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Exploring How Rivals and Complementors Affect Evolutionary Rate of B2C Apps: An Empirical Study

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Abstract: The hyper competition among rivals and enveloping threats from complementors are crucial external sources that influence app update strategies of B2C platforms. However, prior app-related literature largely focuses on factors affecting app performance, with scant attention on external drivers of the continuous app evolution, that is app updates. Besides, the results of app updates on market performance are mixed in extant literature. Therefore, this study is motivated to explore how competitive pressures from rivals and enveloping threats from complementors affect evolutionary rate of B2C apps and its subsequent effects on market performance. Our empirical study demonstrates that quick evolution of rival and complementor apps increases evolutionary rate of B2C apps. In contrast, a greater number of better performed rival and complementor apps decreases the evolutionary rate. Furthermore, we unveiled an inverted U-shaped relationship between evolutionary rate of B2C apps and market performance. The theoretical implications are also discussed.

Keywords: B2C platform, Red Queen competition, envelopment, evolutionary rate, app updates

1. INTRODUCTION

As with the volume of mobile transactions surpassing that of PC-based online shopping, B2C platforms now mainly rely on mobile applications (shortened as *apps* hereafter) to attract new customers or retain existing ones and thus gain profits. However, B2C platforms are often caught in a strategic dilemma regarding the rate at which they should update their apps. On the one hand, B2C platforms should frequently update their apps in response to the intense competitive pressures rivals and enveloping threats from complementors. Due to the low developing costs of apps and easy entry to app markets[1], B2C platforms not only face hyper-competition among rivals but also confront enveloping threats from their complementors[2], that is suppliers of products and services of B2C platform. In particular, complementors could cultivate brand loyalty, as well as operational experiences by providing products or services to B2C platforms. Thus, when eligible complementors start to develop their own apps and further update their apps to entrench customers, it would cause enveloping threats to B2C platforms. On the other hand, B2C platforms should dedicatedly update their apps since frequent changes would bring excessive learning costs for customers, harming usage experiences. If customers reacted negatively to frequent app updates, B2C platforms' endeavors would be counterproductive. Therefore, understanding how the competitive pressures from rivals and enveloping threats from complementors affect the rate of app updates and the subsequent consequence on market performance are imperative for B2C platforms to formulate effective app update strategies.

Apps are software application that can be installed and run on portable digital devices such as smartphones and tablets[3]. App updates refer to adding new features to existing apps[4]. Extant app-related studies largely focus on factors that affecting market performance of apps[5]-[7]. The factors include app characteristics (e.g., age, category, and price), developer actions (e.g., update activities, app positioning, pricing, and portfolio

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strategies)[8]. Although these studies help developers or firms to achieve better performance in app markets, scant attention has been drawn on how external drivers that affect focal B2C platforms' app update strategy. Those external-driven events are important elements in the overall app updates strategy because overlooking responses to both types of competitive pressures are likely to engender competitive problems.

Furthermore, extant studies on consequences of app updates have drawn inconsistent conclusions regarding the impact of update frequency on market performance. The majority holds that update more frequently would significantly improve apps' market performance, e.g., downloads[6][9], user ratings[10][11], survival rates in app markets[7][8], and ranks[12]. However, some recent studies have found the negative impact of app updates[4]. For example, Feorderer and Heinzl[4] found that major app updates would attract new consumers to increase app downloads while alienate existing ones by posting more negative ratings. These mixed findings in extant literature could not give B2C platforms adequate evidence on the rate at which and the extent to which should they update their apps to gain superior market performance.

Therefore, our study is motivated to bridge the gaps in the literature by addressing the following research questions: *(1) how do competitive pressures from rivals and enveloping threats from complementors affect evolutionary rate of B2C apps*, and *(2) how does the evolutionary rate of B2C apps affect the market performance?*

Based on the theoretical lens of Red Queen competition and platform literature, we conduct a two-stage empirical study to address our research questions with a panel dataset collected from Apple's App Store and econometric analyses. The dataset consists of 495,712 customer reviews, release notes of each version, and daily rank for iOS apps of 7 online travel platforms and 17 traditional firms in China. And the observation window ranges from January 1, 2012, to September 31, 2015, i.e., 45 months in total. Then, panel-corrected standard error (PCSE) estimation and negative binomial (NB) model for panel data are justified in the estimation procedure.

