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Asymmetric Within and Between Popularity Effects: Evidence From Multihoming

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A B S T R A C T

Observational Learning (OL) in Information Systems (IS) literature, inferring product quality from the popularity as an aggregated summary of the purchase history, differs from Word of Mouth (WOM) effects in that OL offers less information and thus leaves more room for interpretation of the quality signal. Our study empirically tests the asymmetric effect of the popularity of a platform on a sale conducted on that platform (within-popularity effect) and the asymmetric spillover effects of the popularity of a platform on sales conducted on the other platform (between-popularity effect) using multihoming games across two representative mobile platforms, i.e., Google Play and Apple's App Store. Consideration of the multihoming games gives salience to the asymmetries by controlling for matched game quality, a possible cause of simultaneity. We exploit a diverse panel data framework to systematically address unavoidable econometrical issues and a dynamic panel data model to control endogeneity of autoregression. Finally, by applying z-test to compare two matched pairs of coefficients, we found that the within-popularity of the Google Play is significantly greater than that of the App Store, whereas the between-popularity is significantly less. We speculate that contextual information, that is, information publicly available about a platform's policy, moderates the interpretation of OL signals, causing asymmetric effects.

Keywords: Multihoming, Platforms, Asymmetric Effects, Observational Learning

Ⅰ. Introduction

Consumers often take the crowd opinion into account in their purchase decisions. They may read or hear about what other customers have to say about a product. In Marketing and Information Systems (IS) literature, numerous studies on Word-of-Mouth (WOM) established that customers are affected by reviews, specifically, from the aggregate review metrics such as average quality rating, the number of

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customer reviews, variance of ratings, textual content of the ratings, etc (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Zhang et al., 2013). In addition to what others say about a product, customers are also affected by what others do about a product by observing the crowd's attitude towards a product. In housing markets, a house staying too long on the market, even with a fantastic location and reasonable price, raises skepticism around its value over time. Restaurants that many people are waiting in the line to get into may encourage customers to wait for a long time with higher quality expectation. "Observational learning (OL)," draxg inferences about product or service quality from a mere observation of the crowd's choice, has been studied analytically in the economic and psychological literature (Bikhchandani et al., 1998, 2008) and, more recently, empirically in the marketing (Chen et al., 2005; Zhang, 2010) and IS literature (Dewan and Ramaprasad, 2012).

OL literature demonstrates that the information gathered through observational learning signals the quality and taste of a product or service, and differs from WOM in that the OL embodies less information than WOM (Chen et al., 2005). Prior research regarding OL in an online environment shows that the exposure to information about popular products results in making those products even more popular, often leading to winner-take-all outcomes in the markets (e.g., Chen et al., 2005; Salganik et al., 2006). The customers tag along with the collective actions of a similar group and engage in herding behavior (Banerjee, 1995). When doing that, customers interpret the OL signals differently depending on the context. For instance, customers interpret the same OL information more influentially for narrow appeal products than for broad appeal products (Tucker and Zhang, 2011). Dewan and Ramaprasad (2012) show that the OL effect becomes bigger in the tail than in the body because people obtain a clearer signal of quality. The insights from the contextual research of the online OL effect are very important from the perspective of the platform owners and the service provider that determines the exposure timing and channel of the product. Understanding what parts customers perceive before making a purchasing decision will be inevitably beneficial for service providers who decide on appropriate time and circumstances and support the platform managers to provide a sustainable and better service. However, the asymmetric effects of OL have been understudied compared to the importance of the topic for practitioners and academicians. In this study, we investigate the asymmetric effects of OL in the context of mobile application platforms, namely Apple's App Store and Google Play, due to their dominance in the market. Since OL is based on drawing quality perception given what others have chosen, we take app popularity, which is communicated in the form of ranking of an application on a platform, as a signal for potential buyers to infer how well an application is received among other customers. Considering two separate platforms on which the same applications are launched, we investigate (1) if there are any popularity effects within and between the two platforms and (2) if there are any popularity effects, whether these effects are asymmetric within and between the platforms. To address our research questions, we collected data from AppAnnie.com, an online platform providing data analytics for app developers to position their brands in the mobile app ecosystem.

Based on our investigation of the policies of the two platforms and their exposure to the public through the news, we identify platform-specific accreditation policies for a newly-registered game. For example, the App Store imposed a six-day review process of a game candidate before it is published to their platform. Note that, according to Macworld and Snell (2009), around 20% of apps are rejected before they are registered to the platform. However, Google Play drops unpopular games out of the basket after publication on the platform. Given that each consumer adopts a single platform, we hypothesize that the two platforms may have asymmetric OL effects since consumers selectively ingest the available information about the applications on the platforms.

To show this asymmetry, we exploit multi-homing games that are launched on both platforms. Since we can control game specific attributes, the multi-homing games are well-matched with addressing our research questions. The multi-homing strategy has become very common in the mobile application industry. The proportion of multi-homing applications on the two platforms was bided in 2.7% (Mashable, 2010) in 2010 and reached 37% (VisionMobile, 2015b) in 2015. Since multihoming became almost a typical practice, such commonality partially reduces selection bias.

