ESTIMATING DEMAND FOR MOBILE APPLICATIONS IN THE NEW MOBILE ECONOMY

Completed Research Paper

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Abstract

A fundamental change brought forth by the advent of the mobile internet has been the widespread adoption of mobile phone based applications (apps). Mobile apps are now being used worldwide to perform a variety of tasks - access social networks, read ebooks, play games, listen to music, watch videos and so on. As consumers increasingly use mobile apps, it is important to understand the drivers of demand for these apps. We build a builds a structural model of user demand for mobile apps and jointly estimate it with supply-side equations. We estimate the change in consumer surplus from the usage of mobile apps. We use a panel dataset consisting of apps' sales, prices, and characteristics data from the two leading app stores – Apple App Store and Google Play for 4 months in the South Korean market. Our results show that demand increases with the file size, app age (time since release), app description length, and number of screenshots. In terms of age-restriction, compared to "everyone" (or 4+) apps, "low maturity" (or 9+) and "medium maturity" (or 12+) apps lower demand. Compared to lifestyle apps, gaming apps have a positive impact on app demand while multimedia and education apps have a negative impact on demand. Notably, we find consumer preferences show strong correlation across apps from the same group (i.e., either within free apps or paid apps). We incorporate consumer heterogeneity in the model and find that older and male consumers tend to be less sensitive to the price of apps than younger and female consumers, respectively. In the supply-side we find app file size and app age are major cost component in app development. Also, our findings suggest there exist significant returns to scale in app development. Our counterfactual experiments show price discount strategy results in a greater increase of app demand in Apple App Store compared to Google Play and the effects of price discounts increase non-linearly. Our findings also indicate strong substitution effects between game apps and other apps such as utility and education apps. Using the estimated demand function, we find the top ranked apps in both app stores enhanced consumer surplus by approximately US $158 million over the 4 month period in South Korea

Keywords: mobile economy, mobile apps, demand and supply estimation, BLP, consumer surplus, Apple, Android, app characteristics, random coefficients nested logit

Introduction

The rapid innovation in mobile platforms within the IT-enabled digital infrastructure is challenging the traditional business model used by mobile telecom operators. These mobile platforms have had a more dynamic approach to digital innovation, and hence they are able to shift business model strategies at a faster pace than telecom operators, reflecting on a diversified value chain for the delivery of digital services. Conventional wisdom suggests that knowledge and experience is typically passed from the mature markets in the US and Western Europe on to emerging markets in Asia, Eastern Europe and South America. However, in the mobile industry, this outlook is fracturing rapidly. The belief today is that mature markets have as much, if not more, to learn from emerging markets in the area of mobile. Mobile operators in emerging markets already have ample experience in operating in extremely price- and margin-sensitive environments, and many mature-market operators, including the US now find themselves in exactly the same situation.

One particular aspect of smart phones that have rapidly grown in emerging markets is the adoption and usage of mobile apps. Among the emerging market economies, the Asian “growth miracle” is the most conspicuous success story According to the media press (Distimo 2011a), the download volume in Asian countries grew significantly in the past six months in the Apple App Store for iPhone. In particular, the adoption of mobile apps in China and South Korea, have been particularly dramatic. Hence it becomes increasingly important for not only app developers but also advertisers to understand what kinds of apps and app features consumers in emerging markets like to purchase and use. For example, such knowledge on consumer demand in emerging markets can provide insights to app developers on whether to offer the same features of apps in emerging markets as they do in other markets (i.e., the US market) or to offer localized content to be successful when then enter emerging markets. Moreover, it can help advertisers who are marketing within apps to find the best outlet (i.e., popular apps) even before they become very popular.

There is a long history of consumers paying for content on mobile devices that goes back many years and this has transitioned effectively to the modern day mobile internet. These new emerging business models are also more complex, with revenue being generated not just from the purchase of applications, but also from micro-transactions within an app or as an additional revenue channel to an existing business. This new trend also calls attention to the need for understanding what factors influence sales and popularity of different kinds of mobile apps. Mobile apps are now being used worldwide to perform a variety of tasks - access social networks, read ebooks, play games, listen to music, watch videos and so on. According to a new Nielsen report, already one in four US adults have smart phones that are more powerful than the computers initially used to send men to the moon. Nielsen predicts that by the end of 2012, the majority of mobile subscribers in the US will have smart phones and will be spending most of their time on apps.

