An empirical analysis of revenue drivers in the mobile app market

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Abstract

Mobile app market is booming and will exceed $46 billion by 2016. In this paper, we take the perspective of developers. Based on data from two major app stores (Apple Store and Google Play), we construct an econometric model to investigate the factors influencing apps' success in terms of revenue.

Keywords: Mobile App Market, Revenue, Econometric analysis.

Introduction

Mobile app market is booming. As a matter of fact, a report released by Forrester Research predicts that the revenue created from customers buying and downloading apps for smartphones and tablets will reach $38 billion by 2015 (Bilton 2011). In the same vein, ABI Research echoes 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).

In the early 2000s the Mobile Content Market was dominated by the Mobile Portal model. Mobile Portals were mostly managed by Mobile Network Operators (MNO), which constructed a highly centralized model (Kuo and Yu 2006). This relatively stable context was dramatically shaken in 2008 by Apple Inc., which, launching the App Store, introduced a new distribution paradigm in Mobile Commerce: the application store. An application store is a web distribution platform from which a generic user can download software applications for mobile devices to increase the utility associated to their usage. Mobile applications (apps, hereafter) are typically developed by third parties, which can be either software houses or individuals. This model can be categorized as a two-sided market, which can generate a mutual advantage (Hagiu 2007). By means of developers, Apple can exploit indirect network externalities that increase the value of its own devices. In fact, the higher the number of apps running on a device, the higher the potential functionalities of such device. On the other hand, developers are interested in selling their apps via App Store, because it allows them to reach a multitude of consumers worldwide, that they might not be able to reach on their own. Developers set the price of their apps and appropriate 70% of the revenue for each transaction, whereas Apple retains 30% of it.

Numerous mobile device makers, such as RIM, Samsung, etc, have followed Apple's move. Such a 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. Nowadays, OS developers or device manufacturers typically own the app stores, whereas app developers provide contents that increase the value of app store owners' correlated businesses.

With this growing number of existing portals and available devices, a multitude of developers try to catch new business opportunities as they can introduce more products and serve different platforms. At the same time, they 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, thus, which app store to target, which business model to choose for each app. All these decisions certainly affect apps' success in the market. However, in contrast to the huge popularity, not sufficient attention from the academic world has been reserved to the dynamics of this market. In this paper, we take the perspective of developers. Specifically, we construct an econometric model to investigate the factors influencing apps' success in terms of comparative revenue. We test our hypotheses relying on a sample of top grossing apps for smartphones provided by the Italian versions of the two major app stores, namely App Store and Google Play.

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

In this paper we explore the factors that might play a role in the success of an app. We measure the product performance in terms of revenue. This is quite reasonable due to the negligible marginal cost faced by developers. Furthermore, information about app revenue is largely available, although in an indirect manner. In fact, the two major app store owners publish the top grossing app ranking in their own markets. Numerous 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). These papers assume that rank and sales are linked via the well-known power law function. Garg and Telang (2012) provide 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. Their work is actually one of the very first relevant studies focusing on the app market. At any rate, previous works support our choice of using top grossing app rankings to measure revenue (at least in a relative manner), and, thus, market success of an app. In the following, we formulate and test a number of hypotheses based on existing literature on similar contexts and industry articles on the app market.

Category

The first hypothesis concerns the thematic category. Games, utilities, music, social network, finance, customization are some common categories that can be found in all the app stores. Intuitively apps of very different categories have different nature, which may mean different user segment with significantly different size and willingness to pay. For instance, industry evidence suggests that games are the most successful apps (Canalys 2012). Ceteris paribus, we expect that apps of very different categories have different ranking.

Hypothesis 1 (H1): The category significantly affects the success of an app.

Free vs. Paid vs. Paid with free business models

The app store distribution model allows developers to adopt a variety of business models. We can identify at least three different models utilized by developers in the app stores. Some developers choose a free app strategy, giving the app for free. We refer to this strategy as *free*. Others market only paid apps. We refer to it as *paid*. Finally, some other developers provide a paid app, but also release a free version of it. In this case, there are some differences between the two versions. Such differences might be due to the presence of exclusive features in the paid version or might be due to the presence of substantial advertising in the free version. Many developers also adopt the in-app purchase policy, i.e., additional features can be purchased directly within the app. We refer to this mixed strategy as *paid with free* model.