Our empirical analyses yield three key findings. First, faster evolution of rival and complementor apps increases evolutionary rate of a B2C app, among which the impact of complementors is greater. Second, a greater number of better performed rival and complementor apps decreases the evolutionary rate of a B2C app. Third, we found that increasing levels of evolutionary rate significantly increase market performance, but up to a certain level, further increasing the rate will decrease market performance. Theoretical implications are also discussed.

2. THEORETICAL FOUNDATIONS AND HYPOTHESES

In this section, we draw on the theoretical lens of Red Queen competition and literature on platforms to propose our theoretical model and develop our hypotheses. Our research model is shown in Figure 1.

2.1 Theoretical Foundation: Red Queen Competition

The term "Red Queen" first comes from evolutionary biology Van Valen who borrowed from Lewis Carroll's Through the Looking-Glass to describe the coevolution of dynamically interacting species[13]. Barnett and Hansen[14] first introduced the "Red Queen Competition" to organization studies. The overarching idea of Red Queen Competition lies twofold. Above all, it implies that an entity must evolve progressively faster just to stand still relative to its cohort of rivals[15]. Second, it emphasizes the competitive interaction among rivals. Specifically, the competitive move initiated by rivals and their better performance would impose competitive pressures on focal firm, triggering focal firm respond to its rivals.

We extend the basic ideas of the Red Queen Competition to apps of B2C platform context by explicitly incorporating competitive pressures from rivals and enveloping threats from complementors. The suppliers of a

B2C platform is called complementors in extant platform literature[16]. Compared with dominant software platforms like Apple's App Store and Google Play that third-party developers seldom develop another platform to compete with the dominant platform sponsor, B2C platform often faces enveloping threats by its complementors[2]. The main reason is because complementors of B2C platform could readily develop their self-build platforms.

Therefore, we propose the following research model by placing the evolutionary rate of B2C apps as our central focus. The overarching idea of our model is the evolution of rival and complementor apps (that is updates of rival and complementor apps), and number of better performed rival apps or complementary apps would stimulate the evolutionary rate of a focal B2C app, which further impacts its market performance. Following the arguments of Red Queen Competition [14], an entity evolves to compete for scarce resources. In our context, a B2C app updates for better fulfilling customers' needs. Accordingly, we define market performance as the valence of customer evaluations of app updates[11].

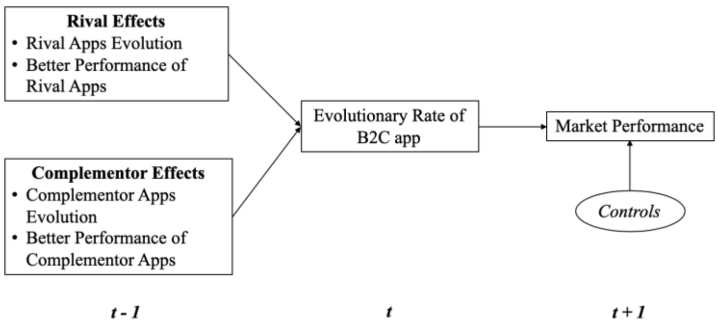

Figure 1. Research Model

2.2 Rival Effect on Evolutionary Rate

Rival effect on the evolutionary rate of B2C app lies twofold: rival apps evolution and their better performance. We define the evolutionary rate of B2C app as the rate at which a B2C app introduces new features to attract customers. Rival apps refer to equivalent B2C apps that have a similar business model with the focal B2C app and thus compete directly among each other. Correspondingly, rival apps evolution is the rate at which rival apps introduce new features. Owing to rival apps compete head-to-head with focal B2C app for customers, if the focal B2C app did not take any responding actions when rivals' evolutionary rate is high, it would face the risk of losing behind and failing [17]. Therefore, the competitive pressures imposed by rival app evolution would stimulate the faster evolution of focal B2C app.

