on the Top Grossing charts. We retrieved additional data from Apptopia to calculate firm age and obtain the number of categories in which the 12,741 app publishing firms in our sample had apps. Our data collection resulted in data for 122,208 lifestyle apps. The final number of apps included in our dataset is 12,505.

Variables and measures

Dependent variables. To capture app performance, we focus on two important aspects: new installs and revenue generation. These two aspects are important because they represent platform users' initial consumption of a complement and their subsequent purchasing associated with the complement, which are critical for app success. We measure apps' new installation with the average daily download, $Download_{it}$, for each app i in week t. We measure apps' revenue generation with the average revenue per user, $RevPerUser_{it}$, for each app *i* in week *t*, where revenue covers all three major revenue sources, namely download revenue, in-app purchase revenue, and advertising revenue.

Explanatory variable. We use *Lifestyle*, a dummy indicator that takes a value of 1 for Apple Lifestyle apps, which are subject to the impact of Apple's categorization adjustment and 0 for lifestyle apps on Google Play, to mark the "treatment group" and the "control group", respectively. *After*, is a dummy variable that takes a value of 1 for weeks after the lifestyle categorization event, and 0 for weeks before the event. Then, the interaction term DD (*Lifestyle***After*) is created to identify the treatment effect of the homogenization of the lifestyle category on Apples' app store.

Control variables. Following previous literature on mobile apps and app performance (Angus, 2019; Kapoor & Agarwal, 2017; Lee & Raghu, 2014; Wen & Zhu, 2019), we included a set of control variables at the app-, publisher-, and category-levels. First, we controlled for app-specific characteristics, including *Rating* (average rating scores the app received in the focal month), *Ranking* (average rank of app *i* in the Top Gross Chart in week *t*), *Popularity* (logged number of ratings of app *i* in week *t* since its last version), and *App update* (the number of updates the app released in the focal month). Second, at the publisher level, we controlled for *Publisher's product scope* (number of categories of app publisher *j* in week *t*). Finally, at the app category level, we controlled for *Competition within the category* (HHI index based on revenue). We also included app and time fixed effects into the model. We report the summary statistics and correlation coefficients in Table 3.

Insert TABLE 3 Here

Statistical approach

For statistical inference, we adopt the ordinary least squares (OLS) for straightforward interpretation of the results. To strengthen our inference, we further implement coarsened exact matching (CEM). CEM is increasingly adopted in management research due to its advantages such as the inclusion of monotonic balance bounding (Blackwell, Iacus, King, & Porro, 2009) that reduces model-dependence, bias, and inefficiency (Iacus, King, & Porro, 2012). Specifically, to achieve greater balance between the treatment and control groups, we match not only on all covariate controls within our observation window as differences in the covariates may also associate with app performance. Given the difference-in-differences research design, we estimate the following model specification to examine the treatment effect of homogenized app category on app performance:

$$\mathrm{Y_{it}} = \beta_0 + \beta_1 \mathrm{DD_{it}} + \delta_2 \mathrm{X_{it}} + \mathrm{T_t} + \mathrm{I_i} + \varepsilon_{\mathrm{it}} \tag{1}$$

where $\mathrm{Y_{it}}$ is the dependent variable for app *i* in week *t*; β_0 is the intercept; β1 identifies the treatment effect of $\mathrm{DD_{it}}$ (*Lifestyle*After*); $\mathrm{X_{it}}$ are covariate controls; $\mathrm{T_t}$ is a vector of week fixed effects; $\mathrm{I_i}$ is a vector of individual app fixed effects; and $\varepsilon_{\mathrm{it}}$ is the error term.

RESULTS

Assessment of the parallel trend assumption

To validate the parallel trend assumption, which is critical to our research design, we combine statistical analysis with data visualization following prior research (e.g., Wen & Zhu, 2019). Specifically, we aggregate the values of temporally neighboring observations of each app and use the periods further away from the treatment as the benchmark to estimate the dynamic DD effects of app performance before and after the treatment and plot these effects in Figure 1. The graph shows that before the homogenization of lifestyle category on Apple's app store, the performance of lifestyle apps on Apple's App store ("treatment group") and Google Play ("control group") show a similar trend. As such, the results suggest that the parallel trend assumption required in our empirical design is relatively valid.