Mobile apps have existed for years, but clunky user interfaces on devices and hard-to-use apps stores made it difficult for consumers to download apps. And then came Apple in 2008 with its App Store for the iPhone. The iPhone, which was easy to use, coupled with the App Store that allowed users to search and download apps from iTunes, turned mobile apps into an overnight success. Today, Apple App Store is considered the largest and most successful mobile app storefront out there. According to IDC (2010), in 2010 more than 300,000 apps were downloaded 10.9 billion times and in 2014 global downloads are projected to reach 76.9 billion downloads worth approximately US$35 billion. According to Nielsen (2012), in just a year, the average number of apps per smartphone has jumped 28 percent, from 32 apps to 41. Consumers are increasingly spending more time using apps as compared to using the mobile web.

As consumers increasingly use mobile apps, it is important to understand consumer demand for mobile apps and quantify the value created by the availability of these apps. Knowledge of heterogeneous consumer demand towards app characteristics in mobile apps markets can help app developers and managers to design and improve their app features, to determine optimal pricing strategies, to better monetize their apps, and eventually to increase profits. For example, there are so called premium “grossing apps” which are becoming popular. TomTom Navigation app is $99.99 and Golfshot: Golf GPS app is $29.99. Such grossing apps are about 4-times more expensive than other popular apps (Distimo 2011a). In contrast, there are thousands of popular free apps as well. A free version of Angry Birds gaming app has more than millions of downloads. This example demonstrates that some consumers are willing to pay more for additional features or/and high quality apps while some consumers are only downloading free versions of apps with limited features. App developers use such consumer demand information to determine whether to offer an app for free, and if not free, how much to charge it. Moreover, given that app stores often collect one-off or subscription fees for paid-apps, it can be critical for them to obtain precise estimates of user demand. Such demand-side information can also be used for app stores to determine whether to develop mobile apps in-house or to outsource high-quality app developers, or both.

From a broader perspective, mobile technologies facilitate the delivery of many new products and services across mobile platforms. As these platforms develop and mature, it will be important to quantify their value for customers, firms and society. While much of the attention in academic research and in the press has been on examining user behavioral differences in the mobile channel versus traditional channels, we believe that important benefits lie in new products and services made available through these mobile platforms. While prior work has studied the impact of the mobile web on users' multimedia content creation and consumption behavior (for example, Ghose and Han 2011a, 2011b), the value of new apps and services made available through mobile platforms has remained unquantified. This paper contributes by producing the first study that builds a structural model of user demand for mobile apps and jointly estimate it with supply-side equations. Moreover, using the estimated demand function, we present results on counterfactual analyses to discuss managerial insights for app developers, app stores, and advertisers, and discuss the welfare impact from the availability of mobile apps.

In demand estimation, prices in general are correlated with the error term. Hence, the estimate of the price will be biased due to the unobserved product characteristics. This is because prices are a function of marginal cost and a markup term, and moreover, the markup term is a function of the unobserved product characteristics, which is also included in the error term in the demand equation (Nevo 2000). Moreover, apps are usually grouped into two predetermined groups – free apps and paid apps – in major app stores, so consumer preference towards apps in the same group may be correlated. We address the price endogeneity issue intrinsic in demand estimation and potential hierarchical preference structure by building a random coefficient nested logit demand model in a similar vein to the BLP (1995) method. We use a panel dataset consisting of top 200 ranked apps' sales rank, prices, and characteristics data from the two leading app stores – Apple App Store and Google Play for 4 months in the South Korean market. The observed app characteristics in our sample include app file size, app age (days elapsed since app release), length of textual app description, umber of screenshots, and app age-restriction levels. We also have information on app categories and user reviews such as review volume and rating.

Our results show that demand increases with the file size, app age (time since release), app description length, and number of screenshots. In terms of age-restriction, compared to "everyone" (or 4+) apps, "low maturity" (or 9+) and "medium maturity" (or 12+) apps lower demand. Compared to lifestyle apps, gaming apps have a positive impact on app demand while multimedia and education apps have a negative impact on demand. Also, number of user app review has a positive linear impact as well as negative quadratic impact while the average rating has a positive impact on app demand. Notably, we find consumer preferences show strong correlation across apps from the same group (i.e., either within free apps or paid apps), as one would expect. We incorporate consumer heterogeneity in the model and find that older and male consumers tend to be less sensitive to the price of apps than younger and female consumers, respectively. In the supply-side we find app file size and app age are major cost component in app development. Also, our findings suggest significant returns to scale in app development.

Moreover, by conducting two sets of counterfactual experiments, we examined how pricing policy changes will affect app demand. We also looked into how price changes in one app category will affect the demand for other app categories. Our findings show price discount strategy results in a greater increase of app demand in Apple App Store compared to Google Play and the effects of price discounts increase non-linearly. Our findings also indicate strong substitution effects between game apps and other apps such as utility and education apps. Further, using the estimated demand function, we measure changes in consumer surplus from the availability of mobile apps. We find that availability of the top ranked applications in both Apple and Android platforms enhanced consumer surplus in South Korea by approximately $158 million over the time period of our study.