In this study, we first empirically show that thxre is a platform's popularity effect on sales that accrue on that platform ecosystem, which is called the within-popularity effects. We explore whether platform-specific entrance policies create different competition environments for the applications hosted on individual platforms, that result in asymmetric within-popularity effects. The asymmetric effects of OL can be identified at the quasi-experimental level with multihoming. A game developer tends to roll out a game of similar quality onto two different platforms, sequentially or simultaneously, with the same title. Therefore, we can partially control for quality, which would otherwise potentially raise an endogeneity issue. Second, we can identify asymmetric spillover effects between the platforms. For example, the high ranking of a game on the App Store might not affect the sales of that application on Google Play to the same extent that the same information on Google Play affects sales on the App Store. We call the popularity effect of a platform on sales on the other platform as the between-popularity effect. Asymmetric strength of between popularity suggests sequential market entrance or multihoming strategy of a game.

The rest of the paper is organized as follows. The next section provides an overview of the literature on within and between popularity effects and hypothesis development. In section 3, we describe data, and a model is presented to estimate our hypotheses. In section 4, we report the results of the estimations. We conclude our paper with a discussion and directions for future research in section 5.

Ⅱ. Literature Review and Hypothesis Development

In this section, as we provide a literature review of our research questions, we also develop our hypotheses. Our literature review covers the main topics of platform policies, and within/between popularity effects.

2.1. Observational Learning (OL)

Observational Learning (OL) in the Bandura's social learning theory originally refers to learning through observation with consistent social interaction (Groenendijk et al., 2013), that is, the process of acquiring information through observing other people's behaviors. In certain environments, ranking information of product and service is provided as an indicator of online OL. The prior literature on

OL also covers the research on herding behaviour (Qiu et al., 2021), because herding and OL are affected from information such as rankings or online WOM that the information provided from the existing consumers influences potential consumers' decision making (Lu et al., 2021; Qiu et al., 2021). As an extension to this research stream, we hypothesize that the OL behaviors of consumers may differentiate depending on the platform characteristics

2.2. Multihoming

In the context of the mobile applications market, multihoming refers to utilizing multiple platforms as channels to achieve the same purpose. Multihoming on various platforms occurs for both app providers and consumers when they sell and purchase the same service or product, respectively (Li and Zhu, 2021). With technological advancement, multihoming becomes more general and prevalent for both buyers and sellers on the platforms (Bakos and Halaburda, 2020). This study focuses on multihoming for the consumers side, which leads to variety in platform policy designs and advertising strategies (Zhang et al., 2022).

2.3. Mobile App Stores and Platform Policies

The representative mobile app ecosystems include Android-based Google Play and iOS-based Apple's App Store (Karhu et al., 2020; Mcllroy et al., 2016; Yoon, 2014). Although competing platforms in the same market tend to have their policies converge into each other over time, the two representative mobile platforms have their own review policy at the time of our data gathering. In the case of the first mover, Apple's App Store, security is enhanced by borrowing a closed policy, but compared to the late comer, Google Play, access to participate in the market is not easy (Karhu et al., 2020). Apple's App Store has a stringent qualification process for an application in order to assure the app quality with respect to safety, performance, business, design, and legal issues. The policy states "don't simply copy the latest popular app on the App Store, or make some minor changes to another app's name or UI and pass it off as your own" to avoid clones of popular apps (Apple, 2016). In sharp contrast, Google Play has a relatively low entrance barrier. An application is automatically checked only for security concerns, and immediately published onto the market (Corral et al., 2014). Google Play emphasizes autonomy while raising concerns about low security from the high freedom in the market (Karhu et al., 2020). However, Google Play removes unpopular applications from the market every quarter (AppBrain, 2016). That said, Google Play provides developers with initiative and an autonomous development environment in order to stimulate the market, whilst Apple's App Store rigorously strives to protect users and enhance security.

Interestingly, there appears to be a difference between users' perception of security and personal information protection depending on what platform the specific consumer uses (Greene and Shilton, 2018; Martin et al., 2017). That said, these two ecosystems are giving consumers a different impression with their own operational policies. Most consumers are, whether consciously or unconsciously, aware of the difference between these two markets (Greene and Shilton, 2018; Martin et al., 2017). Likewise, the public exposure of the two unique policies may give strong signals to both participants of the platform. Given the differences between the App Store and Google Play's app admission policies, such a platform policy gives consumers a signal that games on that platform are differentiated (horizontally different) or at least the game quality is minimally guaranteed (vertically qualified). Given this signal, in this paper, we demonstrate that the policy information moderates the relative importance of OL for consumers when they make purchase decisions. For example, consumers rely less upon the popularity information if they believe that they need more alternative accessible information such as detailed textual comments or descriptions

2.4. Within Popularity Effects

OL contains less information compared to WOM and exposes only the actions of other consumers, not the reasons behind their actions. Information cascade theory explains that even there is a limited amount of information available when heterogeneous consumers observe the purchase actions of a high fraction of other consumers in the population, the publicly-observed information overwhelms their private beliefs, causing all subsequent consumers to hold similar beliefs. Therefore, what game a user downloads largely depends on the share of prior choices in the basket of consideration (Bikhchandani et al., 1998).

With over 150 thousand newly posted mobile games a year on a platform (PocketGamer, 2016), a platform recommends top-ranked games to help consumers find more enjoyable ones by category. The Apptentive (2012) shows that about thirty percent of users find their apps from top-ranked apps. Therefore, we hypothesize that the popularity of a game on a platform further drives the sale of that game on that platform, hence within popularity effect.

H1: There exists the within popularity on both platforms.

