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Factors influencing prices in the mobile apps' store distribution model: An empirical study

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Abstract

Mobile apps are expected to generate $38 billion by 2015. With a growing number of app stores and devices, developers try to catch new business opportunities. However, apps' pricing has become a critical issue. Based on data collected from major app stores, this study explores the factors influencing apps' price.

Keywords: App store distribution model, Pricing, Smartphone industry, Empirical analysis.

1. Introduction

The Mobile Commerce (or, sometimes referred to as Mobile e-Commerce) could be defined as the electronic commerce over mobile devices (Anckar and D'Incau, 2002) or alternatively as the product resulting from the interaction among business transactions, Internet applications and mobile communications (Grami and Schell, 2004).

In the early 2000s the context was dominated by the Mobile Portal model, which has been the foundation of the Mobile Commerce value chain according to Barnes (2002). Mobile Portals were mostly managed and strongly controlled 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 the launch of the Apple App Store by Apple Inc., that introduced a new distribution paradigm in Mobile Commerce. Ghezzi et al. (2010) emphasize that the strategy of leveraging on strong assets such as brand reputation and the innovative iPhone device launch, linking the App Store model to other businesses, i.e., iTunes, to exploit synergies and cut down investments and learning from the NTT Docomo imode environment with a high level of third parties independence and revenue sharing led Apple to change the rules of the game in such competitive environment and relegate MNOs to a marginal role.

An application store is a web portal from which a generic user can download software applications for mobile devices increasing the utility associated to their use. Mobile applications (apps, hereafter) are typically developed by third parties, which can be either software firms or individuals. Therefore, an app store works as a distribution platform that allows developers to reach end users. According to Hagiu (2007), this model can be classified as a two-sided platform that generates a mutual advantage mechanism. By means of apps developers, Apple can exploit indirect network externalities that increase the value of its own devices, e.g., iPhone. 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 through App Store, because it allows them to reach many consumers worldwide. Differently from the digital music market, where the Pure Merchant model is predominant, developers usually choose the prices of their apps. However, according to the Apple's App Store revenue sharing model, developers receive 70% of the retail price for each transaction, whereas Apple retains 30% of it. The 70-30 rule has been set by Apple and applies to all the developers and transactions in the store.

The new distribution paradigm has allowed a latecomer such as Apple to enhance the competitive advantage in the fast-growing smartphone industry. In response to the great success obtained by Cupertino's mobile devices, since 2008 several firms, competing with Apple in the device market, such as RIM, Nokia and Samsung, have launched their application store. Such a rapid proliferation of app stores has involved not only traditional players of the mobile industry, but also important new entrants such as Google, which launched its Android mobile Operating Systems (OS) in 2008 and made the app store Android Market available to users in the same year. As a result of all these moves, the mobile apps store distribution model currently captures the attention of several actors in the smartphone industry, especially, OS owners, Device Manufacturers and apps' Developers. OS developer and/or device manufacturers own the app stores, whereas developers provide contents that increase the value generated by app store owners' correlated business. More importantly, in spite of its recent introduction, mobile commerce is growing enormously. According to Gartner (2011) mobile apps have generated revenues for $5.2 billion in 2010, whereas a report released by Forrester Research predicts that the revenue created from customers buying and downloading apps to smartphones and tablets will reach $38 billion by 2015 (Bilton, 2011).

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. This is demonstrated by the considerable increase of the number of apps available in the stores: for instance, App Store counts more than 540,000 apps on December 2011 (source: 148apps.biz), whereas less than 300,000 were available in the same month of the former year, Android Market has more than doubled in terms total apps (going from around 150,000 to 330,000 apps) in less than one year (source: www.appbrain.com). At the same time, developers have to make several non-trivial decisions: to cite a few of them, they have to choose what kind and how many apps to market, which mobile operating systems to develop for and, thus, which app store to target. All these decisions certainly affect apps' price set by developers and, consequently, the success in the market.

Due to the novelty of the app distribution model, only a few related works are available on this topic in the literature. Furthermore, at this early stage, several research directions can be taken in order to understand the dynamics arising in this emerging digital market. For instance, Ghezzi et al. (2010) analyze how the introduction of the new app store distribution paradigm affects and transforms firm's resources and assets portfolio, from the perspective of the MNOs. They show that the core MNO's resources endowment is significantly changed after the launch of the store model, with the fall of some traditional unique assets and the rise of emerging new resources and capabilities. On the other hand, Holzer and Ondrus (2011) look at the developer's perspective. After presenting an accurate overview of mobile apps market and relative trends, they formulate eight propositions that can be useful starting points for further research. These propositions emphasize how factors such as portal centralization, technology openness, device variety and platform integration can influence mobile apps developers' behavior.

Similarly to Holzer and Ondrus (2011), we take the perspective of developers interested in developing and marketing successful apps. Specifically, in this paper, we investigate what major factors can influence their apps pricing decisions. To the best of our knowledge, there are no previous works focusing on this issue. However, during the last years several scholars have analyzed pricing issues in similar contexts. The most interesting case is related to the digital music market (Bauxmann et al. 2007; Shiller and Waldfogel 2009). While the two markets show numerous similarities, they certainly differ from the pricing perspective. As a matter of fact, pricing decisions for mobile apps are made directly by developers and not by the apps store owners (i.e., Apple, Google, Nokia) as it happens for digital music. While according to Hagiu (2007) we can define the Digital Music Stores (e.g., iTunes) as a pure-merchant model, application portals can be associated to two-sided platforms (Rochet and Tirole 2003). In fact, in the app store model, registered developers choose the prices of their apps to reach a vast scale of registered users by means of an intermediary platform, whereas in an iTunes-like model, store owners operate just as music resellers, which makes their business model more similar to the pure-merchant one. As a result, the 99 cents per song uniform price policy is an entirely Apple's merchant-oriented decision designed to promote sales of Cupertino's associated devices (Hagiu 2007). On the other hand, we argue that in a setting in which developers can independently make several decisions related to the pricing of their apps, we do not expect, a priori, to observe uniform price. Therefore, the issue of which determinants affect pricing decisions becomes quite interesting. In particular, since developers are called to choose which app distribution platform to target and one can arguably think of the applications portals as of different markets where different pricing strategies might be required to succeed, it is necessary to understand their impact on pricing decisions. In sum, we pose the following research questions. What are some of the main factors influencing the price of successful apps? And, specifically, does the targeted distribution platform matter when setting prices?

