Understanding the drivers of the daily app rank: the role of revenue models

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Abstract

In this paper, based on data from two major app stores (Apple Store and Google Play), we study the role of several revenue models adopted by developers in the success of an app measured in terms of daily rank.

Keywords: Mobile App Market, Online distribution, Econometric analysis.

Introduction

Software especially developed for mobile phones has been around for well over a decade. In fact, before the term application (app) store was popularized, distribution of mobile content was dominated by the Mobile Portal model. However, the ecosystem was initially unclear and did not attract enough developers and users to really take off. This relatively stable context was dramatically changed in 2008 by Apple Inc. which introduced a new distribution paradigm in Mobile Commerce: the application store. An application store is a web distribution platform from which users can download software applications for mobile devices to increase the utility associated to their utilization (Roma et al. 2013).

Mobile app market is now soaring. As a matter of fact, ABI Research predicts that total mobile app revenues from pay-per-download, in-app purchase, subscriptions, and in-app advertising will soar over the next five years, growing from $8.5 billion in 2011 to $46 billion in 2016 (ABI Research 2012). Mobile applications (apps, hereafter) are typically developed by third parties, which can be either software houses or individuals, so the market model can be categorized as a two-sided market, which can generate a mutual advantage for both developers and store owners (Hagiu 2007). By means of developers, app store owners can take advantage of indirect network externalities that increase the value of its own devices. In fact, the potential functionalities of a device increase with the number of apps running on such device. On the other hand, developers are extremely attracted by distribution platforms, because it allows them to reach a plethora of consumers worldwide, that they would hardly reach on their own. The revenue sharing rule usually common to all app stores implies that developers set the price of their apps and appropriate 70% of the revenue for each transaction, whereas usually app stores retain 30% of it (Roma et al. 2013). Finally, consumers derive higher utility from the presence of a higher number of developers in the app store as they have more product variety available for purchase. Numerous mobile device makers, such as RIM, Samsung, etc, have followed Apple's move. This rapid proliferation of app stores has involved not only traditional players of the smartphone industry, but also important new entrants such as Google, which launched its Android mobile Operating Systems (OS) and made the Android Market (now known as Google Play) available to app users in 2008 (Roma et al. 2013). Nowadays, app stores are typically owned by OS developers or device manufacturers, while app developers provide contents that increase the value of app store owners' correlated businesses (Roma et al. 2013). At the same time consumers are now increasingly turning to recommendation engines, friends, social networking or advertising to discover mobile applications rather than sorting through the thousands of mobile apps available. As a consequence, less than 0.01% of consumer mobile apps will be likely to be a financial success by their developers (Gartner 2014).

This environment implies that developers have to make several non-trivial decisions. For instance, they have to choose what kind of and how many apps to market, which mobile operating systems to develop for and, hence, which app store to target, which business model to choose for each app (Roma et al. 2013). These decisions naturally affect apps' success in the market. However, in contrast to the huge popularity, scant attention from the academic world has been reserved to the dynamics of success of this market. In this paper, by taking the perspective of developers, we build on a previous work of Roma et al. (2013). In Roma et al. (2013) the authors study the major drivers of app success measured as the daily app rank with no specific focus on the role of the revenue model adopted for apps and its relationship with the selected store. In the present paper, we considerably differ from the above study as we construct an econometric model to examine how the decision on the revenue model adopted for a given app affects daily revenue rank and, more importantly, how such relationship might be contingent upon the distribution platform where the app is marketed, by explicitly controlling for all the factors identified in Roma et al. (2013). In particular, we formulate a number of hypotheses. Two of these focus the direct effect of the revenue models proposing that the freemium model should outperform the paid model in the terms of revenue performance (as implied by the daily revenue rank), and, in turn, the paid model should guarantee a higher revenue performance than the free model. A third hypothesis examines the effect of the presence of in-app purchase. More importantly, the remaining hypotheses investigate the effect of the interaction of the revenue model and the in-app purchase option with the distribution platform chosen for marketing the given app, to highlight the difference among such stores. We test our hypotheses relying on a large sample of top grossing apps for smartphones provided by the Italian versions of the two major app stores, namely App Store and Google Play. By way of anticipation, our findings show that the effects of the revenue models and the in-app purchase are strongly contingent upon the distribution platform where the given app is market.