Prior literature also demonstrates our suspicion about asymmetric OL effects on two platforms. According to Tucker and Zhang (2011), the popularity of a narrow-appeal product can step up its sales more than that of an equally popular broad-appeal product. The logic behind this interesting finding is that a broad-appeal product fits to general taste and thus has a higher chance of being chosen, inducing customers to estimate higher quality for the narrow-appeal product. Dewan and Ramaprasad (2012) show that the popularity effects of niche music sales are asymmetric in the body and in the tail. Interestingly in the tail, the popularity effects are stronger because it offers a relatively stronger signal of music quality for niche music which has greater quality uncertainty for the user. In our context of application platforms, the popularity effect for a product positioned among apps that are allowed to enter into the platform based on a stricter screening process (the policy of Apple's App Store) would be different than for the same product when entering into the app market through a less limiting entrance policy (the policy of Google App). Therefore, we hypothesize that popularity effects are asymmetric across two platforms of our focus.

H2: The within popularity effects are asymmetric in platforms.

2.5. Between Popularity Effects

Although between-popularity effects across platforms have been understudied, a similar concept of 'spillover effects' is explored in the marketing literature. Spillover effects are well documented for a product category competing across different brands (Roehm and Tybout, 2006) or for a specific brand hosting different products (John et al., 1998; Lei et al., 2008). Spillover effects among different products in a brand are relevant to brand recognition and its updating (Lei et al., 2008). The popularity of a brand product increases the awareness of the consumers about both brand and the product. Moreover, a strong association between a new product and a brand product renders information about the expected quality of the new product, creating a positive or negative spillover, depending on how the customer's expectations about the new product are met.

Spillover effects are also studied in the IS literature to an extent. For example, a promotion from a store on a location-based service platform not only increases that store's check-ins but also improves the sales of its neighbors due to the fact that customers are more likely to be aware of the neighbors (Liu et al., 2014). In IT innovation literature, an innovation success gives rise to other companies' recognition, bringing out active information sharing and collaboration and eventually creating positive spillover effects on productivity (Cheng and Nault, 2012). In the app market, the sales rankings of an app in a particular platform bring spillover effect to another platform, which confirms cross-platform correlation (Ghose and Han, 2014). In this paper, we consider the games that are launched on two platforms. Therefore, in our context, we hypothesize that there exists a positive spillover effect because the popularity of a game on a platform makes that game visible to all the users and also renders its quality and possible fitness to a customer's taste.

H3: There exist the between popularity effects across both platforms.

The spillover effects can be observed across firms in a pairwise relationship, where firms operate in related businesses. In such a relationship, firms derive asymmetric benefits from each other depending on the context. For example, the spillover effect from an organic search click-through on paid ad clicks is three times stronger than vice versa (Yang and Ghose, 2010), and bars' promotions benefit neighboring restaurants in the same location but restaurants' promotions do not (Liu et al., 2014). Similarly, in our context, we hypothesize that the success of a multihoming game on a platform does not provide symmetric influence on the other platform hosting the same game, since consumers of a platform may interpret the success differently depending on the platform policies and context.

H4: The between popularity effects are asymmetric across platforms.

Ⅲ. Data and Economic Estimation

To empirically test our hypotheses, we collected mobile game data from AppAnnie.com, in which, the details of games hosted by the App Store and Google Play are available. The data include top charts, app ranking history, price changes, reviews, and app descriptions across Apple and Google Play (AppAnnie, 2012). Since our interest is in understanding within and between popularity effects and their asymmetry, we believe AppAnnie data is appropriate because AppAnnie lists only the high-ranking popular games on respective platforms, that is, a game is listed at AppAnnie only when its rank is below 540 and 1500 for Google Play and the App Store platforms, respectively.

Since a subset of the games listed at AppAnnie was overlapping for the App Store and GooglePlay, we ended up pairing 661 games by matching their titles from the two platforms. For these paired titles, we traced all the details of the games on a weekly basis from March 2013 to March 2015, making panel data with 25,451 observations. Due to the limitation of data availability of AppAnnie – neither below 540 ranked in Google Play nor 1,500 in the App Store is available in AppAnnie and the rankings of the games may change from one week to another-, we considered the unavailable time periods of a game as missing values, making our dataset an unbalanced panel with fifty percent of games missed.

Unlike online markets for books, music, and movies, the market for apps is more welcoming to making any changes in the pricing strategy or the set of app features (Lee and Raghu, 2014). Because of that, we removed the games of which the pricing strategy, either from free to paid or from paid to free, has been changed during the two-year period of data collection. In addition, if a game had multiple versions, we considered only the first version of that game because a newer version of that game may offer additional features, providing higher quality with relatively less user feedback and lower ranking.