2. Hypotheses

Given the high number of factors that might theoretically affect the price of an app and the consequent difficulty in identifying all of them in such a dynamic environment, we formulate and test a number of hypotheses based on a critical analysis of the literature concerning pricing in similar markets, as in case of developer reputation, or on intuitions specifically derived in the context of the app store distribution model as in case of variables of particular interest i.e., the distribution platform. In addition, we include other general variables such as the type of developer, i.e., whether firm or individual, as control variables. In turn, we present and discuss all the testable hypotheses.

2.1 Category effects

The first hypothesis concerns the thematic category of the app. Games, utilities, entertainment, music, social network, finance, photo & video are some common categories that can be found in all the app stores. In general, app stores such as App Store, Android Market and Blackberry App World have very similar category systems, which simplifies the process of homogenizing apps' classification in our dataset. As mentioned above, intuitively apps of very different category have different nature, which may mean non-comparable development cost and different user target. Therefore, *ceteris paribus*, we expect that apps of very different categories have different prices, whereas apps of similar categories share a similar price. For those sharing similarities in terms of development costs and user target, another factor can determine price differences. That is, the existence of two-sided market effects for a specific category might have a significant influence on the pricing decisions compared to other categories. 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). Some examples of two-sided platforms include credit cards (composed of cardholders and merchant), TV platforms (viewers and advertisers), newspapers (readers and advertisers), operating systems (end users and software developers), social networking (users and advertisers). It is known from theory that the possibility to rely on revenues, e.g., advertising revenues, from one side, i.e., producers, can provide an incentive to lower the price or subsidize the other side, i.e., end users, in numerous settings such as digital goods and media industries depending on cross-price elasticities as well as the relative sizes of the two sided-network effects (Caillaud and Jullien, 2003; Rochet and Tirole, 2003; Parker and Van Alstyne, 2005). Therefore, we expect that app categories that work as two-sided markets, particularly social networking and news, as developers can profit from advertising will have a lower prices than other categories, which do not differ much especially in terms of development costs. We can formulate the following hypothesis to empirically test predictions of two-sided network theory:

Hypothesis 1 (H1): Prices are expected to differ significantly across very different categories. Specifically, prices of apps' categories (e.g., Social Networking) that work as two-sided markets are lower than those of similar categories that are not two-sided platforms.

2.2 Developer's Reputation effect

Whether seller's reputation affects his pricing decisions has been widely investigated in the literature. Economic theory typically suggests the existence of a positive relationship between the reputation of the seller and the price (Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984), mainly because the seller's reputation is a proxy for quality characteristics that are unobservable to consumers before the transaction takes place. Empirical analyses conducted in industries such as wine (Landon and Smith, 1997) or software industries (Banerjee and Duflo, 2000) have tended to support the theoretical results. However, only with the introduction and growth of e-commerce, empirical researches on the issue have flourished in number. Also, in the e-commerce environment, the importance of reputation increases as payment and delivery rarely occur simultaneously (Standifird, 2001). Different from off-line markets, Internet allows 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). Numerous recent studies empirically demonstrate that such feedback systems have positive effects on price and/or probability of selling online as they are a vehicle to signal quality to customers in presence of product quality and (re)seller reliability uncertainty and increase their trust (Brynjolfsson and Smith, 2000; Houser and Wooders, 2001; Standifird, 2001; Ba and Pavlou, 2002; Melnik and Alm, 2002; Resnick and Zeckhauser, 2002; Bruce et al., 2004; Lucking-Reiley et al., 2007). Dellarocas (2003) provides a comprehensive review of this stream of literature, whereas, based on a panel data, Duan et al. (2008) argue that in presence of endogenous online reviews, ratings have no influence on increasing firm's revenue in the movie distribution industry.

Apps can be classified as *experience goods*. Although the reputation of app store owners such as Apple, Google and Blackberry and their adoption of strict and high quality standards that developers have to satisfy to publish their apps on such platforms, often users are still uncertain about the real value an app can generate to them before they use it. For this reason, most of the app store owners offer to users the possibility to rate the apps they download, and, as a result, assess the quality level of developers. Therefore, we follow the stream of literature supporting the benefits of feedback systems in terms of price and state the following:

Hypothesis 2 (H2): The higher the developer's rating, the higher the app's price.

2.3. Trialability effect

Software developers often provide free trial versions of their products so that users can download to test them before purchasing. For instance, these products could be initially sold in the form of limited/demo or time-expiring versions. Trialability measures the extent to which potential adopters perceive that they have an opportunity to experiment with the innovation prior to committing to its usage (Rogers, 1983; Moore and Benbasat, 1991;

Agarwal and Prasad, 1997). According to Rogers (1995) trialability is an important factor when adopters are evaluating products and services. Agarwal and Prasad (1997) show that trialability is crucial in current usage of information technologies. In fact, through the trial version users can test the product and resolve the uncertainty about its real value to them. Trialability can be assumed as a signal for quality as the knowledge that a product is available in a free trial version is some sort of guarantee to software customers (Gallaucher and Wang, 2002). In this sense, trialability plays a role similar to reputation, although in the short term and in the early stages of product marketing. Therefore, it is expected that consumers given the opportunity to test a product before buying will pay a higher price. As a matter of fact, Gallaucher and Wang (2002) empirically find that products whose trial versions are available are associated with price premiums in the web server sector. In fact, *ceteris paribus*, firms offering a trial version enjoyed a price premium of roughly 110 to 120 percent. In the same vein, we formulate a similar hypothesis for the apps:

Hypothesis 3 (H3): The apps whose free-trial versions are available to users have higher prices.