Prior Literature

In this section, we discuss multiple streams of relevant literatures such as user behavior in mobile media and demand and welfare estimation from the introduction of new goods.

User behavior in mobile media

Our paper builds on and relates to the literatures on user behavior in mobile media. A stream of relevant literature has discussed users' usage patterns of voice calls and short message service (SMS) in the mobile phone setting. For example, Danahar (2002) and Iyengar et al. (2008) study how many phone call minutes are consumed under different pricing packages. Kim et al. (2010) examine to what extent the usage of mobile phone voice service can substitute short message service.

In addition, our study is related to the emerging stream of literatures on user behavior on the mobile internet. A stream of work has investigated the economic and social impact of user-generated content on the mobile internet by mapping the interdependence between content generation and usage (Ghose and Han 2011a); modeling how consumers learn about different kinds of content (Ghose and Han 2011b); documenting differences in search costs and location effects on mobile phones vs. PCs (Ghose, Goldfarb, and Han 2012), and analyzing the impact of network characteristics on social contagion on the mobile internet (Ghose, Han, and Iyengar 2012). Further, our study builds on an emerging stream of literature on mobile marketing. Shankar and Balasubramanian (2008) provide an extensive review of mobile marketing. Sinisalo (2011) examines the role of the mobile medium among other channels within multichannel CRM communication. Spann et al. (2012) discuss location-based advertising on the mobile Internet and Danaher et al. (2012) evaluate the effectiveness of mobile phone promotions.

Recently there is a stream of literature on economic studies of mobile apps. For example, Carare (2012) examines how past app sales rank affects demand (and hence market share). He provides evidence of the causal impact of today's bestseller rank information on tomorrow's demand using Apple App Store data. Garg and Telang (2012) calibrate sales ranking and sales quantity relationship for paid apps using publicly available data from Apple App Store. To our knowledge, no previous study has examined a structural model of consumer demand in a mobile app setting using the data from two major app stores – Apple App Store and Google Play. Further, our paper quantifies the welfare impact from the availability of such mobile apps. Our paper aims to fill this gap in the literatures.

Demand and welfare estimation of new products

A long literature documents the models of demand estimation. One model that has made a significant contribution to the field is the random-coefficients discrete-choice model of demand (Berry, Levinsohn, and Pakes 1995, henceforth BLP). The BLP method is superior to the logit model because it can be estimated using only market-level price and quantity data and it deals with the endogeneity of prices (Nevo 2000). The wider literature on demand estimation using the BLP method also estimated the welfare consequences of the introduction of new products. Such welfare gains have been documented in a variety of industries such as automobiles (Berry et al. 1993, Petrin 2002), computers (Greenstein 1994), cellular phones (Hausman 1999), books (Brynjolfsson et al. 2003, Ghose et al. 2006), direct broadcast satellites and cable TV (Goolsbee and Petrin 2004), and elsewhere. We add to this literature by estimating consumer demand for apps and by linking it to the existing literature on the economics of the Internet.

Empirical Data

We provide an overview of the empirical background for our data, describe variables in the data, and provide brief theoretical explanation on why the various app characteristics should influence the demand for an application.

Empirical Background

A massive number of apps are installed each month, with the rapid growth in Asian countries. For example, in March 2012, of the 3.1 billion apps were downloaded worldwide from two leading app stores – Apple App Store and Google Play, more than a quarter of that came from Asian markets (Xyologic 2012). In particular, the download volume in South Korea is most remarkable. According to the recent report (Distimo 2011a), it is higher than in larger countries like Germany and France. Compared to Japan and China which both have larger populations, the high download volume in the South Korean market stands out even more. South Korea is a leading country for mobile broadband penetration and 3G handset penetration (ITU 2011). We collected mobile app profile and demand panel data from the two leading app stores in South Korea. Since neither app stores provide information on the download of apps, we first calibrate the relationship between sales ranks and sales quantity using an additional panel data in which we have information on ranks and actual download of apps from a mobile carrier's app store. Then we predict download of apps in both Apple App Store and Google Play, which are used in actual demand estimation. Details on sales quantity imputation are provided in Appendix B. In addition, Apple apps are not compatible with Android. That is, one cannot use an Apple app on an Android, and vice versa. We use such information to delineate the boundary of a market for an app.