Since either platform does not disclose the sale data of a game, we infer it from publicly available rank data from AppAnnie. In their paper, Garg and Telang (2014) assume that the relationship between app sales ranks and actual sales follows the Pareto distribution (sales = b × (rank) - a + u), where a logarithmic transformation of the same expression provides ln(sales) = ln(b) - a × ln(rank), and a, b, and u are the model parameters. To identify the diminishing marginal impact of within popularity effect, we used the prior week's ranking information, $\ln(RankB_{i,t})$, as a proxy to the popularity effect in the current week. Thus, we created a dynamic panel model framework (Menon and Kohli, 2013) below.

$$\ln(RankB_{i,t}) = \beta 0 + \beta 1 \ln(RankB_{i,t-1}) + \beta 2 Top100A_{i,t} + \beta 3 \ln(ReviewB_{i,t}) + \beta 4 RatingB_{i,t} + \beta 5 \ln(AgeB_{i,t}) + \gamma t + \delta_i + \varepsilon_{it} \qquad \text{[Model 1]}$$

In Model 1 above, we have the following control variables: First, we introduce $Top100A_{i,t}$ to estimate the between popularity effect on sales. That is, if a game ranks highly on a platform, the popularity of that game will ignite an increase in sales of the same game on other platforms. Second, we also consider the two aggregate metrics of online WOMs, the number of reviews ($ReviewB_{i,t}$) and average rating ($RatingB_{i,t}$), because these two metrics have been known as factors to influence sales by reducing the uncertainty of the product (Chevalier and Mayzlin, 2006; Liu, 2006). We also include the logarithmic transformation of a game's age, $\ln(AgeB_{i,t})$, to reflect the diminishing marginal impact of time after the release of a game (Ghose and Han, 2014). To control for time-variant unobservables, we also incorporate γ_t – week dummies - into our model 1. Finally, δ_i denotes unobserved time-invariant characteristics of a game, and the variable $\varepsilon_{i,t}$ represents unobserved factors that change over time and across games which both affect the dependent variable.

In Model 1, the Ordinary Least Squares Regression (OLS) estimation can be biased because of the correlation between δi and $\ln(RankB_{i,t-1})$. Therefore we eliminate δi by first difference transformation:

$$\triangle \ln RankB_{i,t} = \beta 1 \triangle \ln RankB_{i,t-1} + \beta 2 \triangle Top100A_{i,t} + \beta 3 \triangle \ln ReviewB_{i,t} + \beta 4 \triangle RatingB_{i,t} + \beta 5 \triangle \ln AgeB_{i,t} + \triangle \gamma t + \triangle \varepsilon_{it} \qquad \text{[Model 2]}$$

Since $\triangle \ln(RankB_{i,t-1})$ is correlated with $\triangle \varepsilon_{it}$ by construction, we consider 2SLS-IV based approach

<Table 1> Description of the Variables

Variables	Definition	Mean	Min	Max
$Rank^{the\ A.S}_{i,t}$	iTune, download rank for current week t	336	1	1458
$Rank^{GP}_{i,t}$	Google Play, download rank for current week t	201	1	538
$Review^{the\ A.S}_{i,t}$	iTune, cumulative # reviews for current version by week t	108	0	8260
$Review^{GP}_{i,t}$	Google Play, cumulative # reviews for current version by week t	379	0	14764
$Rating^{the\ A.S}_{i,t}$	iTune, average rating for the version by week t	3.9	0	5
$Rating^{GP}_{i,t}$	Google Play, average user rating for the version by week t	3.7	0	5
$Age^{the\ A.S}_{i,t}$	iTune, # weeks since the version released	20	1	211
$Age^{GP}_{i,t}$	Google Play, # weeks since the version released	28	1	276
Variables	**Definition**	**Value**	**Freq.**	**%**
$Top100^{the\ A.S}_{i,t}$	1 if a game enters top 100 of iTune by week t. 0, otherwise	1	363	55%
		0	298	45%
$Top100^{GP}_{i,t}$	1 if a game enters top 100 of Google Play by week t, otherwise 0	1	515	78%
		0	146	22%

(Anderson and Hsiao, 1982) which instruments $\triangle \ln(RankB_{i,t-2})$ for $\triangle \ln(RankB_{i,t-1})$. Since consistent estimations of the dynamic panel models require longer panels (Tambe and Hitt, 2013), we first apply Arellano and Bond generalized method of moments (GMM) that uses lagged differences as instruments to account for endogenous variables (Arellano and Bover, 1995; Blundell and Bond, 2000). Note that GMM is known to provide more effcient estimation for over-identified instruments. Since lags over two time periods were found insignificant, we only include the two lags of the ranking into the instrument

<Table 2> Results for Hypotheses 1 and 2 for Google Play Platform

	Model 1 (FD-GMM)	Model 2 (System-GMM)
$lnRank^{GP}_{i,t-1}$	0.936*** (0.036)	0.672*** (0.030)
$Top100^{the\ A.S}_{i,t}$	-0.992*** (0.033)	-0.079 (0.048)
$lnAge^{GP}_{i,t}$	-0.085** (0.033)	0.123** (0.041)
$lnReviews^{GP}_{i,t}$	0.085** (0.043)	-0.080* (0.048)
$Ratings^{GP}_{i,t}$	-0.045 (0.049)	-0.004 (0.039)
Fit Statistics	Wald × 2 (107) = 1265.15	Wald × 2 (107) = 1765.91

Note: ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$. Standard errors are shown in the brackets

<Table 3> Results for Hypotheses 1 and 2 for the App Store Platform

	Model 1 (FD-GMM)	Model 2 (System-GMM)
$lnRank^{the\ A.S}{}_{i,t-1}$	0.607*** (0.045)	0.659*** (0.031)
$Top100^{GP}{}_{i,t}$	-0.797*** (0.081)	-0.090 *(0.049)
$lnAge^{the\ A.S}{}_{i,t}$	0.035** (0.033)	0.109** (0.041)
$lnReviews^{the\ A.S}{}_{i,t}$	0.085** (0.018)	-0.080* (0.024)
$Ratings^{the\ A.S}{}_{i,t}$	-0.043 (0.037)	-0.112** (0.039)
Fit Statistics	Wald × 2 (108) = 153652.31	Wald × 2 (108) = 223015.53

Note: ***p < 0.001, **p < 0.05, *p < 0.1. Standard errors are shown in the brackets

matrix. Since we implement GMM after difference transformation, we name our model as FD-GMM. The results for FD-GMM are posted in the second column of <Tables 2> and <Tables 3>. As a robustness check, we run fixed effect estimation as well as Least Squares Dummy Variable (LSDV) estimation and we obtain quantitatively the same results with FD-GMM.