Better performance of rivals refers to the number of rivals that gain better market performance than the focal B2C app. The gains of rivals in the performance normally associate with the losses of focal B2C app's performance. And the shortfall in performance would trigger the search of the focal B2C app to achieve satisfactory performance outcomes [14], resulting in faster evolution of the focal B2C app. We, therefore, hypothesize that:

Hypothesis 1a (Rivals' Evolution): *Faster evolutionary rate of rival apps would increase the evolutionary rate of a B2C app.*

Hypothesis 1b (Rivals' Better Performance): *Better performance of rival apps would increase the evolutionary rate of a B2C app.*

2.3 Complementor Effect on Evolutionary Rate

Complementor effect on the evolutionary rate of B2C app also lies twofold: complementors' platform evolution and their better performance. Complementors are suppliers to B2C platform. B2C platforms like Tmall (the largest B2C platform in China) do not have product stocks themselves but rely on suppliers to provide products or services to customers. Complementors' apps are those that complementors develop themselves to directly sell their products or services to customers. Complementor app evolution refers to the rate at which complementors add new features to their apps to attract customers. Better performance of complementors' app refers to number of complementors' apps that gain better market performance than the focal B2C app. If the rate was high and more complementors' apps received better performance, it would increase the enveloping pressures on the focal platform. Thus, focal B2C app is stimulated to evolve faster to eliminating the threats come from its complementors. Based on the above discussion, we conjecture that:

Hypothesis 2a (Complementors' Evolution)*: Faster evolutionary rate of complementor apps would increase the evolutionary rate of a B2C app.*

Hypothesis 2b (Complementors' Better Performance)*: Better performance of complementor apps would increase the evolutionary rate of a B2C app.*

2.4 Evolutionary Rate and Market Performance

On the one hand, faster evolutionary rate of B2C app enhances its market performance. First, faster evolution of a B2C app indicates quick responses to market opportunities, thus the focal B2C app could potentially better meet a known customers' needs and discover unmet ones[8]. Second, a faster rate of evolution indicates more features introduced by focal B2C app, which would attract more customers and improve existing customers' experiences. Existing studies have also confirmed that apps with more features increase customers' perception of its capabilities[18]. Third, the continuous evolution of a B2C app is deemed as ongoing adaption. Through trial-and-error-based learning, the B2C app could accumulate competitive experiences and turn temporal competitive advantages into long-term success.

On the other hand, up to a certain level of evolutionary rate, after which further increases in the rate would potentially harm its market performance. Despite the above benefits, frequent evolution of a B2C app would interrupt customers' habitual usage. The further increases in the evolutionary rate would also increase the learning costs of customers. Additional cognitive resources are required for customers to adapt to changes. Furthermore, the fast evolution of a B2C app may bring about the inconsiderate new feature and inadequate pretests, which can potentially harm user experience, resulting in negative responses to overly fast evolution. Based on the above discussion, we hypothesize that:

Hypothesis 3*: Evolutionary rate of a B2C app exhibits an inverted U-shaped relationship with its market performance, that is, increasing levels of evolutionary rate would increase the market performance, up to a certain level, further increasing the rate would decrease the market performance.*

3. DATA AND METHODS

To empirically test above hypotheses, we chose the online travel industry in China as our research context. We further specify our samples and provide an overview of our dataset, describe variables and measurements. Model specification and econometric models are discussed in the end.

3.1 Data Collection

We chose the online travel industry in China as our research context. The prevalence of competitive interaction among rivals (i.e., online travel platforms) and arising enveloping threats from complementors manifest in the online travel industry in China. As the transactions achieved through mobile applications increases year by year, reaching 78.3% in 2016[1], mobile apps become an important intermediary for both online and traditional travel firms to attract new customers and retain existing ones. Thus, most of the online travel platforms (OTPs) have invested heavily in mobile apps and competed intensively among each other. Moreover, traditional travel firms like travel agencies, airlines, and hotels distribute their products on OTPs and act as complementors to OTPs. Moreover, owing to the wide application of information technology within the industry, they also develop their own websites and mobile apps, causing enveloping threats to OTPs. The clear distinction between direct competition and envelopment in the online travel industry in China gives us a unique opportunity to investigate how focal B2C app responds differently to rivals and complementors.

We further restricted our data analysis to iOS apps of 7 OTPs (Ctrip, Qunar, eLong, Tuniu, Fliggy, LY, Lvmama) and 17 traditional travel firms in China over a period from January 2012 to September 2015, i.e., 45 months in total. Our unit of analysis is the iOS apps of online travel platforms.