2.4 Distribution platform effect

The last, but the most important, hypothesis regards the effect of the different type of distribution platform, e.g. App Store, Android Market or Blackberry App World on price formation. It is important for a developer to understand whether targeting a certain store rather than another one might require changes in the pricing strategy in order to be successful. However, while the preceding hypotheses, e.g., the effect of reputation, are, somehow, supported by consolidated theoretical or empirical literature related to similar markets, no study sheds light on the effect of the (online) store on prices in a context such as the app store distribution model. In fact, there is a consistent body of economics and marketing literature that investigates price dispersion in online retail markets and make comparisons with conventional retail markets (Bailey, 1998; Brynjolfsson and Smith, 2000; Tang and Lu, 2001; Clay et al., 2002; Clemons et al., 2002; Pan et al., 2002; Chevalier and Goolsbee, 2003; Ancarani and Shankar, 2004; Baye et al., 2004a, 2004b; Tang et al., 2010). However, most of the works in this stream of literature focus, with contrasting results, on understanding whether, due to easier and faster availability of price information, Internet has put downward pressure on prices and led all the online retailers to charge the same price for mass produced goods, e.g., books or CDs, compared to conventional retail channels. In particular, in line with our scope, Clay et al. (2002) demonstrate a strong evidence of a store effect on price, but such effect is not well explained by store attributes such as online reviews, loyalty programs and recommendations. However, there is a fundamental difference between the markets analyzed by the above works and the mobile apps market. First of all, online stores of products such as books, CDs, airline tickets and digital music mainly operate just as resellers who purchase from producers/providers and resell to customers by charging a retail price based on the wholesale price set by the upstream firms. According to Hagiu (2007), such a business model can be defined as a pure merchant model. On the other hand, application portals are conceived as two-sided platforms where registered developers choose the prices of their apps to reach a vast scale of registered users by means of an intermediary. The developer and the platform owner share the revenue for each unit sold according to pre-determined revenue sharing rule set by the latter.[1] Therefore, different from the pure merchant model, the price available to users in the major app stores is that set by developers. The consequence is that in pure merchant model, the store effect depends on the different pricing policies experimented by stores, store competition as well as store attributes. In the app store model, the store effect is

[1] All the major app stores, e.g., App Store, Android Market, Blackberry App World, utilize the same revenue sharing rule (70-30), initially utilized by Apple. The revenue sharing and applies to all the developers and transactions.

related to different factors. Based on our current knowledge, there are several factors that might affect prices in the app store distribution model. The level of in-store competition is potentially one of the major factor: intuitively, a fierce level of in-store competition, driven by a high number of developers and a low level of in-store concentration, may result in low prices. Second, recall that apps run on mobile OS (e.g., iOS, Android) and devices (e.g., iPhone, Samsung) often developed/manufactured by the same firms that own the app store. For instance, Apple, Blackberry and Nokia are simultaneously device makers, OS developer and app store owners. Therefore, there are strong technological and strategic interconnections between apps developers, OS owners and device makers, which might end up affecting the level of prices. As Lin and Ye (2009) suggest, the smartphone industry can be modeled through an analogy with natural ecosystems and food webs. In the "smartphone food web", the whole ecosystem is fed by end-customers. As a matter of fact, they generate revenue to device makers by purchasing smartphones and to content providers by downloading apps and other mobile contents from service platforms, such as App Store or Android Market. Furthermore, by exploiting their impact on both device makers and content provider, OS owners, e.g., Google, pursue the objective of increasing the value of businesses that are correlated to the mobile industry, e.g., search engines. Therefore, due to these strategic interconnections, it is unavoidable that the consumer segments targeted by the device maker and/or the OS provider developers' business and in turn their pricing decisions. Finally, the relationship between app's development cost and the OS/device for which the content provider chooses to develop might also translate into a store effect on price. Holzer and Ondrus (2011) argue that technology openness might lower the development cost of an app, but also remark how device variety can increase the customization costs related to several smartphones. They suggest that, *ceteris paribus*, the openness of OS such as Android should decrease app development costs compared to closed systems such as iOS and RIM. On the other hand, developing for the latter requires less customization costs because the app has to run only a few (or even one) devices. In a multi-device and multi-device makers platform, such as Android, developers who desire to target several devices in order to reach more potential customer segments have to work more on compatibility issues and fine-tune their apps for most of the devices. As a result, according to Holzer and Ondrus (2011), a developer willing to distribute via Google's app store might incur higher customization costs to make the app available for such devices. Lomas (2010) echoes pointing out that the basic rule is: "the more platforms you want an app on (i.e., the higher the device variety), the more money you will have to fork out in development costs".

In-store competition, the different type of segment as well as different required development costs driven by the degree of technology openness and level of customization might significantly change across different platforms and combine in a way that makes the distribution platform effect on prices unclear. With such a potential tangle of related factors, we just hypothesize that the kind of distribution platform will affect the price in the sense that apps' prices vary significantly across distribution platforms:

Hypothesis 4 (H4): The distribution platforms (e.g., App Store, Android Market, Blackberry App World) have strongly different effect on apps' prices.

3. The Econometric model

3.1 Data

In order to test our hypothesis, we collected data of paid apps for smartphones from the Italian version of the major app stores, namely Apple's App Store (iTunes - App Store), Android Market (https://market.android.com) and Blackberry App World (http://appworld.blackberry.com/webstore).[2] Specifically, we explored and recorded weekly

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[2] We did not include the Nokia Ovi Store since we were not able to obtain an aggregate top ten including all the apps' categories due to the fact that in this app store Games are a separate category.

(every Friday) data of the top (i.e., the most downloaded) paid apps ranking publicly available in each of these three stores in a period randomly selected from May 6th to September 2nd, 2011 (18 weeks in total).[3] We restricted to the top ten paid apps due to data collection effort. More importantly, recall that the main objective of this paper is to investigate factors influencing prices from the perspective of developers. Profit-maximizing developers are interested in developing and marketing successful apps. Thus, a sample composed by the most popular apps is a reasonable choice, also in light of the discussion provided in Footnote 3. Recording the top ten paid apps from the three stores for all the 18 weeks yielded a dataset of 540 observations. We explored a weekly ranking, thus we did not know a priori how many "successful" apps would have been considered in our sample, i.e., the statistical units were initially unknown. Furthermore, depending on the amount of downloads, an app might appear in the top ten rankings for more than one week. In this case, we would have more than one observation for the same app, which can help investigate for the existence of a temporal effect on price. As a matter of fact, at the end, the total number of observations, i.e., 540, is related to 206 "successful" apps[4], that have been at least once in at least one of the three rankings during the specified period. Therefore, the resulting sample contains all the top ten paid apps