A condition for the validity of Arellano and Bond estimation is that the differenced error term is not second-order serially correlated. However, our data suffers from different serial correlation across the differenced error term, i.e., first-order to fourth-order serial correlations are significant. Arellano and Bover (1995) and Blundell and Bond (2000) revealed that the lagged levels are often rather poor instruments for first differenced variables, especially if the variables are close to a random walk and they offer System-GMM to address this issue. The modification of the estimator, System-GMM, includes lagged levels as well as lagged differences. Therefore, we also consider System-GMM. The results of this estimation are shown in the third column of <Tables 2> and <Tables 3>.

The Pagan-Hall test for heteroskedasticity suggests that our data are heteroskedastic. We estimate two-step standard robust errors with Windmeijer's (2005) correction. Results of all models are obtained by applying Roodman's program (Roodman, 2009). We also test FGLS estimation to control for heteroskedasticity and find the same results with Windmeijer correction.

Ⅳ. Interpretation and Conclusion

In this section, we first discuss our findings and present our concluding remarks.

4.1. Results and Further Analysis

According to our findings, the estimates for the popularity of prior time are positive and significant on both platforms. That is, a lower-ranking (higher

<Table 4> Summary of Asymmetries

	Within-Popularity	Between-Popularity
Model 1	5.63***	-8.51***
Model 2	-0.95	-7.47***

Note: ***p < 0.001, **p < 0.05, *p < 0.1.

popularity or higher customer downloads) of a game induces users to easily identify and download that game, bringing the ranking further down and making the game more popular. Second and more interestingly, estimates of T op100iT are negative and significant. It means that the popularity of a game on a platform entices users to download the game on the other platform, by attracting the attention of users of those platforms. The results for Hypotheses 1 and 3 are shown in <Tables 2> and <Tables 3>.

To test the asymmetric effects of popularity effect that is proposed in Hypothesis 2 and 4, we deploy the z test (Clogg et al., 1995), which is a commonly used method to compare the coefficients of the same model for two different platforms, where $z = \frac{\beta_1^{iOS} - \beta_1^{GP}}{\sqrt{(SE\beta_1^{iOS})^2 + (SE\beta_1^{GP})^2}}$ The results of the comparison of coefficients that are reported in <Tables 2> and <Tables 3>. are shown in <Table 4>.

From the results above, we conclude that within-popularity effects are partially supportive but between-popularity effects are significantly different in two platforms. With regards to within-popularity, Google Play has higher observational learning effect than the App Store does. Consumers of the App Store will credit ranking information less since games will be differentiated as well as their quality is guaranteed and so consumers are more likely to follow recommendations. However, consumers of Google Play tend to take the ranking information more seriously and prefer games that are more appealing to the general population.

Moreover, between-popularity in the direction of the App Store to GooglePlay is eight times stronger than that in the other way. Holding other factors fixed, if a game gets into the top 100 on Apple App Store, sales of that game on Google Play will increase by 80%. The logic behind this interesting finding is that consumers of Google Play may consider the highly ranked games at the App Store Platform due to the policies enforced at the App Store to differentiate a game from the others.

4.2. Robustness Analysis

When testing our hypotheses, we consider only the top 100 games to identify between-popularity effects, which may raise concerns about the cut-offs used as game selection criteria. Therefore, we consider different ranking criteria, e.g., top 25 and top 50, and the corresponding results are presented in <Tables 5> and <Tables 6>, respectively. The results show that within and between popularity effects in both platforms remain the same regardless of the cut-off criteria. In addition, popularity effects get more critical for higher rank lists, i.e., the top 25 spillover effect is higher than the top 50, and the top 50 is stronger than the top 100 one. Moreover, the z-test to compare the coefficients of the two models reports all significant results. Consequently, the robustness analysis gives us more confidence about our empirical model.

Finally, we considered possible sampling bias since we only consider top-ranked games. Therefore, we ran the Heckman model to control for any possible self-selection bias. Even if the results do not support our hypotheses of asymmetry (not significantly different), the signs of gaps are the same as our expectation, as shown in <Table 7>.