Insert FIGURE 1 Here

Main results

We report the results testing the main hypotheses (i.e., H1 and H2) with Table 4. Results in Columns 2 and 4 indicate that after Apple's adjustments to the lifestyle category, lifestyle apps enjoy an increase in average download count. Specifically, the positive coefficient on the DD term indicates that iOS lifestyle apps receive about 9% more downloads ($p < 0.001$), compared with lifestyle apps on Google Play. Further, results in Column 2 indicate that after Apple's adjustments to the lifestyle category, lifestyle apps suffer from a decrease in revenue per user. Specifically, the negative coefficient on the DD term indicates that iOS lifestyle apps receive about 4% less revenue per user ($p = 0.001$), compared with lifestyle apps on Google Play. Hence, our H1and H2 are supported.

Insert TABLE 4 Here

Robustness checks

We examine the robustness of our results in several ways. First, we adopt a more comparable subsample of lifestyle apps for a more conservative estimation. While generally comparable, lifestyle apps only available on Apple's App Store may be different from the ones that are only available on Google Play. Such an endogenous difference may affect our estimation. To mitigate this concern, we rerun the regressions with a more conservative subsample of multi-homing lifestyle apps which are available on *both* Apple's App Store and Google Play. Such availability further enhances our empirical identification. As shown in Columns 1 and 2 of Table 5, the results are consistent with our main findings.

Insert TABLE 5 Here

Second, we use an alternative control group to further assess the robustness of our main findings. Specifically, we use Health & Fitness apps on the App Store as the alternative control group. Health & Fitness category includes apps related to healthy living, including stress management, fitness, and recreational activities. Thus, the contents and business models of these apps are rather comparable to those of lifestyle apps. The sample construction procedure is similar to that for the main sample. As shown in Columns 3 and 4 of Table 5, the results continue to be consistent with our main findings.

Third, to assess the generalizability of our findings, we rerun our estimations using the full sample (the sample without CEM matching). As shown in Columns 5 and 6 of Table 5, we continue to find coefficients on the DD variable to have signs, magnitudes, and levels of p-values that are qualitatively similar to the results using the CEM sample, indicating that our results are robust to both unmatched and matched samples.

Last, we follow the recommendation by Bertrand, Duflo, and Mullainathan (2004) to perform a placebo simulation to assess the treatment effect. Specifically, in each simulation iteration, we randomly assign the value of the treatment indicator to lifestyle apps in the CEM sample to simulate a placebo condition (i.e., an iOS app may accidently receive a value of 0 for the treatment indicator, and a Google app 1). Then, we re-estimate our models and summarize the distribution of the statistics obtained in 2,000 simulation runs. As shown in Figure 2, the effects we identified in our main study are unlikely to be observed accidentally in our placebo simulations, further corroborating the validity of our main findings.

Insert FIGURE 2 Here

Supplementary analyses

We conducted multiple supplementary analyses to verify the key assumptions and check mechanisms we proposed. First, an assumption we made in hypotheses development is that customers can install complements for free. If installations are costly for customers, the selection effect may emerge in the first stage of customer-complement interaction, making local homogenization increase new installs to a lesser extent. We tested the moderating effect of the business model of the complement (Columns 1 and 2, Panel A, Table 6). Concurring with our proposition, paid business model negatively moderates the relationship between platform categorization and *Downloads*, and has no effect on *RevPerUser*.

Insert TABLE 6 Here

Second, we expect that platform categorization influences matching between a customer and a complement only if the complement is visible in the category (e.g., has a high rank) (Duan, Gu, & Whinston, 2009). If a complement is invisible to customers in the category (e.g., has low rankings), customers will not be able to match with it through search in the category. The complement may interact with customers through other channels (e.g., customer referrals) and therefore its performance is unlikely to be influenced by platform categorization. In line with this argument, we found that after platform categorization, apps with high ranks will have more new installs, but generate marginally less revenue from each installed customer than apps with low ranks (Columns 3 and 4, Panel A, Table 6).