There are several reasons driving firms to introduce a free version or, even, adopt free product business model. Perhaps, one of the most important is that apps might work as two-sided markets. A two-sided market is an economic platform having two distinct user groups that provide each other with intra- and/or inter-network benefits (Rochet and Tirole 2003, Parker and Van Alstyne 2005). In our context, apps might attract not only final users, but also third parties who are interested in final users, when they are available in large numbers. 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 are subsidized, whereas third parties end up paying handsomely. Therefore, developers benefit from other revenue streams, i.e., advertising or non-personally identifiable information selling. Another reason is related to the fact that firms might want to segment the market in presence of heterogeneous customers. For instance, low valuable customers will buy the free version and, perhaps, afford to tolerate the "nagging" amount of advertising or the presence of limited features, others will update to the paid version, thus acceding more features, and some others will purchase additional or exclusive features even at a higher price (e.g., through in-app purchase). Finally, the free version in the market might be extremely limited or time-locked. In this case, the role of the free version is to let 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). Whatever the underlying reason is, the choice of the business model for a product naturally affects the relative performance in the market. More and more claims from industry insiders suggest that the app market is moving toward free apps due to the higher revenue they can generate (Spriensma 2012). We investigate which of the aforementioned business models (i.e., *free*, *paid*, and *paid with free*) is more likely to result in a market success for the given app. It is noteworthy that, since we study the success of single apps, the *paid with free* model is related to a paid app for which a free version is available, whereas the *free* model is related to a free app no matter whether the paid version is released or not. Without any strong *a priori* motivation, we just hypothesize that the success of an app in terms of revenue depends on which business model is chosen by the developer. In other words, the business model strongly affects the success of an app in the market. We formulate the following hypothesis accordingly:

Hypothesis 2 (H2): The business model (i.e., free, paid, paid with free) adopted for a certain app strongly influences its success in the market.

In-app purchase

More and more developers 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. This practice is known as in-app purchase. In its essence, in-app purchase can be assimilated to versioning and upgrading. There is a considerable amount of theoretical studies on versioning of information goods (Bhargava and Choudary 2001, Bhargava and Choudary 2008). These works suggest that versioning is optimal only under certain conditions. On the other hand, basic evidence shows that in-app purchase has been quite successful in App Store, and it has reached large popularity in Google Play as well (ABI Research 2012). 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): Apps allowing for in-app purchase of additional features have higher success.

Developer reputation effect

Economic theory typically suggests the existence of a positive relationship between the reputation of the firm and the price, and, thus, firm profit (Klein and Leffler 1981, Shapiro 1983). This is mainly because seller reputation can be viewed as a proxy for quality characteristics that are unobservable to consumers before the transaction takes place. The introduction of e-commerce has allowed an easy implementation of mechanisms to build reputation, e.g., ratings, comments and reviews provided by buyers, which are commonly referred to as feedback systems (Bolton et al. 2004). In fact, a considerable number of recent studies empirically demonstrates that mechanisms to build reputation, e.g., online ratings, have positive effects on price and/or probability of selling online as they are a vehicle to signal quality and increase customers' trust in presence of uncertainty about product quality and seller reliability. Dellarocas (2003) provides a comprehensive review of this stream of literature. In these papers, premium prices or sales can be viewed as proxies of the success of a product. However, only a few works in this literature have considered revenue as a measure of success (Duan et al. 2008).

Most of the app store owners offer to users the possibility to rate the apps they download, and, as a result, allow developers to build reputation within the store. We follow the stream of literature supporting the benefits of feedback mechanisms. In addition to the effect of online rating mechanisms, there might be positive effects of reputation, which are exclusive to those giant developers who have a fully established reputation worldwide. Therefore, we state the second hypothesis as follows:

Hypothesis 4 (H4): The higher developer and app ratings, the higher the app success. Also, apps of developers with fully established reputation are more successful.

In-store Competition effect

The last hypothesis is quite straightforward due to the characteristics of the app market. As a matter of fact, the nature itself of app stores gives a plethora of developers the opportunity to release an app and compete in the arena. The number of apps released in each of the two major stores is growing tremendously fast, although the rate is higher in Google Play. This suggests that competition is overall growing, at least at the level of a single app. Furthermore, this dynamicity reflects particularly on top 200 apps, as demonstrated by the considerably large amount of new entries in such ranking observed every week. The number of new entries is a more dynamic and focused measure and, thus, better estimates the change in the competition level among top apps. Basic economic intuition suggests that an increased level of competition should result in lower performance. Therefore, we expect that when competition is high, the ranking will be worse and, thus, the app will be less successful:

Hypothesis 5 (H5): The higher the level of competition, the less successful the app.

The econometric model

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 related to all Fridays in the period going from October 19th, 2012 to January 4th, 2013 (12 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, 12 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 14 (12 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 12 weeks yielded a balanced panel dataset of 1368 observations related to 62 apps from App Store and 52 apps from Google Play.