<Table 5> Hypotheses Testing with Top 25

	Google Play		the App Store	
	Model 1	Model 2	Model 3	Model 4
$lnRank^{j}_{i,t-1}$	0.923*** (0.036)	0.609*** (0.044)	0.664*** (0.027)	0.635*** (0.030)
$Top50^{j-1}_{i,t}$	-0.998*** (0.116)	-0.798*** (0.104)	-0.133*** (0.046)	-0.239*** (0.049)
$lnAge^{j}_{i,t}$	-0.066*** (0.031)	0.036* (0.019)	0.115** (0.040)	0.112*** (0.023)
$lnReviews^{j}_{i,t}$	0.075* (0.040)	-0.075** (0.037)	-0.070* (0.048)	-0.106** (0.034)
$Ratings^{j}_{i,t}$	-0.046 (0.045)	-0.061 (0.038)	-0.004 (0.036)	-0.130** (0.046)
Fit Statistics	Wald × 2 = 1454.57	Wald × 2 = 179220.91	Wald × 2 = 2029.20	Wald × 2 = 177939.23

Note: ***p < 0.001, **p < 0.05, *p < 0.1. Standard errors are shown in the brackets

<Table 6> Hypotheses Testing with Top 50

	Google Play		the App Store	
	Model 1	Model 2	Model 1	Model 2
$lnRank^{j}_{i,t-1}$	0.923*** (0.036)	0.611*** (0.042)	0.670*** (0.027)	0.640*** (0.033)
$Top25^{j-1}_{i,t}$	-0.989*** (0.114)	0.805*** (0.107)	0.110*** (0.059)	0.168*** (0.049)
$lnAge^{j}_{i,t}$	-0.061** (0.031)	0.052** (0.018)	0.111** (0.041)	0.116** (0.026)
$lnReviews^{j}_{i,t}$	0.065 (0.040)	-0.100** (0.033)	-0.067 (0.050)	-0.117** (0.038)
$Ratings^{j}_{i,t}$	-0.044 (0.044)	-0.068* (0.036)	-0.018*** (0.039)	-0.151** (0.050)
Fit Statistics	Wald × 2 = 1427.97	Wald × 2 = 154549.47	Wald × 2 = 1959.41	Wald × 2 = 158485.87

Note: ***p < 0.001, **p < 0.05, *p < 0.1. Standard errors are shown in the brackets

Ⅴ. Conclusion

Word of mouth (WOM) and Observational Learning (OL) have different in-fluences on consumers' choices. In particular, since OL offers more limited information than WOM does, consumers' dependency on OL information is coupled with an alternative source of information, which is the policy-related information of a platform in the context of this study. In particular, the ranking information as an indicator of OL in an online environment acts as an alternative index for users to efficiently make

<Table 7> Results from Heckman Model

	Google Play	the App Store
$Top100^{j-1}_{i,t}$	-1.175*** (0.107)	-0.153*** (0.058)
$lnAge^{j}_{i,t}$	0.041* (0.022)	0.318*** (0.026)
$lnReviews^{j}_{i,t}$	-0.068*** (0.019)	-0.377*** (0.027)
$Ratings^{j}_{i,t}$	0.089** (0.034)	0.178*** (0.049)
Constant	5.028*** (0.107)	5.552*** (0.191)
Selection Model		
$lnRank^{j}_{i,t-1}$	-0.803*** (0.025)	-0.726*** (0.018)
$Top100^{j-1}_{i,t}$	-0.386*** (0.087)	-0.384*** (0.057)
$lnAge^{j}_{i,t}$	0.001 (0.020)	0.199*** (0.023)
$lnReviews^{j}_{i,t}$	-0.020 (0.016)	-0.098*** (0.026)
$Ratings^{j}_{i,t}$	0.025 (0.027)	0.079** (0.031)
Constant	5.452*** (0.189)	5.615*** (0.147)
Fit Statistics	Wald × 2 (4) = 134.8	Wald × 2 (4) = 239.75

Note: ***p < 0.001, **p < 0.05, *p < 0.1. Standard errors are shown in the brackets

purchase decisions, but it is also information that can be displayed in different ways depending on the platform's internal operating policies. This study first shows the existence of OL effects and then extends this finding to investigate the asymmetric impact of popularity in different platforms. With the consideration of different policies across two platforms, this study sheds a light on how consumers make purchase decisions for the same product multihoming on two platforms.

Our results provide an explanation for the current practice of app multihoming across platforms. Multihoming is a decision that has to be made strategically by app platforms. Multihoming would allow app developers to have access to a wider user base, but also let the platform owners accommodate more number of developers and users. From the developer's side, multihoming always benefits the app developer, thanks to the between and within popularity effects.

However, this study was conducted based on the cognitive behavior of consumers who use multihoming in purchasing decisions. Consumers are provided with various options when making a purchase decision, but they naturally recognize the background contexts of different options before deciding, so the two platforms show different behavior patterns. That is, consumers tend to use disclosed OL information between/within platforms when they are using each platform. In fact, despite the presence of previous studies on the effects of management differences in existing platforms, the research contributes as an academic addition to the literature of multihoming platforms and online OL that online OL is caught up on with empirical evidence. In addition, the research can suggest several guidelines for platform owners, consumers, and app developers. In addition, the research can be presented to platform owners and developers as guidelines for different methods of product and service exposure, promotion, and operating strategies, as well as additional information for consumers to make the right choice. In particular, game developers who plan to enter the platform, advertising experts who aim to increase app sales using the platform, and companies participating to utilize advertising sales may gain a difference depending on the recognition of the within/between effect. Moreover, the study has made a substantial contribution to game entrepreneurs and platform managers in that the research refers to the perceived tendency of consumers before downloading. Based on this, platform owners establish not only training guidelines for newcomers but also business strategy guidelines for game developers.