[3] All the distribution platforms usually provide top free apps (i.e., the most downloaded free apps) and top paid apps (i.e., the most downloaded paid apps) rankings. Developers of free app make money, for instance, from advertising and/or in-app purchase revenues, which, however, are not publicly available. Therefore, only the latter ranking is considered. Furthermore, we restricted to top apps because our analysis would like to offer a contribution to support end-customers pricing decisions from the perspective of developers interested in developing and marketing successful apps. It should be pointed out that App Store and Android Market also provide a top grossing apps (i.e., the apps generating the maximum combined revenue from both purchase price, advertising and in-app purchase revenues) ranking. Collecting data from such ranking would have probably been the most appropriate choice (in absence of development and marketing costs knowledge), as the apps generating the highest revenue would have been considered. Unfortunately, there are two obstacles that induced us to consider paid apps for our purposes. First, Blackberry App World does not provide this ranking, which would make the comparison impossible. Second, in both App Store and Android Market top ten grossing rankings numerous apps are free. This means that they generate a large amount of advertising and/or in-app purchase. The absence of knowledge regarding the amount of advertising and/or in-app purchase revenue of both zero and non-zero price apps may distort the results of the analysis if the sample were based on this ranking. In addition, several top paid apps are also top grossing apps, which can help extend some implications to the latter category.

[4] The number of apps is 206. However, only 3 apps are available in the top ten rankings of two stores. To avoid multi-dimensional panel complexity, we practice consider these three apps as being six. Therefore, the number of statistic units is 209.

from May to September in the Italian version of the three major stores. Such a sample can be assimilated to an unbalanced panel dataset, where the number of temporal observation for each app available in a given distribution platform varies depending on the permanence of that app in the ranking. That is, more observations are available for apps appearing in a ranking for a longer time so that more successful apps carry higher weight on the analysis. This is, in fact, consistent with our purposes of analyzing factors affecting prices for the most successful apps.

3.2 Variables

In order to test the formulated hypotheses, we define several variables that are of interest for our scopes and record the relative data. First of all, the dependent variable is the weekly price (in Euros) of the given app marketed in one of the three distribution platforms. To account of the effect of app category, as suggested in *H1*, we record the relative category for each app observed in the three stores' rankings. Distribution platforms such as App Store, Android Market and Blackberry App World have very similar category systems, which simplifies the process of homogenizing apps' classification in our dataset. At the end, we count 12 different categories (corresponding to 12 binary variables) as reported in Table 1, which summarize the description and the modalities of all the variables. As discussed in Melnik and Alm (2002), before Internet introduction, measuring and quantifying seller's reputation was quite difficult. Enabling online consumers ratings and reviews, Internet has provided an environment where effects of reputation on variables such as consumers' willingness to pay or sellers' demand can be empirically tested. Therefore, consistent to former literature (Lucking-Reiley et al., 1999; Brynjolfsson and Smith, 2000; Houser and Wooders, 2001; Standifird, 2001; Ba and Pavlou, 2002; Melnik and Alm, 2002; Resnick and Zeckhauser, 2002; Bruce et al., 2004), we consider the developer rating to measure the effect of developer reputation on app's price (*H2*). In general, app stores allows users to provide apps' rating on a 0-to-5 scale where 0 corresponds to the worst valuation and 5 to excellent valuation. For a given app, users usually add a review to the rating. However, no developer rating is available in the three distribution platforms. Therefore, we construct a measure of developer rating at any week by computing the average ratings of all the apps marketed by the given content provider until that week. However, in order to avoid any endogeneity problem, we exclude for each app the rating of the given app when computing the average rating. To cope with the absence of ratings for some developers, for instance because there are no reviews or no other apps have been marketed, we construct three dummies based on the average rating: low rated developers (LOW_DEVELOPER_RATING) category if the average developer rating is below 2.5, medium rated developers (MEDIUM_DEVELOPER_RATING) category if the average developer rating is between 2.5 and 3.5 and high rated developers (HIGH_DEVELOPER_RATING) category if the average developer rating is above 3.5. By doing so, we can compare the effect of low, medium and high developer ratings with respect to those developers that do not have any rating. The effect of trialability (*H3*) can be tested by introducing a binary variable (TRIAL) and retrieving weekly information on the existence or not of a free trial version for the app. Finally, to evaluate whether the distribution platforms have a strongly different effect on apps' price (*H4*), we record the store where each of the top ten apps is available in the given week and introduce three relative binary variables (namely, APP STORE, ANDROID MARKET, BLACKBERRY APP WORLD) in the econometric model. Furthermore we include some control variables. Specifically, we consider the type of developer (DEVELOPER TYPE), i.e., whether the content provider is a firm or (group of) individual(s). Software houses are in fact likely to have better development and marketing competencies and organization and a higher knowledge of the market, which may result in higher quality apps, as well as a better exploitation of the market potential. Therefore, *ceteris paribus*, we reasonably should expect them to charge a higher price compared to individual developers. In the same vein, we include the number of apps marketed by each developer (NUMBER DEVELOPER APPS) at any week in a specific store to control for any development and marketing synergies and the "weight" of the developer in the given market, which might have an impact on prices. Furthermore, in an attempt of depurating the competition factor from the store effect, we also introduce the total number of apps (TOTAL APPS) available in each distribution platform at a given week as a control variable.[5] Such a fairly open app distribution model allows a plethora of small individual developer as well as software houses to reach end customers. As a result, the app market tends to be, in general, quite fragmented.[6] Therefore, a store where a higher number of apps are available should intuitively induce fiercer competition among developers, thus leading to lower prices. Finally, we include a variable measuring the app size (in Megabyte) at any week to control for development costs within a given distribution platform and a specific category. We have already discussed that the distribution platform may have an influence on the app development costs due to the degree of technology openness, which can reduce development efforts of content providers, and level of customization to run on different device models. We have also pointed out that different categories have different nature, which may imply non-comparable development costs. However, apps of a specific category targeted for a specific platform might also require different costs, for instance because of the higher intrinsic quality level of an app compared to others. It is arguably assumable that the app size is a measure of the development costs when comparing apps within the same category and the same

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[5] The total number of apps is computed by referring to the US version of App Store and Android Market for which information is largely available (the sources are http://148apps.biz/app-store-metrics/?mpage and http://www.appbrain.com/stats/, respectively) rather than the Italian version due to the difficulty of retrieving this kind of information for the latter. On the other hand, Blackberry does not distinguish among countries. Thus, we refer to the number of apps provided by for the global version of App World (http://appworld.blackberry.com/webstore/?lang=it). Although forced, this procedure should not affect much the results, as the ranking of the three distribution platforms in terms of total number of apps does not change across different country store versions.