Third, we examine how platform categorization influences total revenue of the complement, which is determined jointly by the number of installs and revenue generation from each install. Data analyses show that platform categorization has no effect on total revenue (Columns 1, Panel B, Table 6). It indicates that the positive effect of platform categorization on *Downloads* and its negative effect on *RevPerUser* may cancel each other out. Note that our research design does not allow us to test the long-term effect of platform categorization (e.g., more than 15 weeks). We will discuss this issue further in the discussion section.

Finally, platform categorization has two co-occurring consequences, i.e., reducing the number of complements and homogenizing complements within the category (as per footnote 3). We attempt to check if homogenization (which is the focus of our theory) alone imposes an effect on complement performance. To this end, we added the complement's ranking changes after the categorization as an additional control variable. Ranking changes can capture the effect of the reduction of complements, as when complements were moved out from the category, rankings of the remaining complements will be automatically changed. Our results with the additional control variable indicate that even controlling for the effect of the reduction of complements, homogenization can still saliently influence both two dependent variables as our theory predicts (Columns 2 and 3, Panel B, Table 6).

DISCUSSION AND CONCLUSION

This study aims to examine the relationship between platform categorization and complement performance. Platform categorization can be viewed as a method of local homogenization. It makes complements within a category more homogenous, without reducing the complement heterogeneity at the platform level. Homogenizing complements within the category makes a customer encounter less search frictions in identifying potentially fitted complements (i.e., the search effect) and accordingly encourages the customer to install more complements, which is often free of charge. Thus, platform categorization increases new installs of complement in the category. However, we also propose and find that as search frictions reduced and installed complements increased, complements face more intense competition in the device layer of the platform. As a result, customers become selective in making payments (i.e., the selection effect), and complementors collect less revenue from each installed customer.

Our study contributes to the platform governance literature (Chen et al, 2022; Kretschmer et al., 2020; Rietveld & Schilling, 2021) by explicating how the platform owner can manage complement heterogeneity of the platform. The goal of platform governance is to improve value creation and appropriation in the platform market. While complements need to be standardized in some aspects to ensure effective value appropriation, existing literature suggests that complement heterogeneity has a positive effect on value creation (Parker & Van Alstyne, 2018; West, 2003), as it contributes to the cross-side network effect and eases complementors from intraplatform competition (Boudreau, 2012). Yet several recent studies pointed out that complement heterogeneity can also lead to the inefficiency of matching customers and complements and accordingly hinders value creation (Halaburda et al., 2018).

A salient difference between our study and prior studies is that while prior studies focused on limiting the choices of complements to customers as a solution of improving matching efficiency (Cullen & Farronato, 2021; Li & Netessine, 2020; Scheibehenne, Greifeneder, & Todd, 2010), our emphasis is the management of the degree of complement heterogeneity. We argue that the platform owner can foster complement homogeneity locally, so that it strikes a balance between promoting the cross-side network effect and maintaining matching efficiency. Moreover, by recognizing that matching on the platform is often localized within platform categories, we suggest that platform categorization can be implemented strategically as an approach of platform governance.

More specifically, building on prior studies (Boudreau, 2012; Chade & Smith, 2006; Jung et al., 2021), we developed a comprehensive theoretical framework to investigate how value is created and distributed on platforms for digital complements. The framework comprises three value creation mechanisms, i.e., the network effect, the search effect, and the selection effect. Searching and selecting are conceptualized as two stages of the matching process (Chade & Smith, 2006). In addition to the tension between the network effect and the matching efficiency, we argue that there exists a tension between search and selection. This is because if a customer identifies more potentially fitted complements at the search stage, she tends to be more selective in making payments, especially when she can consume multiple complements. Although this tension exists in many contexts, it tends to remain latent in platforms for human agents (e.g., dating platforms) or psychical products (e.g., shopping malls) (e.g., Chernev, 2006; Jung et al., 2021), in which search and selecting are often conducted simultaneously and the customer's consumption is exclusive. We demonstrate that in the platform for digital complements, the search and the selection effects do co-exist and can be used to explain different outcomes of complement performance.