Although multihoming appears to be beneficial for all sides involved in the platform ecosystem, it has different implications on the platform owners based on how platforms are governed and what kind of policies they adopt. This study shows that platforms should carefully steer their multihoming strategy considering their policy and regulations. For example, Google Play, as one of the major app development platforms, supports multihoming and chooses to be less selective in terms of which applications to be accepted to their platform, different than the the App Store platform. This divergence in policies of the two platforms gives Google a chance to gain a higher benefit from the introduction of the App Store game into the Google platform but a lower loss from the introduction of its own game to the other platforms. However, with its low-entry barrier, Google Play may disappoint its consumers with low-quality applications. That said, Google Play, with a more effective OL, that is, since Google is more relaxed in its restrictive policies in terms of accepting applications onto the platform, would be better suited to developing a recommendation system that would incorporate suggestions steering customers to lower-ranking applications as well. Otherwise, the platform may be locked into a high-ranking list of popular games that would discourage the involvement of new app developers. That would have a negative long-term effect on maintaining a healthy app ecosystem. Another suggestion for a platform such as GooglePlay that enjoys higher OL effects would be that the platform provides a larger sub-categorization of applications based on consumers' preferences. This would increase the surface space where popular games and consumers interact with each other. On the other hand, even though the App Store may offer a better experience for customers by providing higher quality applications due to its higher entry barrier, the platform simply may deter and discourage developer participation. Apps may mature and develop to their perfection based on the feedback received from the users. It is a tedious task to adjust an optimal level of entrance for the App Store that would let apps into the platform with an acceptable quality but yet delay user feedback that would contribute to the tune-up of the application.

Finally, app developers may choose a strategic sequence of the launching of their applications on both platforms. They may first choose to deliver their product on Google Play with the expectation of early development of the user base and receiving customer feedback. However, it would require an extra effort of showing their head to the audience among an already popular game crowd. On the other hand, developers may first choose to launch their app on the App Store hoping to have access to a user base that considers the application of a better quality due to the App Store imposed standards. Once developers catch momentum on the App Store, it would be considerably easier for them to obtain a user base at Google Play due to between popularity effects.

<References>

[1] Anderson, S. P., Foros, Ø., and Kind, H. J. (2019). The importance of consumer multihoming (joint purchases) for market performance: Mergers and entry in media markets. *Journal of Economics & Management Strategy*, *28*(1), 125-137.

[2] Anderson, T. W., and Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of econometrics*, *18*(1), 47-82.

[3] AppAnnie. (2012). The east asian dragon now number one in google play revenues. Retrieved from https://blog.appannie.com/app-annie-index-november-2012/

[4] AppBrain. (2016). Number of android applications. Retrieved from https://www.appbrain.com/stats/number-of-android-apps

[5] Apple. (2016). App store review guidelines, Retrieved from https://developer.apple.com/app-store/review/guidelines/#copycats

[6] Apptentive. (2012). Technology online survey, q4 2012. Retrieved from https://blog.kissmetrics.com/5-myths-about-aso/

[7] Arellano, M., and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29-51.

[8] Anderson, S. P., Foros, Ø., and Kind, H. J. (2019). The importance of consumer multihoming (joint purchases) for market performance: Mergers and entry in media markets. *Journal of Economics & Management Strategy*, *28*(1), 125-137.

[9] Bakos, Y., and Halaburda, H. (2020). Platform competition with multihoming on both sides: Subsidize or not?. *Management Science*, *66*(12), 5599-5607.

[10] Banerjee, A. V. (1992). A simple model of herd behavior. *The quarterly journal of economics*, *107*(3), 797-817.

[11] Bikhchandani, S., Hirshleifer, D., and Welch, I. (1998). Learning from the behavior of others: Conformity, fads, and informational cascades. *Journal of Economic Perspectives*, *12*(3), 151-170.

[12] Bikhchandani, S., Hirshleifer, D., and Welch, I. (2008). Information cascades. In Steven N. Durlauf and Lawrence E. Blume (Eds.), *The new palgrave dictionary of econometrics* (2nd ed.). U.K.: Palgrave Macmillan.

[13] Blundell, R., and Bond, S. (2000). GMM estimation with persistent panel data: an application to production functions. *Econometric Reviews*, *19*(3), 321-340.

[14] Chen, L., Yi, J., Li, S., and Tong, T. W. (2022). Platform governance design in platform ecosystems: Implications for complementors' multihoming decision. *Journal of Management*, *48*(3), 630-656.

[15] Chen, Y., Wang, Q., and Xie, J. (2011). Online social interactions: A natural experiment on word of mouth versus observational learning. *Journal of Marketing Research*, *48*(2), 238-254.

[16] Cheng, Z., and Nault, B. R. (2012). Relative industry concentration and customer-driven IT spillovers. *Information Systems Research*, *23*(2), 340-355.

[17] Chevalier, J. A., and Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345-354.

[18] Clogg, C. C., Petkova, E., and Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American Journal of Sociology*, *100*(5), 1261-1293.

[19] Corral, L., Sillitti, A., and Succi, G. (2014, August). Defining relevant software quality characteristics from publishing policies of mobile app stores. In *International Conference on Mobile Web and Information Systems* (pp. 205-217). Springer, Cham.

[20] Dellarocas, C., Zhang, X., and Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23-45.

[21] Dewan, S., and Ramaprasad, J. (2012). Research note —Music blogging, online sampling, and the long tail. *Information Systems Research*, *23*(3-part-2), 1056-1067.

[22] Garg, R., and Telang, R. (2013). Inferring app demand from publicly available data. *MIS quarterly*, *37*(4), 1253-1264.