[6] As a matter of fact, the average number of apps per developer in our sample is 1.23. That is, the top ten rankings seem to be accessible to a multitude of developers, leading to a low concentrated market.

distribution platform. Therefore, by controlling for the app size we can separate the *within* effects of development costs on prices from the *between* effects mainly due to different targeted platforms and/or the different nature.

Table 2 shows the descriptive statistics. It can be noticed that the games and utilities are the most represented app categories in terms of both observations (33.33% and 34.26%, respectively) and apps (39.23% and 25.36%, respectively). Very few observations (0.74% at most), and thus very few apps, are related categories such as education, finance, healthcare & fitness, navigation and transport. Therefore, in the next subsection, we also present the results obtained when such categories are removed from the sample. Table 2 shows how the majority of observations are related to developers of top ten apps basically enjoying high-level ratings. Also the number of observations to medium ratings is considerable, whereas less than low ratings are encountered in a very small percentage, i.e. less than 1%. As mentioned above, some developers do not have rating any for their apps or do not market other apps: this event occurs in 11 percent of cases. Almost half of the observations (i.e., 46.11%) are related to apps for which a trial version is available is quite high. Interestingly, while, by construction, the number of observations is the same for all the distribution platforms (it is 180), the percentages of apps in Blackberry App World and App Store are higher (41.15% and 39.71%, respectively) than that in Android Market (19.14%). That is, the apps' turnover in Blackberry and Apple top ten rankings is much more frequent than in Android Market. As expected the number of firms is predominant compared to individual developers (71.26% vs. 28.74%). Such predominance slightly increases if we consider the number of observations, which suggests that firms stay not much longer in the top ten rankings and/or do not market many more successful apps. Overall, these numbers provide confirmation that entry barriers are extremely low in this environment. Regarding the continuous/discrete variables, we observe a low average price of 2.03 Euros ranging from 0.67 up to 10.81 Euros. The average app size is about 25 MB when computed considering all the observations, whereas it is higher (about 37 MB) if replications of the same app versions are omitted, meaning that apps staying longer in the ranking have usually a bigger size.[7] The average total number of apps available in the three markets is reported as well: it is increasing for all the three markets. Specifically, the total number of apps is always higher in the App Store, whereas is always lower in Blackberry App World. However, the number of apps available is increasing faster in Android Market than in App Store. It is worthwhile that only a very few apps (i.e., 3) are present in the top ten ranking of two store and none is present in all three top ten rankings, which demonstrates that while many content providers develop for more than one distribution platform, some kind of exclusive choice is required to develop successful apps.

Apart for some dummies chosen as baseline variables due to perfect collinearity[8], our preliminary analysis suggests that the variable MEDIUM DEVELOPER RATING shows a serious degree of negative correlation with the variable HIGH DEVELOPER RATING (the Pearson correlation index for this couple is about -0.76). We remove MEDIUM DEVELOPER RATING as we are more interested in the effect of high rating on prices. In addition, there is also very high positive correlation (about 0.86) between the dummy APP STORE and the total number of apps. This is intuitive in view of the fact that the total number of apps is the highest in App Store and a perfect ranking of the three stores (in sequence, App Store, Android Market and Blackberry App World) can be made for all the weeks. From the former discussion, it follows that App Store can be still thought of as the most competitive market. Therefore, we remove the control variable TOTAL APPS from the analysis. After removing such variables we observe no further serious degree of collinearity.

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[7] Note that the size of an app can temporally change because new versions or upgrades frequently are released. For this reason we computed the descriptive statistics considering the single versions rather than the apps.

[8] The dummies chosen as baseline variables are SOCIAL_NETWORKING and BLACKBERRY APP WORLD for category and distribution platform variable types, respectively. Specifically, the choice of SOCIAL_NETWORKING is driven by the purpose of testing hypothesis *H1*.

3.3 Empirical results and discussion

As our dataset can be assimilated to an unbalanced panel we use the following regression model to test the hypotheses:

$$
\begin{aligned}
PRICE_{it} = {} & const + \beta_{EDU}\, EDUCATION_{i} + \beta_{ENT}\, ENTERTAINMENT_{i} + \beta_{FIN}\, FINANCE_{i} \\
& + \beta_{GAM}\, GAMES_{i} + \beta_{HF}\, HEALTHCARE\ \&\ FITNESS_{i} + \beta_{MUS}\, MUSIC_{i} + \beta_{NAV}\, NAVIGATION_{i} \\
& + \beta_{PV}\, PHOTO\ \&\ VIDEO_{i} + \beta_{THE}\, THEMES_{i} + \beta_{TRA}\, TRANSPORT_{i} + \beta_{UTI}\, UTILITIES_{i} \\
& + \beta_{LDR}\, LOW\ DEVELOPER\ RATING_{it} + \beta_{HDR}\, HIGH\ DEVELOPER\ RATING_{it} \\
& + \beta_{TRI}\, TRIAL_{it} + \beta_{AM}\, ANDROID\ MARKET_{i} + \beta_{AS}\, APP\ STORE_{i} \\
& + \beta_{BAW}\, BLACKBERRY\ APP\ WORLD_{i} + \beta_{SIZ}\, APP\ SIZE_{it} + \beta_{TYP}\, DEVELOPER\ TYPE_{it} \\
& + \beta_{NDA}\, NUMBER\ DEVELOPER\ APPS_{it} + \beta_{APP}\, TOTAL\ APPS_{it} + WEEK_{t} + \varepsilon_{it},
\end{aligned}
$$

where we also include a temporal dummy WEEK_t for every week. Note that variables such as the category or the distribution platform where apps are available are intrinsically time invariant. On the other hand, trialability, developer ratings and control variable may vary temporally. In fact, all of them but the developer type (for which the observation time span is too short to produce any variation) vary.