By directly testing the relationship between platform categorization and complement performance, we answer the call for research to examine the economic outcomes of platform governance (Chen et al., 2021). We found that platform categorization stimulates customers' consumption, as reflected in the increase of new installs. For platforms pursuing cross-side network externalities, this is a desirable outcome (Katz & Shapiro 1985). Thus, our findings suggest that platform categorization is beneficial to the platform owner. However, we also underscore that the positive effect of platform categorization on value creation in the platform should not be overestimated, as categorization does not necessarily make existing complements more profitable, at least in a short term.

Our findings are also insightful to complementors, who want to understand how actions made by the platform owner may affect their performance. While complementors should not expect to gain an immediate financial return from joining in a more homogeneous product category, categorization does help them to acquire more new customers. Thus, complementors can see local homogenization and categorization as business opportunities, especially when their current goal is to build a large installed base (Casadesus-Masanell & Hałaburda, 2014) or to obtain a good reputation (Boudreau & Jeppesen, 2015; Jiang & Sarkar, 2009). Complementing prior studies that examine how firms position themselves within a given product category to balance differentiation and conformity (Barlow et al., 2019; Cattani et al., 2017), our findings indicate that complementors can select their product categories strategically to ensure efficient matching with customers.

Future research could extend our study in various directions. While boosting complement performance is a key task of platform governance, future research can examine other economic outcomes of platform categorization. Specifically, platform categorization may improve customer satisfaction (e.g., customers may be more satisfied when more choices of complements are presented) (Scheibehenne et al., 2010) and attract more complements to join the platform (e.g., complementors which value installed base) (Boudreau & Jeppesen, 2015). In addition, even though platform categorization may not contribute to complements' short-term revenue performance (i.e., 15 weeks after the categorization), it may enhance complements' long-term revenue performance. For example, a complementor with a larger installed base may be able to better attract advertisers in the future. Due to the limitation of the data, we are not able to examine these economic outcomes in the current study. By analyzing these outcomes, researchers can develop a more comprehensive understanding of the effectiveness of platform categorization as a platform governance approach.

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TABLE 1. Mechanisms of the impact of complement homogeneity on value creation

Mechanism	Description	Predicted relationship between complement homogeneity and value creation in the platform
The cross-side network effect	The platform is more attractive to customers when the size and the degree of heterogeneity of the complement group increase	Negative (–)
The search effect	The customer finds it difficult to search for and identify complements that can potentially match her needs	Positive (+)
The selection effect	In the presence of more choices of complements, the customer becomes more selective and fastidious in making payments	Negative (–)

TABLE 2. Summary of hypotheses

Complement performance	Key features	The search effect	The selection effect	The impact of platform categorization on complement performance
New installs	Installation is often free of charge	Applicable	Not applicable	Positive (+)
Revenue generation from each installed customer	Revenue generation mainly takes place in the device layer	Not applicable	Applicable	Negative (–)

Note: a) Platform categorization has no effect (a trivial effect) on the cross-side network effect, because platform categorization does not affect global heterogeneity (complement heterogeneity of the whole platform); b) We consider complementors that collect fees for installations in supplementary analyses.

TABLE 3. Summary statistics and correlation coefficients

Panel A: Variable definition and summary statistics

Variables	Mean	S.D.	Min.	Max.
Downloads (log)	1.70	1.71	0	8.86
RevPerUser (log)	0.83	0.73	0	3.71
Lifestyle	0.75	0.43	0	1
After	0.50	0.50	0	1
UserAverageRating	4.00	0.59	1	5
Ranking (log)	6.12	0.74	2.56	7.31
Popularity (log)	4.36	1.63	0.69	9.49
AppUpdate (log)	0.02	0.11	0	1.61
PublisherScope (log)	1.45	0.66	0.69	3.09
Competition Intensity (HHI)	0.25	0.14	0.12	1

Note: Panel A repots the summary statistics of the variables in the CEM sample. Please refer to the Data and Methods section for detailed operationalization. N=18,014.