Data Description

We use a panel dataset consisting of top 200 ranked apps' sales rank, prices, characteristics, and user review data from Apple App Store and Google Play. The apps in the data consist of both free and paid apps. The app ranking information is based on a consolidated download data from smartphones and tablets. We collected the data from the South Korean market between October 6, 2011 and February 6, 2012 (4 months). The data includes 1,207 apps in App Store and 1,210 apps in Google Play. The total number of apps from two app stores in the data may not be the same because some apps appear more (or less) often in top 200 listings in each app store. Our dataset includes daily panel data on app sales rank, app prices, app characteristics, and user review data. We capture an exhaustive list of app-related information provided to consumers when they browse for an app in an app store. The observed app characteristics in our sample include: app file size, app age (days elapsed since app release), number of characters in the textual app description, number of screenshots, app age-restriction levels, app categories, and number of apps provided by the same app developer.

We measure the file size of an app in mega bytes. It is possible that there exists a positive relationship between file size and demand. According to the software engineering literature (Denaro and Pezze 2002, Dixon 2008) source code size is an effective predictor of fault-proneness (i.e., the extent to which a source file functions correctly), which is indicative of app quality in our context. We also measure the app age based on the number of days since the first version of the app was launched. According to the software maintenance literature (Arnold 1993) mature software has adequately addressed user requests for new features/functionality and has fewer bugs. Hence, it is possible that there exists a positive relationship between app age and demand. Moreover, we use app developers' textual and visual description of an app to measure the number of characters in app description text and to measure the number of screenshots, respectively. Prior work has shown that textual information embedded in ecommerce affect consumer purchase decisions. For example, Ghose et al. (2009) estimate the impact of buyer textual feedback on price premiums sellers charge in online second-hand markets. Decker and Trusov (2010) use text mining to estimate the relative effect of product attributes and brand names on the overall evaluation of the products. Hence it is possible that there is a relationship between app description length and app demand. Also, Ghose et al. (2012) find that the information extracted from visual images of hotels (i.e., whether the hotel is near the beach) influences consumer decisions on hotel reservation. So it is possible that there is a relationship between the number of screenshots about an app and the app demand.

In addition, we use app developers' self-rating in terms of age-restriction. In both app stores, there are consistently 4 classification levels – "4+", "9+", "12+", and "17+" in App Store and "everyone", "low maturity", "medium maturity", and "high maturity" in Google Play. For example, according to Google Play's (2012) rating guideline, apps that include suggestive or sexual references must be rated "medium maturity" or "high maturity." Apps that focus on suggestive or sexual references must be rated "high maturity." We treat "4+" in App Store and "everyone" in Google Play as the corresponding level, "+9" in App Store and "low maturity" in Google Play as the corresponding level, and so on. Since apps in different levels of age-restriction mainly appeal to different segments of consumers, they can have different impact on app demand. In addition, in accordance with Distimo's (2012a) report on download volumes per app category, we classified apps in our data into 7 most popular categories including games, entertainment, social, multimedia, utilities, education, and lifestyle. In addition to a set of app characteristics used in consumer demand function, we use two app characteristics as additional observable components in the cost function (hence in app pricing equation). Following BLP's (1995), we include the number of apps provided by the same app developer as a proxy for returns to scale.

We also collected user reviews from each app store. Product reviews affect product sales has received strong support in prior empirical studies (for example, Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Liu 2006, Dellarocas et al. 2007, Duan et al. 2008, Forman et al. 2008, Moe 2009). Consistent with prior work, we use the total number of reviews and the average numeric reviewer rating to control for word-of-mouth effects. We also include the squared term for the total number of reviews to control for the non-linear effect. Further, we have aggregate-level information on user demographics such as age and gender for Apple App Store and Google Play, respectively. We also have aggregate-level market share information from app stores other than App Store and Google Play. We use such information to compute the total market size.

Table 1 shows the summary statistics of the key variables used in our model.