When the number of statistic (apps) units is quite large compared to the observation period (number of weeks), i.e., $N >> T$, 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 variables of interest such as the category and the distribution platform 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.[9] The well-known Breusch-Pagan Lagrange Multiplier test strongly indicates the presence of random effects, as highlighted below Tables

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[9] The sample randomness is a pre-condition for the random effects model to be applied. Due to the fact that the observations are drawn from the population of successful apps and the period of observation has been extracted randomly, our sample can be thought of as a random sample from the population of successful apps. Thus, the requirement is satisfied in our setting.

3 and 4. Therefore, we present the results obtained performing a random effects regression. As anticipated, we run two regression models: one includes all the variables (referred to as *Complete Sample*), whereas, in the second (referred to as *Reduced Sample*), the observations related to the categories education, finance, healthcare & fitness, navigation and transport are removed because their occurrences are extremely low. In the *Reduced Sample* the number of observations is 529. The results of the two regression models are reported in Table 3. For sake of parsimony we 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 4. Below Table 4, we also report the F-Test which suggests that the full models does not provide any significant better fit than the restricted ones. Due to the very high similarities between the full and restricted models, we only comment the restricted ones. We observe a considerable robustness across the two samples except for the categories finance, healthcare and fitness and navigation, which are not present in the *Reduced Sample*, while being significant at the 5 percent level in the *Complete Sample*. Such an obvious difference arises because apps belonging to such categories have usually a relatively high price justified by the higher complexity compared to other categories. Therefore, we can reasonably expect a positive relationship between these categories, e.g., navigation, and app price. However, this, in turn, might prevent apps belonging to such categories from appearing among the top paid apps population. Among the six categories considered in both samples, only one, i.e., utilities, has significantly more influence on apps price compared to the baseline social networking. Therefore, apart from the category utilities which is shown to lead to higher prices perhaps due to the quite different nature of this category, the other remaining five categories do not impact on price significantly more than the social networking category. The category effect might be either explained by the two-

sided market effect, which implies lower prices due to the fact that other revenue streams are available, as well as the different nature of the categories, which implies different prices mostly due to different development costs. However, we can reasonably consider categories such as music, entertainment, games, comparable to social networking in terms of development costs. Therefore, only the two-sided market effects should differentiate the social networking category from these categories. Our results seem to suggest that, in contrast with theoretical predictions, two-sided market effects of the category social networking do not emerge compared to similar categories. For instance, this might be due to the fact that advertising revenues are still limited in apps for mobile devices, such as smartphones or tablet, compared to the case of the same categories in traditional Internet connection. A surprising result is related to the effect of developer ratings: it turns out to be consistently not significant. Therefore, the hypothesis *H2* is not empirically confirmed. From the perspective of the hedonic price model (Rosen, 1974), this result seems to suggest that, in contrast with the recent literature on this matter, positive reputation built via online (in-store) ratings does not have any impact on increasing app consumers' willingness to pay. Note that this counter-intuitive result is not related to the presence of low variability within our sample. As a matter of fact, highly rated developers account for the 60% of the observations, whereas the remaining is mainly divided between medium-rated and no rated developers. Thus, there is considerable variability in the samples. It is more likely that the rating role is negligible in the context of successful apps because the fact that an app appears in the top ten ranking represents itself a sort of guarantee to consumers. Therefore, although useful in general, positive reputation built via online ratings does not yield any price premium. A similar surprising result holds also for hypothesis *H3*: that is, contrary to common belief, apps whose free-trial versions are available are not sold at a higher price compared to no free-trial apps. To explain this contrasting result, recall that through the trial version firms allow users discover the real value to them in presence of high uncertainty and information asymmetry. Such an "exposure" of firms is usually compensated by the higher price they will charge for the "full" version. In the top ten paid apps setting, the "risks" for consumers are relatively low due to the relatively low prices. In addition, similarly to the case of developer rating, for an app being in the top ten ranking is a stronger signal of quality than being marketed also in free-trial version. Therefore, the trialability does not play a relevant role in the context of successful apps. The type of developer and app size turn out to be also relevant in explaining price formation. Specifically, firms enjoy higher prices than individual developers. This is intuitive because software houses are likely to have better development and marketing competencies and organization and a higher knowledge of the market, which result in higher quality apps and/or a better exploitation of the market potential. It is also intuitive that, given that we control for the effect of different distribution platforms and different app categories, the effect the conditional effect of the app size on its price turns out to be positive as higher size translate into higher development costs.

Finally, the most interesting result is related to the effect of the distribution platform on prices. Hypothesis *H4* is strongly confirmed by our empirical investigation. As a matter of fact, the distribution platforms have a strongly different influence on prices. Compared to the baseline Blackberry App World, distributing via App Store has a negative impact at least at the 1 percent level of significance, whereas Android Market has a positive impact at least at the 5 percent level. In other words, compared to Blackberry App World, selling via App Store significantly diminishes the app price, whereas selling via Android Market increases it. Therefore, a perfect ranking of distribution platforms can be created where App Store is the "cheapest" store, whereas Android Market is the "most expensive" one. We have already discussed the numerous factors related to the distribution platform effect. In-store competition, the different type of segment targeted by device makers/OS owners as well as different required development costs driven by the degree of technology openness and level of customization are some relevant of them. The strongly positive correlation between the dummy App Store and the total number of apps in the stores (recall it is about 0.86), which has induced us to remove the latter from the regression, seems to suggest the idea that such lower prices in App Store should be driven by the fiercer competition in this store compared to the other two. Recall, indeed, that the higher number of apps available in the market should intuitively, the fiercer competition among developers should be, given the top ten rankings seem to be accessible to a multitude of developers (167 developers for 206 pure apps have been counted in our sample) and the app store distribution model has been, in general, conceived as a fairly fragmented market model. However, only the competition factor would not explain why Android Market has a positive influence on price compared to Blackberry App World since the latter is by far the distribution platform with the lowest number of marketed apps and, also probably, targets the most valuable segments, e.g., managers, and the market size of the former is not only comparable to that of App Store, but it is also increasing faster. One explanation could be related to the different development costs entailed by different app distribution platforms, which may reflect on app price. As pointed out above, several authors (e.g., Lomas, 2010; Ondrus and Holzer, 2011) recently indicate the degree of technology openness and the level of customization as two major drivers that differentiate costs of developing for different distribution platforms, where the former should lower costs due to code-sharing facilitation, while the latter should increase them because it is necessary to remove incompabilities and fine-tune the given app for all the targeted devices of a given platform. The first effect should intuitively play in favor of lower prices in Android Market, as the OS supporting the distribution platform is open source contrarily to iOS and RIM which are proprietary OS. On the other hand, the second effect should lead to higher prices in Android Market as, differently from Blackberry and, especially, Apple, Google adopts an open system strategy serving numerous device models also of different device makers. In absence of development costs information related to similar apps marketed in different stores, we could also consider two simple variables to take into separate the effect of these cost drivers from the store effect. Specifically, a dummy variable measuring whether the OS supporting the given distribution platform is open source or proprietary and the number of device models marketed with the given OS might provide rough measures of the above-mentioned drivers. However, it is straightforward that such a measures are perfectly collinear with the Android Market dummy. Therefore, with our data we cannot hive technology openness, level of customization effort and, not even, in-store competition from the store effect by controlling for their effect separately. As a matter of fact, by substituting the store dummies with these variables, we obtain the same regression results. Therefore, the analysis seems to suggest that the level of required customization is certainly more relevant than the degree of technology openness in determining which markets leads to lower development costs, and, thus, price. In general, the price differences of successful apps among the stores seem to depend more on development costs. Nevertheless, the in-store competition effect may be also important as it helps explain why App Store is the “cheapest” store as far as top paid apps are concerned. This work provides the first evidence of the important role of distribution platforms in influencing app prices. From a pricing perspective, the choice of the distribution platform is, therefore, strategic for developers interested in marketing successful apps as several, and also contrasting, factors such as development costs, competition level and the type of targeted segments may combine differently in different stores. This, in turn, will reflect on different pricing strategies and, ultimately, different profitability. However, in such a complex and interconnected environment such as the smartphone industry, a deeper analysis of the store-related factors supported, for instance, by a extensive surveys from both developers and users side is strongly required in order to better unravel such factors and their relationships.