In the next section, we introduce and discuss the testable hypotheses by connecting them to the existing literature. Afterwards, the econometric analysis is presented. Specifically, we describe the dataset, the explanatory variables and the regression model, and discuss the empirical findings. Finally, conclusions are presented.

Theory and hypotheses

The aim of this paper is to investigate the role of the revenue model adopted for the given app and its interaction with the distribution platform factors that lead apps to success. As the marginal costs faced by developers are usually negligible in this market we can measure the product performance in terms of revenue (at least in comparative terms). Information regarding app revenue can be collected using the top grossing app ranking published by the two major app store owners' in their own markets. Indeed several studies have investigated the relationships between actual sales (in quantity and/or in value) and rank (Brynjolfsson et al. 2003, Chevalier and Goolsbee 2003, Garg and Telang 2012). In particular, they assume that rank and sales are linked via the well-known power law function. Moreover Garg and Telang (2012) offer a methodology to infer the relationship between app rank and sales using publicly available data alone, i.e., in absence of information on actual sales or revenue.

The app store distribution model allows developers to adopt a variety of business models. Three different models are commonly utilized by developers in the app stores: *free, paid*, and *freemium.* In the *free* model developers choose a free app strategy, allowing app download for free. On the other hand, in the case of *paid* strategy, developers market only paid apps, whereas in the case of the *freemium* model, some other developers provide two versions of the same app. One version is given for free and the other is paid. There exist some differences between them. Such differences might be due to the presence of exclusive features in the paid version or the presence of substantial advertising in the free version. It is important to highlight that our sample includes only data to the paid version of such type of apps for which the developer has chosen a freemium model.

We also examine the role of the in-app purchase practice in determining the rank of an app. In-app purchase, relates to the practice often utilized by developers to give app users, who have downloaded their app at a given price (or free), the opportunity to purchase additional features, e.g., additional levels or credits in case of a game, or upgrade to more complete product versions directly inside the app.

In the following sections, we formulate and test a number of hypotheses based on existing literature on similar contexts and industry articles on the app market.

Free vs. Paid

One of the main questions we would like to investigate is whether a paid model drives to better performances than a free one. It is well known that free apps, on their own micro-environment, might work as two-sided markets, so when apps are available in large numbers they might attract third parties who are interested in final users. Some intuitive examples of third parties are advertisers or info seekers. In this case, app developers give the app for free to final users to create a large base of users who are very appealing to such third parties. As a result, final users enjoy the service for free and developers benefit from the opportunity to monetize from third parties, i.e., advertising or non-personally identifiable information selling. However, making significant profits on free apps requires a huge number of downloads to generate cross-side externalities. In order for their app to perform well in terms of downloads, developers need to reach a high exposure in the selected store, which means getting onto those top 200 or top 100 or top 10 lists. In order to rise in the ranking and thus emerge among millions of apps competing for users' attention, it is required a high marketing expenditure for most of free apps. According to Bresnahan et al. (2014) these campaigns average approximately $0.5 million per app. In contrast, industry evidence (Gartner 2013) as well as a preliminary study in the literature (Roma et al. 2013) reports that paid apps are more likely to be profitable. These considerations would suggest that adopting a paid model will allow apps to rise in the ranking and thus generate higher revenue (at least in comparative terms) than a free app model. Therefore we hypothesize as follows:

Hypothesis 1 (H1): A paid revenue model leads to higher revenue ranks than a free revenue model.