[23] Ghose, A., and Han, S. P. (2014). Estimating demand for mobile applications in the new economy. *Management Science*, *60*(6), 1470-1488.

[24] Greene, D., and Shilton, K. (2018). Platform privacies: Governance, collaboration, and the different meanings of “privacy” in iOS and Android development. *New Media & Society*, *20*(4), 1640-1657.

[25] Groenendijk, T., Janssen, T., Rijlaarsdam, G., and Van Den Bergh, H. (2013). The effect of observational learning on students’ performance, processes, and motivation in two creative domains. *British Journal of Educational Psychology*, *83*(1), 3-28.

[26] John, D. R., Loken, B., and Joiner, C. (1998). The negative impact of extensions: can flagship products be diluted?. *Journal of Marketing*, *62*(1), 19-32.

[27] Karhu, K., Gustafsson, R., Eaton, B., Henfridsson, O., and Sørensen, C. (2020). Four tactics for implementing a balanced digital platform strategy. *MIS Quarterly Executive*, *19*(2), 105-120.

[28] Lee, G., and& Raghu, T. S. (2014). Determinants of mobile apps’ success: Evidence from the app store market. *Journal of Management Information Systems*, *31*(2), 133-170.

[29] Lei, J., Dawar, N., and Lemmink, J. (2008). Negative spillover in brand portfolios: Exploring the antecedents of asymmetric effects. *Journal of Marketing*, *72*(3), 111-123.

[30] Li, H., and Zhu, F. (2021). Information transparency, multihoming, and platform competition: A natural experiment in the daily deals market. *Management Science*, *67*(7), 4384-4407.

[31] Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74-89.

[32] Liu, Z., Duan, J. A., and Ter Hofstede, F. (2014). Marketing spillovers of location-based mobile services. Available at SSRN 2578335.

[33] Lu, J., Su, X., Diao, Y., Wang, N., and Zhou, B. (2021). Does online observational learning matter? Empirical evidence from panel data. *Journal of Retailing and Consumer Services*, *60*, 102480.

[34] Macworld, J. S. (2009). Macworld. Retrieved from https://www.macworld.com/article/1142406/apple_fcc_google_voice.html

[35] Martin, K. D., Borah, A., and Palmatier, R. W. (2017). Data privacy: Effects on customer and firm performance. *Journal of Marketing*, *81*(1), 36-58.

[36] Mashable. (2010). How many developers develop for ios and android? mashable. Retrieved from https://mashable.com/2010/07/02/ios-android-developer-stats/\#HMG17pDALGqF

[37] McIlroy, S., Ali, N., and Hassan, A. E. (2016). Fresh apps: an empirical study of frequently-updated mobile apps in the Google play store. *Empirical Software Engineering*, *21*(3), 1346-1370.

[38] Menon, N. M., and Kohli, R. (2013). Blunting Damocles’ sword: A longitudinal model of healthcare IT impact on malpractice insurance premium and

quality of patient care. *Information Systems Research*, *24*(4), 918-932.

[39] Mital, M., and Sarkar, S. (2011). Multihoming behavior of users in social networking web sites: a theoretical model. *Information Technology & People*, *24*(2), 378-392.

[40] PocketGamer. (2016). Count of active applications in the app store. *Pocketgamer*. Retrieved from https://www.pocketgamer.biz/metrics/app-store/app-count/

[41] Qiu, L., Chhikara, A., and Vakharia, A. (2021). Multidimensional observational learning in social networks: Theory and experimental evidence. *Information Systems Research*, *32*(3), 876-894.

[42] Rochet, J. C., and Tirole, J. (2006). Two sided markets: a progress report. *The RAND Journal of Economics*, *37*(3), 645-667.

[43] Roehm, M. L., and Tybout, A. M. (2006). When will a brand scandal spill over, and how should competitors respond? *Journal of Marketing Research*, *43*(3), 366-373.

[44] Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, *9*(1), 86-136.

[45] Salganik, M. J., Dodds, P. S., and Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, *311*(5762), 854-856.

[46] Tambe, P., and Hitt, L. M. (2014). Job hopping, information technology spillovers, and productivity growth. *Management Science*, *60*(2), 338-355.

[47] Tucker, C., and Zhang, J. (2011). How does popularity information affect choices? A field experiment. *Management Science*, *57*(5), 828-842.

[48] VisionMobile. (2015). Developer economics: State of the developer nation q3 2015. *VisionMobile 42*.

[49] Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25-51.

[50] Yang, S., & Ghose, A. (2010). Analyzing the relationship between organic and sponsored search advertising: Positive, negative, or zero interdependence?. *Marketing Science*, *29*(4), 602- 623.

[51] Yoon, I. (2014). *Platform policy and its effect on diffusion: the case study of Android and iOS* (Doctoral dissertation, Massachusetts Institute of Technology).

[52] Zhang, J. (2010). The sound of silence: Observational learning in the US kidney market. *Marketing Science*, *29*(2), 315-335.

[53] Zhang, Z., Zhang, Z., Wang, F., Law, R., and Li, D. (2013). Factors influencing the effectiveness of online group buying in the restaurant industry. *International Journal of Hospitality Management*, *35*, 237-245.

[54] Zhang, X., Xu, H., Yue, W. T., and Yu, Y. (2022). Consumer Privacy Concerns, Multihoming, and Platform Competition in Two-Sided Markets. *Multihoming, and Platform Competition in Two-Sided Markets (July 15, 2022)*.

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