First, we identified rival apps by focusing on the seven dominant OTPs in online travel industry in China. The seven OTPs were the dominant competitors in the online travel industry, which ensures the existence of significant coevolution between their apps. The dominance of the seven B2C online travel platforms is supported by both quantitative and qualitative evidence. Quantitatively, the seven OTPs together had approximately 90% of the online travel industry market in 2015[2]. Qualitatively, the dominance of these seven OTPs was acknowledged in their top executives' public speeches or letters to employees. The seven OTPs also received prominent attention in media coverage of competition in the online travel industry. This sampling strategy meets well with the established criterion of resource similarity and market commonality established in competitive dynamics [19]. Second, complementor apps were 17 traditional travel firms in China who were major complementors to the seven OTPs. Their mobile apps normally appear on the Top 100 chart within travel category in Apple's App Store, indicating the popularity of their own apps and the potential threats to OTPs. The traditional firms include airlines like China Southern Airlines, hotels like BTG HOMEINNS Hotels Group, car rentals like Hertz, travel agencies like PLATENO TRIP, and ticket companies like Keyun12308.

Next, the time window was set between January 2012 to September 2015 because the most intense competitive interaction among the seven OTPs occurred in that period. Moreover, the seven OTPs started to deploy their apps since 2012 and customers gradually got used to using them for reserving and managing their trips since then. Therefore, we chose January 2012 as the starting point of data collection. The acquisition of Qunar by Ctrip in October 2015 fundamentally reshapes the industry status and marked the end of the intense competitive interaction between the seven OTPs. We, therefore, terminate the data collection at the end of September 2015.

Subsequently, we collected data from Apple's App Store on 24 sampled apps between January 2012 to September 2015 and constructed a panel dataset for further analyses. Specifically, our data collection consists of three aspects. Firstly, we obtained 495,712 reviews on our sampled apps. The data involves the reviewer's ID, review date, review title, review content, and rating. The rating scheme presented in App Store is some "stars" from 1 up to 5. Secondly, app details including app name, description, initial release date and updating notes of each version were collected. Thirdly, we collected daily top free rankings within the travel category in China.

3.2 Variables and Measurements

Dependent variables. We have two dependent variables (DV): *evolutionary rate of B2C apps* and *market performance*. Extant studies mainly use update dummy[4][7] or version number [8] [11] to measure the rate of app evolution. In contrast, we operationalize the *evolutionary rate of B2C* apps by calculating the number of

[1] https://www.analysys.cn/analysis/22/detail/1000268/
[2] https://www.analysys.cn/analysis/trade/detail/1000800/

updating items for B2C app *i* in month *t*. This way of operationalization reflects the rate at which and the extent to which a focal B2C platform updates its apps. The updating items in release note include adding new features or improving existing ones, introducing promotions, and bug fixes etc. [10]. *Market performance* is the valence of customer evaluation of quality of updated apps[4][11]. In reference to online review literature, we measured market performance by average ratings of posted reviews for B2C app *i* in month *t+1* [20]. We log-transformed the value to address the skew in distributions.

Independent variables. We construct two sets of independent variables: (1) *rival-related*, and (2) *complementor-related variables*. And we dynamically calculated all variables for focal B2C app *i* in month *t-1*. Rival-related variables are rival apps evolution and better performance of rivals. *Rival apps evolution* is measured by the average number of updating items of rival apps. Apple's App Store ranking takes account of downloads, active usage, and app searches into the ranking algorithm since 2013. Thus, the ranking is a comprehensive indicator of performance for an individual app and reflect its popularity, which is the key for OTPs to achieve the success of the mobile strategy. Accordingly, we use the number of rivals that rank ahead of focal B2C app within the travel category in Apple's App Store in month *t-1* to operationalize *better performance of rivals*. Complementor-related variables are *complementor apps evolution* and *better performance of complementors*. And they are operationalized the same as rival-related variables.

Control variables. Extant studies have demonstrated the significant impact of software platform (e.g., Apple's App Store in our context) governance on app updates[11][21]. B2C apps are distributed through app markets. We, therefore, include the *upgrades of iOS systems* as dummy variables in month *t-1* to capture the potential impact of app market governance [22] on B2C app updates. Furthermore, seasons or holidays are exogenous factors that could influence the demand for OTP apps. And the age of OTP apps, i.e., time passed since the OTP app first released, could also affect how end users evaluate the platform. Refer to previous studies [24], we also add *time trends* to control for these time-related factors. And it is operationalized by the number of days passed since the beginning of the data.

3.3 *Econometric Analysis*

Since our study involves two sets of dependent variables (i.e., evolutionary rate and market performance), we conduct model specification and construct econometric models respectively.