We defined a set of variables and some controls to test the formulated hypotheses and recorded the relative data. They are reported in Table 1 (see Appendix), which provides the description and the modalities of all the variables in detail. For sake of length, we only clarify how we measure the developer rating. In general, app stores allow users to rate an app on a 1-to-5 scale where 1 corresponds to the worst valuation and 5 to excellent valuation. However, no developer rating is available in the two distribution platforms. Therefore, we construct a measure of developer rating every week by computing the average ratings of all the apps marketed in the given store by the given content provider until that week. For each app we exclude the relative rating when computing the average developer rating as we additionally introduce two specific variables measuring the rating of that app. To cope with the absence of ratings for some developers, for instance because there are no ratings or no other apps have been marketed, we construct two dummies based on the average rating: low rated developers (*Low Developer Rating*) category if the average developer rating is below 4 and high rated developers (*High Developer Rating*) category if the average developer rating is above or equal to 4. By doing so, we can compare the effect of low and high developer ratings with respect to those developers who do not have any rating.

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

Empirical results and discussion

As our dataset is a balanced panel and the number of statistic (apps) units is quite large compared to the observation period (number of weeks), three basic regression models, namely pooled OLS, fixed effects and random effects models, are usually suggested in the literature (Wooldridge 2002). However, the fixed effects model is not appropriate a priori in our setting because some 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 analyze 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, 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 due to length constraints. For sake of parsimony, we also use a stepwise procedure to eliminate the least relevant variables under both complete and reduced samples. We gradually delete the least significant variable and stop only when the estimated coefficients are significant at least at the 10% level. The results of the restricted models are reported in Table 3. Below Table 3, we also report the F-Test, which suggests that the full model does not provide any significant better fit than the restricted one. Due to the very high similarities between full and restricted models, we only comment the restricted one. As reasonably expected, most of the categories generate less relative revenue compared to games as there is a negative impact on app ranking compared to such category. Only for a few categories, e.g., social and customization, there is no significantly different effect compared to the game category. These results are expected as, in addition to games, these are in fact the most popular app categories. Most importantly, contrary to claims from numerous industry articles (e.g., Spriensma 2012), there is strong evidence that "paid can be successful". As a matter of fact, the fact that an app is paid (no matter whether a free version is available or not) rather than free determines a higher ranking, thus higher comparative revenue. This is a relevant result as it suggests 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. Regarding hypothesis H3, it is consistently observed that the presence of in-app purchase is not significant. Perhaps, the prediction of literature, which suggest that only under limited circumstances versioning is optimal, turns out to be correct, despite the fact that the amount of apps allowing in-app purchase is rapidly increasing. Developers should consider whether introducing only a single version could generate higher revenue, as in-app purchase seems to be not so effective. A further interesting result is related to the effect of both developer and app ratings: they are consistently not significant. It is likely that the role of ratings is negligible in the context of successful apps because the fact that an app appears in the top 200 ranking represents itself a sort of guarantee to consumers. However, this does not mean that no effect of reputation exists. As a matter of fact, our analysis shows that being a developer with fully established worldwide recognition leads to a high comparative app performance. Finally, as expected, the effect of in-store competition at the app level has an obvious negative effect on app ranking. When the number of new entries, i.e., new successful apps, increases, competition gets fiercer and, ceteris paribus, app comparative revenue decreases. Regarding control variables, only the store, the number of app developer and the time since market launch are shown to be significant.

Conclusions

This work provides the first basic evidence of the major factors that affect the app success in terms of comparative revenue, exploiting the relationship between ranks and sales previous works have demonstrated. Particularly, the effect of the business model on app performance is remarkable as well as surprising. In contrast to many claims from industry insiders (e.g., Spriensma 2012) our analysis seems to suggest that paid apps seem to pay more than free apps. There are numerous directions for future research in this field. However, more closely related to the present work, a dynamic panel data analysis where the dependent variable is lagged and introduced among the independent variables would be needed, as rankings are usually quite persistent due to network externalities. In addition, the number of observations could be further extended.

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Appendix

Table 1. Variables description

Variables	Description
App Category (Customization; Education; Entertainment; Games; Healthcare & Fitness; Money & Finance; Music; News & Magazines; Photo & Video; Social Network; Travel & Navigation; Utility)	12 binary variables, each equal to 1 if, in the given week, the app belongs to the respective category; 0 otherwise.
Ranking (Dependent variable)	Positive integer variable indicating the position of the given app in the given week in the specific store.
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 (No Developer Rating; Low	3 binary variables, each equal to 1 if, in the given week and store, the app rating belongs to the respective category; 0 otherwise.