Panel B: Correlation coefficients

Variables	1	2	3	4	5	6	7	8	9
1 Downloads (log)									
2 RevPerUser (log)	-0.01								
3 Lifestyle	0.27	-0.21							
4 After	0.04	-0.02	0.03						
5 UserAverageRating	0.10	0.09	-0.26	-0.03					
6 Ranking (log)	-0.21	-0.19	0.40	0.02	-0.21				
7 Popularity (log)	0.40	-0.02	-0.18	0.02	0.30	-0.47			
8 AppUpdate (log)	0.04	-0.02	0.00	-0.01	0.02	-0.05	0.03		
9 PublisherScope (log)	0.02	-0.15	0.16	0.02	-0.08	0.11	0.03	-0.01	
10 Competition Intensity (HHI)	-0.16	0.19	-0.75	-0.06	0.21	-0.37	0.16	0.02	-0.14

Note: Panel B repots the correlation coefficients among the variables in the CEM sample. N=18,074.

TABLE 4. Difference-in-differences results for app performance (CEM)

Variables	(1) Downloads	(2) Downloads	(3) RevPerUser	(4) RevPerUser
DD (Lifestyle*After)		0.096***		-0.044***
		(0.000)		(0.001)
UserAverageRating	0.129*	0.127*	-0.002	-0.002
	(0.066)	(0.069)	(0.930)	(0.949)
Popularity	0.113	0.127*	0.045*	0.039
	(0.134)	(0.098)	(0.088)	(0.153)
Rank	-0.365***	-0.364***	-0.124***	-0.124***
	(0.000)	(0.000)	(0.000)	(0.000)
AppUpdate	0.018	0.018	0.006	0.006
	(0.577)	(0.567)	(0.748)	(0.739)
PublisherScope	0.272	0.324	0.045	0.023
	(0.324)	(0.230)	(0.699)	(0.845)
Competition Intensity	-0.196	-0.091	0.032	-0.016
	(0.282)	(0.622)	(0.765)	(0.883)
Observations	18,014	18,014	17,615	17,615
Number of Apps	916	916	916	916
Adjusted R-squared	0.532	0.533	0.142	0.143
Week FE	Yes	Yes	Yes	Yes
App FE	Yes	Yes	Yes	Yes

Note: This table reports results using the CEM sample. The unit of analysis is the app-week level. The dummy variables *Lifestyle* and *After* are dropped out because of perfect collinearity with the fixed effects. P-values based on standard errors clustered on the individual level are reported in parentheses.

TABLE 5. Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Multi-homing Apps Only		Fitness Apps as Control		Full Sample	
Variables	Downloads	RevPerUser	Downloads	Downloads	Downloads	RevPerUser
DD (Lifestyle *After)	0.160***	-0.047*	0.138***	-0.015**	0.083***	-0.047***
	(0.000)	(0.054)	(0.000)	(0.019)	(0.000)	(0.000)
Observations	9,885	9,676	77,323	77,323	48,336	45,084
Number of Apps	452	452	3,638	3,638	2,394	2,327
Adjusted R-squared	0.678	0.228	0.496	0.125	0.601	0.646
Lagged DV	No	No	No	No	No	No
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
App FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports results for the robustness checks for the main findings. The unit of analysis is the app-week level. The dummy variables *Lifestyle* and *After* are dropped out because of perfect collinearity with the fixed effects. P-values based on standard errors clustered on the individual level are reported in parentheses.

TABLE 6. Supplementary analyses

Panel A. Moderation Explorations

Variables	(1) Business Model Moderation Downloads	(2) RevPerUser	(5) Gross Rank Moderation Downloads	(6) RevPerUser
DD (Lifestyle*After)	0.215***	-0.048***	0.914***	-0.297**
	(0.000)	(0.006)	(0.000)	(0.036)
DD*PaidApp	-0.223***	0.004		
	(0.000)	(0.873)		
After*PaidApp	0.026	0.026		
	(0.440)	(0.274)		
DD*GrossRank			-0.134***	0.040*
			(0.000)	(0.084)
Lifestyle*GrossRank			0.394***	0.073
			(0.000)	(0.134)
After*GrossRank			0.020	0.002
			(0.380)	(0.881)
Observations	18,014	17,615	18,014	17,615
Number of Apps	916	916	916	916
Adjusted R-squared	0.537	0.144	0.539	0.148
Other Controls	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
App FE	Yes	Yes	Yes	Yes