3.3.1 Evolutionary Rate

Model Specification. Since the dependent variable evolutionary rate of B2C app is a count variable which is discrete and nonnegative, making traditional ordinary least square (OLS) regression inappropriate. Poisson model and negative binomial model are common methods used to estimate such model[23]. Poisson model assumes equal mean and variance. However, we observed over-dispersion in our data. We, therefore, apply the negative binomial model that allows over-dispersion of count variable. Besides, our panel data enables us to use fixed effects (FE) or random effects (RE) models to address unobserved individual-specific effects (e.g., the firm's management policy, culture etc.). In our case, the Hausman test was insignificant (Hausman Specification Statistic = *2.16*, p-value <*0.83*), thus we adopted random effects model.

Econometric Models. We estimate the following model to investigate how the evolution and better performance of rivals and complementors affect evolutionary rate of B2C apps.

$$\mathrm{Evolution}_{i,t} = \beta_0 + \beta_1 \mathrm{Rivals}_{i,t-1} + \beta_2 \mathrm{Complementors}_{i,t-1} + \beta_3 \mathrm{Control}_{i,t-1} + \mu_i + \varepsilon_{i,t} \quad (1)$$

where < *i, t* > represents mobile B2C *app - month* combination, *Evolution* represents evolutionary rate of B2C app, *Rivals* and *Complementors* represents a vector of lagged variables related to rivals and complementors, Control represents control variable for app market governance, μ_i denotes the unobserved individual effect,

3 http://www.adweek.com/digital/apple-app-store-ranking-changes/?red=im

$\varepsilon_{i,t}$ denotes the remaining stochastic disturbance term, and $\beta_0, \beta_1, \beta_2, \beta_3$ are the regression model coefficients.

3.3.2 Market Performance

Model Specification. We executed OLS regression with panel-corrected standard error (PCSE) to examine the relationship between the evolutionary rate of B2C app and market performance (i.e., log-transformed average user rating). Since our data is time-series and cross-sectional data with a small set of entities (i.e., 7 mobile B2C platforms) and a large number of the time period (i.e., 45 months), the data is potentially subjected to serial correlation and group-wise heteroscedasticity. Therefore, we performed Wooldridge test to check whether there is serial correlation[24], Wald tests to check the existence of heteroscedasticity[25] and Breusch-Pagan LM test to examine the dependence between panel units. Our Wooldridge test for autocorrelation indicated the absence of autocorrelation and the existence of group-wise heteroscedasticity. In addition, the Breusch-Pagan LM test shows the cross-sectional correlation in our data. Following the prescription of Beck and Katz[26], we conducted panel-corrected standard error to address the above issues.

Econometric Models. We estimate the following model to explore the impact of evolutionary rate of B2C app on market performance.

$$\mathrm{MarketPerformance}_{i,t+1} = \alpha_0 + \alpha_1 \mathrm{Evolution}_{i,t} + \alpha_2 \mathrm{Evolution}^2{}_{i,t} + \alpha_3 \mathrm{t} + \alpha_4 B2C_i + \varepsilon_{i,t} \qquad (2)$$

where <*i, t*> represents app-month combination, $MarketPerformance_{i,t+1}$ represents the market performance for B2C app *i* in month *t+1*, *Evolution* represents evolutionary rate of B2C app, *t* represents the time trend controlling for time-related factors, $B2C_i$ represents dummy variables of B2C apps to control individual effects, $\varepsilon_{i,t}$ denotes the remaining stochastic disturbance term, and $\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the regression model coefficients.

4. RESULTS

The correlation matrix shows that our variables are not highly correlated. Furthermore, we computed the variance inflation factors (VIF) to test for any possible multicollinearity. The VIFs for all variables are less than the critical value of 10 (the highest is 1.80), eliminating potential multicollinearity problems.

Table 1. Random effects estimation on evolutionary rate of B2C app

Variables	Evolutionary Rate of B2C App	
	Coefficients	IRR
Control		
App Market Governance	-0.002 (0.11)	1.00 (0.11)
Rival Effect		
Rival Apps Evolution	**0.05**** (0.02)	**1.05**** (0.02)
Better Performance of Rivals	**-0.09***** (0.03)	**0.91***** (0.03)
Complementor Effect		
Complementor Apps Evolution	**0.11*** (0.06)	**1.11*** (0.06)
Better Performance of Complementors	**-0.13**** (0.05)	**0.88**** (0.05)
Constant	0.30* (0.19)	1.36* (0.25)
N	308	
Log likelihood	-780.23	

Note: *p<0.1, **p<0.05, ***p<0.01, IRR refers to Incidence Rate Ratio.