Freemium vs. Paid

The common argument in favour of a freemium revenue model over a paid revenue model is that in presence of customer heterogeneity a single price would reduce firm profitability in two way: it would lead to price out lowly valuable people who might have been willing to pay less and buy low-end versions and it would to under-pricing with regard to those people who would have been willing to pay more and buy more sophisticated versions. Through the adoption of a *freemium* model, i.e. the co-existence of a paid and a free version of the same app, firms take advantage of the opportunity to segment the market in presence of heterogeneous customers. Indeed, a free version containing nagging ads can be offered to less valuable consumers who can afford the inconvenience of having ads within the app in exchange of a low price, whereas the paid app can be offered to those consumers are more willing to pay to enjoy a version without ads or with less amount of ads (Roma et al. 2013).

In addition, *freemium* apps give users the ability to use and experiment with their app before spending any money on it. In this case usually the free version in the market is extremely limited or time-locked. The role of the free version is to allow customers test the product and resolve the uncertainty about the real value to them, prior to committing to the purchase (Rogers 1983; Moore and Benbasat 1991; Gallaugher and Wang 2002).

The opportunity that the *freemium* model gives on the one hand to solve the consumers' uncertainty and on the other hand to better practice market segmentation suggests that this model should be more profitable than the *paid* model. Hence, we hypothesize the following:

Hypothesis 2 (H2): A freemium revenue model leads to higher revenue ranks than a paid revenue model.

In-app purchase

In its essence, in-app purchase can be assimilated to versioning and upgrading. There are several theoretical studies on versioning of information goods (Bhargava and Choudary 2001, Bhargava and Choudary 2008), suggesting that is optimal only under certain conditions.

In spite of these researches, evidence seems to shows that in-app purchase has been quite successful in App Store as well as it has reached large popularity in Google Play (ABI Research 2012; Roma et al. 2013). Thus, it seems reasonable to expect that, ceteris paribus, apps allowing for in-app purchase might be more successful than apps offering no in-app purchase. Therefore, we formulate the following:

Hypothesis 3 (H3): The presence of in-app purchase leads to higher revenue rank.

Revenue models, in-app purchase and the store effect

In this section, we posit that the relationship between the revenue models and our measure of revenue, i.e., the top grossing rank, as well as the effect of the presence of in-app purchase are contingent upon the distribution platform whether the given app is marketed. In fact, industry evidence suggests that there are strong differences between the two stores in terms of consumer willingness to pay. Apple App Store is on average accessed by consumers characterized by a higher willingness to pay than those served by Google Play (Ghose and Han 2014). As a result, the effect of the type of the revenue model adopted for the given app as hypothesized in *H1* and *H2*, and the effect of in-app purchase as hypothesized in *H3* might naturally hinge upon the store where the given app is marketed. In particular, the paid revenue model should be more successful than the free revenue model particularly in the App Store as consumers in this store display a higher willingness to pay. Moreover, the advantage of the freemium revenue model over the paid revenue model should be weakened (if not removed) in Google Play due to the low willingness to pay of consumers accessing this store, which would provide consumers with the incentive to use only the free version of the app without downloading the paid version. As a result, product cannibalization should hurt the revenue advantage of a freemium strategy over a paid strategy. Finally, as in-app purchase is a versioning practice to enable a better segmentation of consumers we should expect that such a practice would be particularly successful in a setting whether there consumers are willing to pay for increased functionalities. Therefore, in-app purchase should be more successful in the App Store than in Google Play.

Hence, based on the above considerations, we can make the following hypotheses:

Hypothesis 4 (H4): It is more likely that a paid revenue model leads to higher revenue rank than a free revenue model in the Apple App Store.

Hypothesis 5 (H5): The revenue rank advantage of adopting a freemium revenue model will be weakened (if not removed) in Google Play.

Hypothesis 6 (H6): The effect of the presence of in-app purchase on the app revenue rank should be particularly strong in the App Store.