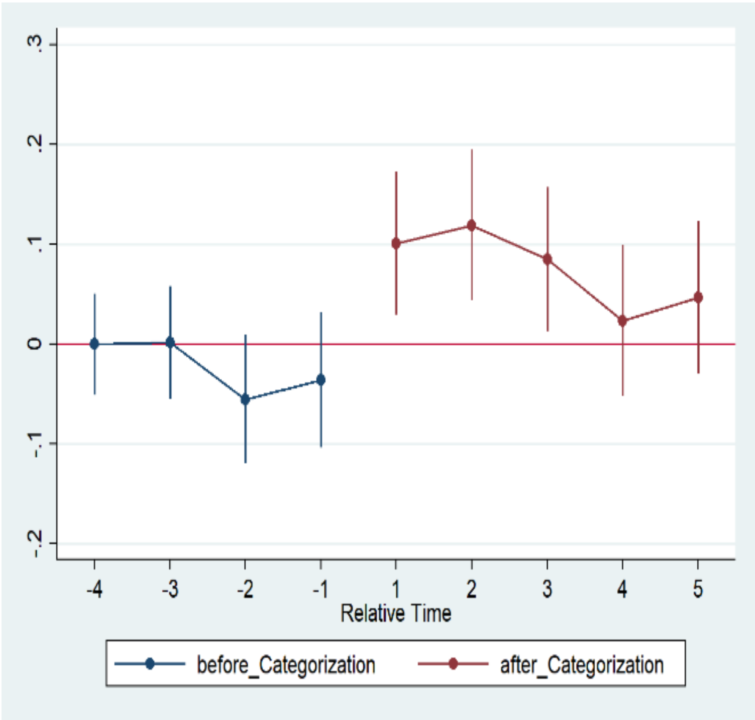
Note: The unit of analysis is the app-week level. The dummy variables *Lifestyle*, *After*, *Lifestyle*PaidApp*, and *Lifestyle*PreGrossRank* are dropped out because of perfect collinearity with the fixed effects. P-values based on standard errors clustered on the individual level are reported in parentheses.

Panel B. Additional Analyses

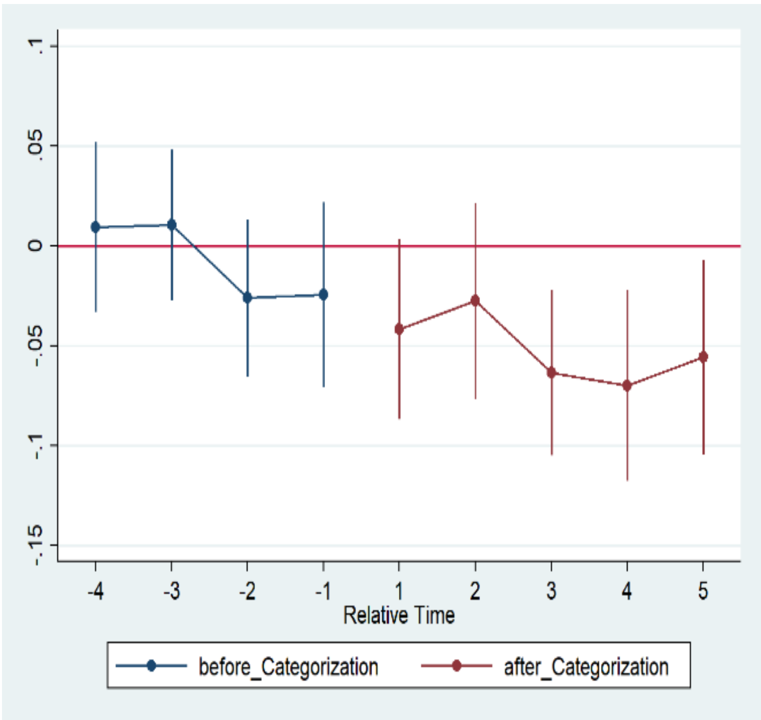
Variables	(1) Alternative DVs TotalRevenue	(2) Control for Rank Change Downloads	(3) RevPerUser
DD (Lifestyle*After)	-0.088	0.097***	-0.044***
	(0.208)	(0.000)	(0.001)
RankChange		-0.013***	-0.001
		(0.000)	(0.254)
Observations	17,615	18,014	17,615
Number of Apps	916	916	916
Adjusted R-squared	0.152	0.535	0.144
Other Controls	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
App FE	Yes	Yes	Yes