Table 1 presents random effects estimation on evolutionary rate of B2C app. As we can see from Table 1, both rival-related variables and complementor-related variables have a significant effect on the evolutionary rate of B2C app. Specifically, rivals and complementors evolution are positive and statistically significant on evolutionary rate of B2C app, suggesting that if rivals or complementors increase the rate and the extent of their apps would drive focal B2C app update its apps faster and introduce with more features. Moreover, the impact of complementors is greater than rivals. The Incidence Rate Ratio (IRR) indicates that with Rival Apps Evolution increases one unit, evolutionary rate of B2C app would increase 1.05 times, while Complementor Apps Evolution increases one unit, evolutionary rate of B2C app would increase 1.11 times. Accordingly, Hypothesis 1a and 2a are supported.

However, contrary to our hypotheses, *Better Performance of Rivals* and *Better Performance of Complementors* are negative and statistically significant on evolutionary rate of B2C app, indicating that if there are more rivals' and complementors' platform that ranks ahead of the focal B2C app, the focal app is reluctant to update its apps more frequently. And the negative impact is greater for *Better Performance of Rivals* with an IRR of 0.88 compared with 0.91 for *Better Performance of Complementors*. Therefore, Hypothesis 1b and 2b are not supported. The control variable for App Market Governance is not significant.

Table 2 presents PCSE estimation of market performance. Model 1 includes the evolutionary rate of B2C app, and two control variables and Model 2 adds the square term of evolutionary rate of B2C app. The results show that the coefficient for *Evolutionary Rate of B2C app* is both positive and significant in Model 1 ($p<0.05$) and 2 ($p<0.01$) and the coefficient for the square term of evolutionary rate of B2C app is negative and significant ($p<0.05$). The results testified an inverted U-shaped relationship between the evolutionary rate of B2C app and Market Performance. Thus Hypothesis 3 is supported. This finding suggests that increasing levels of evolutionary rate are associated with increases in the average customer ratings (i.e., market performance), up to a certain level of evolutionary rate, after which further increases of the rate are associated with decreases in its market performance.

Table 2. PCSE Estimation on Market Performance

Variables	Market Performance	
	Model 1	Model 2
Evolutionary Rate of B2C app	**0.04****(0.02)	**0.05*****(0.02)
Evolutionary Rate X Evolutionary Rate		**-0.001**** (0.0003)
Time Trends	0.001(0.00)	0.001(0.001)
Individual Effects	YES	YES
N	315	315
R-squared	0.22	0.23

Note: *p<0.1, **p<0.05, ***p<0.01, panel-corrected standard errors in parentheses.

5. CONCLUSIONS AND DISCUSSIONS

In this study, we firstly investigated how the evolution and better performance of rival apps and complementor apps affect the evolutionary rate of B2C app. And we subsequently examined the impact of evolutionary rate of B2C app on its market performance.

Our empirical study revealed three major findings. First, faster evolution of rival and complementor apps would increase evolutionary rate of a B2C app, while the impact of complementor apps is greater. Second, contrary to our hypotheses, if there are many rival apps and complementor apps that better perform than a focal B2C app, the focal B2C app will decrease its evolutionary rate. Third, we found that increasing levels of evolutionary rate increase market performance, but up to a certain level, further increasing the rate will decrease market performance.

This paper contributes to the literature in two ways. First, extant app updates literature mainly focuses on the impact of app updates on app performance [6][7][27]. In contrast, we focus on drivers of app updates, that is the evolution of apps. We also demonstrate how evolutionary rates are impacted by evolution and performance of rival and complementary apps. Our findings contribute to a better understanding on how app evolution drives by external competitive and enveloping pressures. Second, extant studies on app updates have drawn inconsistent conclusions regarding the impact of update frequency on market performance. Our study uncovers the inverted U-shaped relationship between update rates and market performance, contributing to reconciling the mixed findings in extant literature.

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REFERENCES

[1] Grover, V. , & Kohli, R. . (2013). Revealing your hand: Caveats in implementing digital business strategy. Society for Information Management and The Management Information Systems Research Center.