4. Conclusion

Since the App Store introduction, mobile apps commerce has growth exponentially. According to Gartner (2011) mobile apps have generated revenues for $5.2 billion in 2010, whereas a report released by Forrester Research predicts that the revenue created from customers buying and downloading apps to smartphones and tablets will reach $38 billion by 2015 (Bilton, 2011). An application store is a web portal from which a generic user can download software applications for mobile devices increasing the utility associated to their use. Mobile applications (apps, hereafter) are typically developed by third parties, i.e., the developers. With a 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, developers have to make several non-trivial decisions: to cite a few of them, they have to choose what kind and how many apps to market, which mobile operating systems to develop for and, thus, which app store to target. All these decisions certainly affect apps' price set by developers and, consequently, the success in the market. In this paper we take the perspective of developer interested in marketing successful apps. Therefore, based on a sample of top paid apps for smartphones from the Italian version of the major app stores, namely Apple's App Store, Android Market and Blackberry App World, we construct a regression model to investigate major factors, such as category, developer reputation, trialability, that may influence the price of successful apps and, specifically, study whether a store effect exists in determining different prices.

Our results suggest that a weak category effect arises in the sense that apps belonging to different categories do not show significantly different prices. Therefore, no two-sided market effects differentiate the social networking category (chosen as a baseline) from most of the other categories. The category utilities is the only one having a positive influence on price compared to the baseline probably due to its completely different nature. Surprisingly, our analysis does not confirm the theoretical predictions regarding the positive effect of developer rating and trialability on prices. In fact, such variables are not significant in our regression models. As explained, this may be because such factors are marginal with respect to the fact of being in the most popular apps rankings, which represents itself a sort of guarantee to consumers as well as with respect to the fact that consumers incur in low level of risk due to uncertainty. Variables such as the type of developer and app size have also a positive influence in explaining price formation. Finally, there is strong evidence that the distribution platforms have a different influence on prices. A perfect ranking of distribution platforms can be created where App Store is the "cheapest" store, whereas Android Market is the "most expensive" one. There are numerous factors behind the distribution platform effect. In-store competition, the different type of segment targeted by device makers/OS owners as well as different required development costs driven by the degree of technology openness and level of customization seems to be some of the most relevant ones. However, a deeper analysis of the store-related factors supported, for instance, by extensive surveys from both developers and users side is strongly required in order to better unravel such factors and their relationships. The extension of the analysis to consider non-top apps by means of a large cross-section, rather than temporal observations is another important research directions that should be pursued in order to highlight differences with the most successful apps, if any.

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APPENDIX

Table 1. Variables description

VARIABLES	Description
APP CATEGORY (EDUCATION; ENTERTAINMENT; FINANCE; GAMES; HEALTHCARE & FITNESS; MUSIC; NAVIGATION; PHOTO & VIDEO; SOCIAL NETWORKING; THEMES; TRANSPORT; UTILITY)	12 binary variables, each equal to 2 if, in the given week, the app belongs to the respective category; 1 otherwise.
DEVELOPER RATING (LOW DEVELOPER RATING; MEDIUM DEVELOPER RATING; HIGH DEVELOPER RATING)	3 binary variables, each equal to 2 if, in the given week, the developer rating belongs to the respective category, 1 otherwise.
TRIAL	Binary variable equal to 2 if a free trial version for the app is available in the given week; 1 otherwise.
STORE (ANDROID MARKET; APP STORE; BLACKBERRY APP WORLD)	3 binary variables, each equal to 2 if, in the given week, the app is sold in the respective store; 1 otherwise.
APP SIZE	Continuous variable measuring the size (in Megabytes) of the app in the given week.
DEVELOPER TYPE	Binary variable equal to 2 if, in the given week, the app is developed by a firm, 1 if developed by individual(s).
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.
TOTAL APPS	Total number of apps downloadable from the given store in the given week.
PRICE (Dependent variable)	Continuous variable measuring the price of the app in the given week.