Note: The unit of analysis is the app-week level. The dummy variables *Lifestyle* and *After* are dropped out because of perfect collinearity with the fixed effects. P-values based on standard errors clustered on the individual level are reported in parentheses.

FIGURE 1. Parallel Trend Graphs



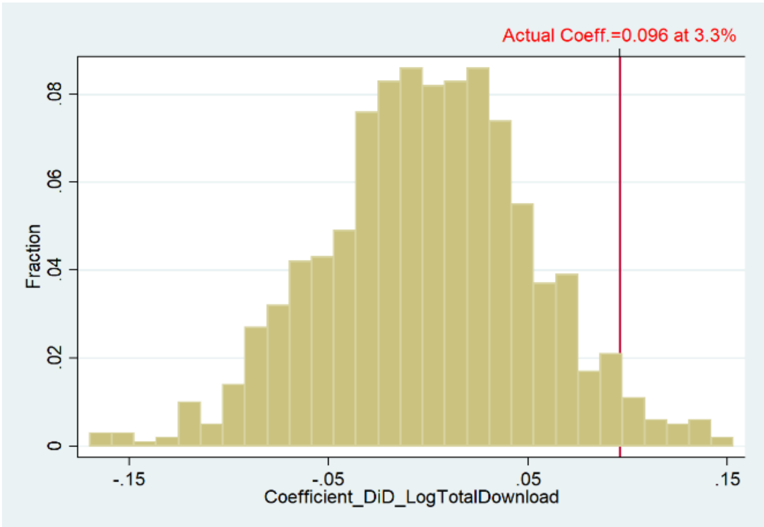
Panel A. Total Download



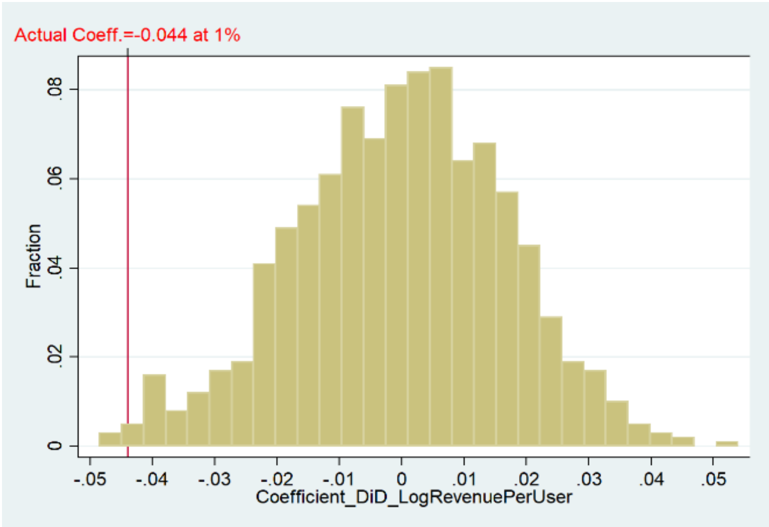
Panel B. Revenue Per User

Note: Each point on the graph represents the coefficient of the interaction term Lifestyle × Three-Week Dummy. The bars surrounding each point represent the 95% confidence interval. All values are relative to the average difference between the treatment and control groups from week -12 to week -15 in the pre-treatment period.

FIGURE 2. Placebo Treatment Simulation



Panel A. Total Download



Panel B. Revenue Per User