Empirical Analysis

Data and Variables

In order to test our hypotheses, we collected data of apps for smartphones by weekly exploring the Italian version of the two major app stores, namely Apple App Store (iTunes) and Google Play (https://play.google.com/store). Specifically, every Friday, we recorded data from the top 200 grossing apps ranking publicly available in these two stores. In case an app was no longer listed among the top 200 apps in the relative store, the actual ranking was retrieved from appannie.com. The observations utilized in the present paper are a considerable extension of the dataset utilized in Roma et al. (2013). Specifically, our observations are related to all Fridays in the period going from October 19th, 2012 to March 8th, 2013 (20 weeks in total). In our preliminary analysis, we selected randomly 50 apps from each of the two top 200 grossing rankings, so that we had initially 100 apps. However, when the observation period actually began, 11 apps from App Store and 2 apps from Google Play were no longer among the top 200 grossing apps of the respective stores. Therefore, we added 13 (11 from the App Store and 2 from Google Play) apps with the same characteristics of those apps. Recording data from the two stores for all the 20 weeks yielded a balanced panel dataset of 2237 observations related to 61 apps from App Store and 52 apps from Google Play (whereas the number of observations in Roma et al. (2013) was 1368).

We defined a set of variables and some controls to test the formulated hypotheses and recorded the relative data. They are shown in Table 1 (see Appendix), where we report the description and the modalities of all the variables in detail.

Table 2 shows the descriptive statistics. Preliminary analysis suggests a high collinearity between the variables *Store* and *Total Apps*, *Low App Rating* and *High App Rating*. Therefore, *Total Apps* and *Low App Rating* are removed. Furthermore, the variables *Games* and *Paid* are considered as baselines for category and business model variables.

Empirical results and discussion

Our dataset is an unbalanced panel and the number of statistic units (apps) is much larger than the observation period (number of weeks), in this case literature usually suggests the use of three basic regression models, namely pooled OLS, fixed effects and random effects models (Wooldridge 2002). However, the fixed effects model is not appropriate a priori in our setting because some of our variables of interest are time invariant. They would be eliminated due to perfect collinearity if a fixed effects model were adopted. Therefore, we preliminarily compare pooled OLS and random effects models to analyse the effects of all explanatory and control variables. We test several functional forms, including power law functional forms with several shape parameters as well as log-forms. In all the cases, the Breusch-Pagan Lagrange Multiplier test strongly indicates the presence of random effects. Therefore, we present the results obtained performing a random effects regression. Specifically, similarly to Roma et al. (2013), Table 3 reports the results related to the power law function with shape parameter equal to 0.6. Other functional forms lead to similar results. Thus, they are omitted in the interest of length. The first model in Table 3 relates to a regression model without the interaction variables between the types of revenue models and store dummies, whereas in the second model, the interactions are introduced. In order to gain a better understanding of results in Table 3, it is helpful to recall that in the second model, the interaction terms relate to the effects of the revenue models (and in-app purchase) in Apple App Store (as the level 1 of the store dummy corresponds to the App Store), whereas the direct terms relate to the effects of the revenue models (and in-app purchase) in Google Play (the dummy store equal to zero).

At a first glance, our results seem to confirm our hypothesis *H1* suggesting that "paid can be more successful than free", consistently with Roma et al. (2013). As a matter of fact, when a free revenue model is associated with lower comparative revenue in the first model. This would imply that developer might be better off developing and marketing paid apps, as customers are not reluctant to spend money on apps, if quality is delivered (Roma et al. 2013). However, when we take a closer look by introducing the interaction terms between revenue models and the dummy store, we find that the dominance of the paid business model emerges only in App Store consistent with *H4* suggesting that the paid business model outperforms the free business model only in the store with sufficiently high consumer willingness to pay, namely the App Store, whereas the two revenue models are shown not to differ significantly in terms of revenue ranks in Google Play due to the lower willingness to pay of consumers accessing this store. The *Freemium* variable, on the contrary, shows no significance in the first model, which would imply that a freemium strategy is no better than a paid strategy. This is confirmed and further strengthened in the second model where the interaction term with the store dummy is introduced. In fact, while still being not significant in the App Store, the freemium revenue model ends up having even significant and negative effect in Google Play. Therefore, our hypothesis *H2* is never supported, whereas our hypothesis *H4* is confirmed as the hypothesized effect of the freemium revenue model is so weakened in Google Play due to product cannibalization as implied by the low willingness to pay of consumers accessing this store that the sign of the relative coefficient is even reverse.