Developer Rating; High Developer Rating)	
Developer Rating (No Developer Rating; Low Developer Rating; High Developer Rating)	3 binary variables, each equal to 1 if, in the given week and store, the app developer rating belongs to the respective category; 0 otherwise.
Developer Type	Binary variable equal to 1 if, in the given week, the app is developed by a firm; 0 if developed by individual(s).
Paid with Free	Binary variable equal to 1 if the app is paid and a free version is available in the given week; 0 otherwise.
Paid	Binary variable equal to 1 if the app is paid and no free version 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.
First Version	Binary variable equal 1 if the app is an initial version; 0 otherwise.
Time since launch	Positive integer variable measuring the time (in months) since the market launch of the given app
Time since last release	Positive integer variable measuring the time (in weeks) since the last released version of the given app

Table 2. Descriptive Statistics

Variables	***Descr. Stat.***	***Variables***	***Descr. Stat.***
Binary Variables	***% 1***	***Binary variables***	***% 1***
Store	54.39%	***Customization***	3.51%
Developer Type	97.37%	***Travel & Navigation***	8.77%
Company Fame	20.98%	***High App Rating***	77.85%
Games	58.77%	***Low App Rating***	21.93%
Social Network	5.26%	***No App Rating***	0.22%
Money & Finance	0.88%	***Paid with Free Trial***	22.37%
Photo & Video	4.39%	***Paid without Free Trial***	25.22%
Entertainment	1.83%	***Free***	52.41%
Education	3.43%	***Initial Version***	5.48%
Healthcare & Fitness	0.88%	***In-App purchase***	70.61%
Music	2.56%	***High Developer Rating***	50.88%
News & Magazines	2.70%	***Low Developer Rating***	37.86%
Utility	7.02%	***No Developer Rating***	11.26%

Variables	***Descriptive Statistics***			
Continuous/Discrete	***Mean***	***Std.D.***	***Min***	***Max***
App Size (Mbyte)	132.94	118771.3	0.02	2355.2
Number Developer Apps	21.41	1357.05	1	168
Time since market launch (Months)	12.44	88.34	0	43

Time since last release (Weeks)	9.31	228.17	0	114
New entries	46.45	368.26	0	90
Ranking	213.11	67568.28	1	1000

Note: The values are computed at the observation level.

Table 3. Random Effects regression results under full and restricted models

	Ranking^(-0.6)	**Full Model**		**Restricted Model**	
	Variable	***Coeff.***	***Robust St.Errors***	***Coeff.***	***Robust St.Errors***
H1	***Social Network***	-0.0223	(0.0457)	-	-
	Money & Finance	0.0174	(0.0214)	-	-
	Photo & Video	-0.0994**	(0.0333)	-0.0922**	(0.0924)
	Entertainment	-0.0716**	(0.0215)	-0.0639**	(0.0184)
	Education	-0.0713***	(0.0197)	-0.0628***	(0.0159)
	Healthcare & Fitness	-0.0818***	(0.0182)	-0.0745***	(0.0135)
	Music	-0.0736*	(0.0307)	-0.0748**	(0.0286)
	News & Magazines	-0.0554†	(0.0336)	-0.0519†	(0.0300)
	Utility	-0.0587†	(0.0331)	-0.0617*	(0.0278)
	Customization	-0.0002	(0.0318)	-	-
	Travel & Navigation	-0.0372	(0.0244)	-	-
H2	***Paid with Free Trial***	0.0218*	(0.0099)	0.0192*	(0.0084)
	Paid without Free Trial	0.0291**	(0.0109)	0.0256**	(0.0096)
H3	***In-App Purchase***	0.0009	(0.0030)	-	-
H4	***High Developer Rating***	-0.0013	(0.0029)	-	-
	High App Rating	0.0074	(0.0072)	-	-
	Company Fame	0.0229***	(0.0060)	0.0252***	(0.0057)
H5	***New Entries***	-0.0040***	(0.0009)	-0.0038***	(0.0009)
Controls	***Store***	0.0450*	(0.0225)	0.0508*	(0.0211)
	Developer Type	0.0209	(0.0422)	-	-
	Number Developer Apps	-0.0403***	(0.0093)	-0.0366***	(0.0078)
	App Size	0.0044	(0.0053)	-	-
	Time since launch	-0.0165	(0.0187)	-0.0142**	(0.0052)
	Time since launch ^2	0.0008	(0.0046)	-	-
	Time since last release	-0.0173	(0.0124)	-	-
	Time since last release ^2	0.0042	(0.0038)	-	-
	Initial Version	0.0018	(0.0043)	-	-
	Constant	0.1770***	(0.0495)	0.1869***	(0.0274)
	R^2				
	within	0.0720		0.0619	
	between	0.0744		0.0768	
	overall	0.0733		0.0751	

Note: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Number of obs.: 1368. Number of groups: 114. Standard errors are robust to heteroskedasticity and serial correlation. Breusch-Pagan Lagrangian multiplier test for random effects: $\chi^2(1) = 6051.28$ (6347.39), p = 0.0 (p = 0.0) for the full (restricted) model. Statistics of F-test (Restricted vs. Full models): F(13, 1340) > 0.9185.