Table 2. Descriptive Statistics for VI dataset

Variables	*Descr. Stat.*	*Variables*	*Descr. Stat.*
Binary Variables	*% 2*	*Binary variables*	*% 2*
EDUCATION	0.37% (0.96%)	TRANSPORT	0.37% (0.48%)
ENTERTAINMENT	10.56% (11.48%)	UTILITIES	34.26% (25.36%)
FINANCE	0.37% (0.48%)	LOW DEVELOPER RATING	0.93%
GAMES	33.33% (39.23%)	MEDIUM DEVELOPER	28.33%

		RATING	
HEALTHCARE & FITNESS	0.74% (1.91%)	HIGH DEVELOPER RATING	59.44%
MUSIC	6.30% (4.78%)	TRIAL	46.11% (32.54%)
NAVIGATION	0.19% (0.48%)	ANDROID MARKET	33.33% (19.14%)
PHOTO & VIDEO	4.44% (6.70%)	APP STORE	33.33% (39.71%)
SOCIAL NETWORKING	5.93% (1.91%)	BLACKBERRY APP WORLD	33.33% (41.15%)
THEMES	3.15% (6.22%)	DEVELOPER TYPE	76.85% (71.26%)

Variables	*Descriptive Statistics*			
Continuous/Discrete	*Mean*	*Std.D.*	*Min*	*Max*
APP SIZE (Mbyte)	25.192 (35.309)	104.848 (119.815)	0.02	936
NUMBER DEVELOPER APPS	27.385 (26.776)	44.805 (44.724)	1	243
TOTAL APPS	229171	160534	29721	471319
- ANDROID MARKET	225683	28761	180616	273452
- APP STORE	425245	28099	386327	471319
- BLACKBERRY A.W.	36585	3921	29721	42592
PRICE (€)	2.03	2.15	0.67	10.81

Note: The values outside the parentheses are computed at the observation level, whereas the values inside the parentheses are computed at the app. However, for DEVELOPER TYPE and NUMBER DEVELOPER APPS the values inside the parentheses are computed at the developer level, whereas for APP SIZE they are computed at the app version level (the total number of different versions is 289). For the three developer rating dummies the statistics are computed considering only the total observations because the rating may not only vary within the 18 weeks period but also among apps due to the fact that for each app we omit its own rating to avoid an endogeneity problem.

Table 3. Random Effects regression results under full models

	Complete Sample		***Reduced Sample***	
Variable	*Coefficient*	*Robust St. Errors*	*Coefficient*	*Robust St. Errors*
constant	-11.531 ***	3.12	-2.176	1.945
EDUCATION	-0.095	0.551	-	-
ENTERTAINMENT	0.401	0.366	0.409	0.366

FINANCE	1.031 ***	0.297	-	-
GAMES	0.021	0.267	0.027	0.267
HEALTHCARE & FITNESS	0.457	0.309	-	-
MUSIC	0.803 *	0.471	0.805*	0.471
NAVIGATION	8.311***	0.62	-	-
PHOTO & VIDEO	0.003	0.301	0.007	0.302
THEMES	0.577	0.488	0.572	0.486
TRANSPORT	-0.302	0.406	-	-
UTILITIES	0.708**	0.342	0.725**	0.343
LOW DEVELOPER RATING	0.113	0.144	0.114	0.143
HIGH DEVELOPER RATING	-0.043	0.096	-0.041	0.096
FREE TRIAL	-0.012	0.094	-0.011	0.093
ANDROID MARKET	0.891**	0.369	0.877**	0.373
APP STORE	-0.834***	0.205	-0.846***	0.206
DEVELOPER TYPE	0.495***	0.188	0.572***	0.195
APP SIZE	-0.002	0.001	-0.002	0.001
NUMBER DEVELOPER APPS	0.002	0.001	0.002	0.001
WEEK 2	0.033	0.144	0.034	0.144
WEEK 3	-0.055	0.116	-0.053	0.116
WEEK 4	-0.015	0.113	-0.014	0.113
WEEK 5	-0.164	0.2	-0.166	0.199
WEEK 6	-0.075	0.133	-0.073	0.133
WEEK 7	-0.032	0.136	-0.031	0.136
WEEK 8	0.089	0.19	0.09	0.19
WEEK 9	0.152	0.188	0.153	0.188
WEEK 10	0.109	0.162	0.11	0.161
WEEK 11	0.06	0.235	0.061	0.235
WEEK 12	-0.016	0.167	-0.011	0.165
WEEK 13	-0.195	0.249	-0.197	0.25
WEEK 14	-0.036	0.179	-0.034	0.179
WEEK 15	-0.051	0.18	-0.049	0.18
WEEK 16	-0.053	0.1792	-0.052	0.172
WEEK 17	-0.142	0.191	-0.14	0.191
WEEK 18	-0.142	0.18	-0.138	0.179
R-square:				

within	0.0614	0.0617
between	0.362	0.2607
overall	0.2942	0.2765

Note: Standard errors are robust to heteroskedasticity and serial correlation. Breusch and Pagan Lagrangian multiplier test for random effects: Chi^2 (1) = 3348.87, p-value = 0.000 for the complete sample; Chi^2 (1) = 3321.86, p-value = 0.000 for the reduced sample.

Table 4. Random Effects regression results under restricted models

	Complete Sample		***Reduced Sample***	
Variable	*Coefficient*	*Robust St. Errors*	*Coefficient*	*Robust St. Errors*
constant	-8.947 ***	1.006	0.429	0.826
FINANCE	0.812***	0.116	-	-
HEALTHCARE & FITNESS	0.355**	0.158	-	-
NAVIGATION	8.188***	0.544	-	-
UTILITIES	0.528**	0.258	0.522**	0.259
ANDROID MARKET	0.767**	0.341	0.769**	0.355
APP STORE	-0.95***	0.175	-0.965***	0.177
DEVELOPER TYPE	0.487***	0.168	0.492***	0.175
APP SIZE	-0.002*	0.001	-0.002*	0.001
WEEK 5	0.192*	0.106	0.192*	-
WEEK 9	0.179**	0.083	0.179**	36.71%
WEEK 10	0.14*	0.074	0.139*	-
R-square:				
within	0.0303		0.0302	
between	0.3347		0.23	
overall	0.2792		0.2613	

Note: Standard errors are robust to heteroskedasticity and serial correlation. Breusch and Pagan Lagrangian multiplier test for random effects: Chi^2 (1) = 3304.97, p-value = 0.000 for the complete sample; Chi^2 (1) = 3184.65, p-value = 0.000 for the reduced sample. Statistics of F-test (Restricted vs. Full models): F(25, 503) > 1.175 under the complete sample; F(23, 497) > 1.075 under the reduced sample.