Regarding hypothesis *H3*, results in the first model would suggest that the in-app purchase model is likely to lead to a higher revenue rank for an app. This statement is supported by the rapidly increasing amount of apps allowing in-app purchase. However, by looking at the second model where the interaction terms are introduced, we find that this positive effect arises only in the App Store, thus providing support to our hypothesis *H6* rather than *H3*. Furthermore, surprisingly, the effect of in-app purchase in Google Play is shown to be even negative. This is possibly because versioning strategy is not optimal in presence of low valuable customers.

Conclusions

Building on the early work of Roma et al. (2013), which studied on the major drivers of app success, this paper provides evidence of the role of the revenue models in driving app success in terms of comparative revenue (i.e., by looking at the rank), and more importantly, offers unique evidence of how the effect of the revenue model adopted for a given app hinges upon the distribution platform where the app itself is marketed. Our findings suggest that adopting a paid business model is a more profitable strategy than a free strategy in the App Store, but not in Google Play. On the other hand, there is no evidence to support that the freemium model will yield higher app success than a paid model. Rather, there is evidence of a reversed dominance between these two models in Google Play. Finally, no univocal evidence emerges with regard to the role of the in-app purchase. Indeed, while it is confirmed that the in-app purchase practice is more likely to be successful in the App Store, we find that it might be detrimental in Google Play.

There are numerous directions for improvement. Applying matching methods is necessary to reduce the potentially selection bias generating from considering heterogeneous markets. Employing a larger dataset could also improve the reliability of our results. Finally, a dynamic panel data analysis where the dependent variable is lagged and introduced among the independent variables would be also needed, as rankings are usually quite persistent due to network externalities.

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Appendix

Table 1. Variables description

Variables	Description
Ranking (Dependent variable)	Positive integer variable indicating the position of the given app in the given week in the specific store.
App Category	12 binary variables (Customization; Education; Entertainment; Games; Healthcare & Fitness; Money & Finance; Music; News & Magazines; Photo & Video; Social Network; Travel & Navigation; Utility), each equal to 1 if, in the given week, the app belongs to the respective category; 0 otherwise.
App Size	Continuous variable measuring the size (in Mbytes) of the app in the given week.
Company Fame	Binary variable equal to 1 the app developer is a developer with fully established reputation worlwide; 0 otherwise. Based on revenue information and worldwide recognition we identify 9 top developers in our sample, i.e., Apple, Disney, Electronic Arts, Gameloft, Popcap, Rockstar Games, Sega, Ubisoft, Zynga. We also include Garmin, Marvel Entertainment, Norton by Symantec and Tomtom due to their huge popularity.
App Rating	3 binary variables (No Developer Rating; Low Developer Rating; High Developer Rating), each equal to 1 if, in the given week and store, the app rating belongs to the respective category; 0 otherwise.
Freemium	Binary variable equal to 1 if the app is a paid version of a freemium app is available in the given week; 0 otherwise.
Paid	Binary variable equal to 1 if the app is paid is available in the given week; 0 otherwise.
Free	Binary variable equal to 1 if the app is free in the given week; 0 otherwise.
In-App Purchase	Binary variable equal to 1 if the app allows for purchase of optional features in the week; 0 otherwise.
Number Developer Apps	Positive integer variable indicating the number of apps marketed by the developer of the given app in the given week in the specific store.
Store	1 binary variable equal to 1 if the app is available for download in App Store; 0 if available for download in Google Play.
New Entries	Positive integer variable indicating the number of new entries in the top 200 ranking in the given week in the specific store.
Time since launch	Positive integer variable measuring the time (in months) since the market launch of the given app