[2] Eisenmann, T., Parker, G., and Van Alstyne, M . (2010). Platform envelopment. Strategic Management Journal 32(12): 1270-1285.

[3] Liu, C. Z. , Au, Y. A. , & Choi, H. S. . (2014). Effects of freemium strategy in the mobile app market: an empirical study of google play. Journal of Management Information Systems, 31(3), 326-354.

[4] Foerderer, J. , & Heinzl, A. . (2017). Product updates: attracting new consumers versus alienating existing ones. *Thirty eighth International Conference on Information Systems*. Seoul.

[5] Claussen, J., Kretschmer, T., and Mayrhofer, P.. (2013). The Effects of Rewarding User Engagement: The Case of Facebook Apps. *Information Systems Research* 24(1):186-200.

[6] Ghose, A. , & Han, S. P. . (2014). Estimating Demand for Mobile Applications in the New Economy. *Management Science* 60(6):1470-1488.

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

[8] Kajanan, S., Pervin, N., Ramasubbu, N., and Dutta, K. (2012). Takeoff and sustained success of apps in hypercompetitive mobile platform ecosystems: an empirical analysis.

[9] Comino, S., Manenti, F. M., and Mariuzzo, F. 2015. Updates Management in Mobile Applications. Itunes Vs Google Play, Medical Journal of Malaysia (37:4), pp. 354-356.

[10] Mcilroy, S. , Ali, N. , & 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.

[11] Tiwana, A . (2015). Evolutionary competition in platform ecosystems. Information Systems Research, 26(2):266-281.

[12] Tian H., Zhao J. (2018) Antecedents and Consequences of App Update: An Integrated Research Framework. In: Cho W., Fan M., Shaw M., Yoo B., Zhang H. (eds) Digital Transformation: Challenges and Opportunities. WEB 2017. Lecture Notes in Business Information Processing, vol 328. Springer, Cham

[13] Valen, L. V. . (1973). A new evolutionary law. Evolutionary Theory, 1, 1-30.

[14] Barnett, W. P. , & Hansen, M. T. . (1996). The red queen in organizational evolution. Strategic Management Journal, 17(S1):139-157.

[15] Agarwal, R. , & Tiwana, A. . (2015). Editorial-Evolvable Systems: Through the Looking Glass of IS. *Information Systems Research* .26(3): 473-479.

[16] Mcintyre, D. P., and Srinivasan, A . (2017). Networks, platforms, and strategy: emerging views and next steps. Strategic Management Journal, 38(1):141-160.

[17] Giachetti, C., Lampel, J., and Li Pira, S . (2017). Red queen competitive imitation in the uk mobile phone industry. Academy of Management Journal, 2015(1):16015-16015.

[18] Sela, A., and Berger, J . (2012). How attribute quantity influences option choice. Journal of Marketing Research, 49(6):942-953.

[19] Chen, M. J. , & Miller, D. . (2012). Competitive dynamics: themes, trends, and a prospective research platform. The Academy of Management Annals, 6(1), 135-210.

[20] Rosario, A. B., Sotgiu, F., De Valck, K., and Bijmolt, T. H. A . (2016). The effect of electronic word of mouth on sales: a meta-analytic review of platform, product, and metric factors. Journal of Marketing Research, 53(3): 297-318.

[21] Song, P. J., Xue, L., Rai, A., and Zhang, C. (2018). The Ecosystem of Software Platform: A Study of Asymmetric Cross-Side Network Effects and Platform Governance. MIS QUARTERLY,42(1):121-A6.

[22] Kapoor, R. , & Agarwal, S. . (2017). Sustaining superior performance in business ecosystems: evidence from application software developers in the ios and android smartphone ecosystems. Organization Science, 28(3):531-551.

[23] Hausman, J. 1978. Specification Tests in Econometrics, Econometrica 46(6):1251-1271.

[24] Wooldridge, J. M. (2006). Introductory Econometrics: A Modern Approach. Bethesda: Thompson Publishing.

[25] Greene, W. (2007). *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.

[26] Beck, N., and Katz, J. N. (1995). What to Do (and Not to Do) with Time-Series Cross-Section Data. American Political Science Review89(3): 634-647.

[27] Roma, P. , Zambuto, F. , & Perrone, G. . (2016). The role of the distribution platform in price formation of paid apps. Decision Support Systems 91: 13-24.