Table 2. Descriptive Statistics

Binary Variables	Descr. Stat.	Variables	Descr. Stat.
Games	58.35%	Customizations	3.54%
Social Network	5.32%	Travel & Navigations	8.86%
Money & Finance	0.89%	High developer rating	51.93%
Photo & Video	4.43%	Company fame	21.00%
Entertainment	1.82%	Store	54.67%
Education	3.50%	Free	53.48%
Healthcare & fitness	0.89%	Freemium	21.93%
Music	2.61%	Paid	24.59%
News & Magazines	2.70%	In-app purchase	70.67%
Utility	7.09%		

Continuous/Discrete Variables	Descriptive Statistics			
	Mean	Std.D.	Min	Max
New entry	44.772	15.836	0	90
Number developer apps	21.788	37.142	1	168
Size (Mb)	137.361	349.063	0.02	2355.2
Time since market launch (months)	268.388	377.848	0	2025
Ranking	213.11	67568.28	1	1000

Table 3. Results under Random Effects regression models

	Ranking^-0.6	Model 1		Model 2	
	Variable	*Coefficient*	*Std. Errors*	*Coefficient*	*Std. Errors*
Controls	***Company fame***	*0.0211***	*(0.0064)*	*0.0240****	*(0.0068)*
	Number developer apps	*-0.0013****	*(0.0003)*	*-0.0014****	*(0.0003)*
	High app rating	*0.0016*	*(0.0064)*	*0.0012*	*(0.0065)*
	ln(Size)	*0.0033*	*(0.0042)*	*0.0043*	*(0.0044)*
	Time since mrkt launch	*-0.0029****	*(0.0008)*	*-0.0030****	*(0.0008)*
	Social Network	*-0.0137*	*(0.0358)*	*-0.0146*	*(0.0349)*
	Money & Finance	*0.0406**	*(0.0204)*	*0.0254*	*(0.0177)*
	Photo & Video	*-0.0573**	*(0.0280)*	*-0.0486**	*(0.0230)*
	Entertainment	*-0.1049****	*(0.0300)*	*-0.1140****	*(0.0320)*
	Education	*-0.0149*	*(0.0180)*	*-0.0049*	*(0.0191)*
	Healthcare & fitness	*-0.0152*	*(0.0176)*	*-0.0330+*	*(0.0170)*
	Music	*-0.0553*	*(0.0372)*	*-0.0048*	*(0.0483)*
	News & Magazines	*-0.0238*	*(0.0339)*	*-0.0163*	*(0.0295)*
	Utility	*-0.0208*	*(0.0279)*	*-0.0090*	*(0.0234)*
	Customizations	*0.0065*	*(0.0382)*	*-0.0193*	*(0.0340)*
	Travel & Navigations	*-0.0189*	*(0.0180)*	*0.0088*	*(0.0154)*
	Store	*0.0735***	*(0.0233)*	*-0.0267*	*(0.0213)*
	New entry	*-0.0001***	*(0.0000)*	*-0.0001***	*(0.0000)*
H1	***Free***	*-0.0348****	*(0.0083)*	*0.0055*	*(0.0165)*
H2	***Freemium***	*0.0043*	*(0.0245)*	*-0.0378**	*(0.0155)*
H3	***In-App purchase***	*0.0511**	*(0.0218)*	*-0.0535***	*(0.0194)*

H4	***Free*Store***			*-0.0444**	*(0.0178)*
	Freemium*Store			*0.0300*	*(0.0527)*
H5	***In-App*Store***			*0.1564****	*(0.0286)*
	Costant	*0.0855***	*(0.0306)*	*0.1443****	*(0.0295)*

Note: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Number of obs.: 2237. Number of groups: 114. Standard errors are robust to heteroskedasticity and serial correlation. Breusch-Pagan Lagrangian multiplier test for random effects: $\chi^2(1) = 2119.44$ (2409.70), $p = 0.0$ ($p = 0.0$) for the first (second) model.