Table 1. Summary Statistics

	Total		**Apple App Store**		**Google Play**	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Market Share (%)	0.37	0.71	0.35	0.64	0.39	0.78
Price (US$)	3.20	9.80	5.59	12.75	0.44	2.37
File Size (Mega Bytes)	68.61	207.81	125.80	271.61	2.97	3.98
Description Length (Characters)	2350.33	1315.93	2746.21	1059.20	1900.34	1429.76
App Age (Days)	315.22	196.43	326.64	242.05	302.11	123.72
Number of Screenshots	5.24	1.53	5.38	0.62	5.08	2.13
Age Restriction (+4)	0.84	0.35	0.79	0.40	0.91	0.27
Age Restriction (+9)	0.08	0.27	0.12	0.32	0.04	0.20
Age Restriction (+12)	0.06	0.22	0.07	0.25	0.03	0.18
Age Restriction (+17)	0.02	0.11	0.02	0.12	0.02	0.09
Games	0.23	0.42	0.30	0.45	0.15	0.36
Entertainment	0.09	0.28	0.13	0.33	0.04	0.18
Social	0.08	0.28	0.02	0.14	0.16	0.36
Multimedia	0.15	0.35	0.15	0.36	0.15	0.35
Utilities	0.18	0.38	0.10	0.30	0.27	0.44
Education	0.10	0.30	0.13	0.33	0.06	0.24
Lifestyle	0.15	0.36	0.15	0.36	0.15	0.35
User Review Count	54244.90	238584.80	2722.41	6640.81	112810.30	339311.20
User Rating	4.10	0.57	3.91	0.68	4.32	0.29
Apps by the Same App Developer	21.15	34.84	28.74	40.20	12.51	24.85
Number of Observations	49,600		24,800		24,800	
Sample Period: Oct 6, 2011 to Feb 6, 2012						

Model

In this section, we discuss our demand model based on random coefficient nested logit model to estimate the distribution of consumer preferences towards different mobile app characteristics especially when the apps are categorized as free apps and paid apps. We then combine the demand model with a cost function to incorporate the pricing behavior in a differentiated product market. The estimates from this analysis are then used towards conducting counterfactual experiments and calculating consumer welfare gains in the next section.

Demand Side: Random Coefficient Nested Logit Model

In our model, the utility for consumer i from choosing app j in market t can be represented as:

$$u_{ijt} = X_{jt}\beta_i + \alpha_i P_{jt} + \xi_{jt} + \varepsilon_{ijt}, \tag{1}$$

where X_{jt} is a vector of observable characteristics of app j in market t and β_i is a vector of the random coefficients (i.e., taste parameters) associated with those app characteristics.[1] P_{jt} is the price of app j in market t and α_i is a scalar for a random coefficient that captures consumers' heterogeneous tastes towards app price. ξ_{jt} represents the unobserved (by researchers) characteristics of app j. The price parameter allows us to examine the impact of different pricing strategies. For example, we can evaluate the impact on demand as an app developer changes its pricing scheme from paid to free. Moreover, we can assess the impact on demand as it provides 10% or 20% or 50% price discount. In addition, we control for app platform (1: Apple, 0: Android) and a set of user-generated review count and rating variables.

Lastly, $\bar{\varepsilon}_{ijt}$ is a mean-zero stochastic term representing an app-level taste shock, which may be modeled as i.i.d. random variables with an extreme value, as in the standard BLP model. Here we assume that $\bar{\varepsilon}_{ijt}$ follows a more general "nested logit" distribution. This is because apps are usually grouped into two predetermined groups – *free* apps and *paid* apps – in major app stores including Apple App Store and Google Play. So consumer preference towards apps in the same group may be correlated. Suppose we assign each app j to a group g, where the groups g = 0 (outside goods), 1 (free apps), and 2 (paid apps). More specifically, following Berry's (1994) discussion of Cardell (1997), we decompose $\bar{\varepsilon}_{ijt}$ into an i.i.d. shock plus a group-specific component as follows:

$$\bar{\varepsilon}_{ijt} = \zeta_{igt} + (1-\rho)\varepsilon_{ijt}, \tag{2}$$

where ε_{ijt} is i.i.d. extreme value and ζ_{ijt} has a distribution such that $\bar{\varepsilon}_{ijt}$ is extreme value. The parameter ρ is a nesting parameter, $0 \le \rho \le 1$, and can be interpreted as the degree of preference correlation between apps of the same group. As ρ goes one, consumers perceive apps of the same group as perfect substitutes relative to apps in the other group. As ρ goes zero, the within-group correlation goes to zero, thus the model reduces to the standard logit.

We follow BLP (1995) method and model the distribution of consumers' taste parameters. Specifically, our model captures taste heterogeneity of users by incorporating observed and unobserved individual characteristics. Formally, this is modeled as:

$$\begin{pmatrix}\alpha_i\\ \beta_i\end{pmatrix} = \begin{pmatrix}\bar{\alpha}\\ \bar{\beta}\end{pmatrix} + \Pi D_i + \Sigma v_i, \qquad D_i \sim P_D^*(D), \;\; v_i \sim N(0, \mathrm{I}) \tag{3}$$

The vector $(\bar{\alpha}, \bar{\beta})$, which is referred to as the mean utility of price and app characteristics, is common to all consumers. It measures the average weight placed by the consumers. In addition, D_i is a vector of demographic variables that include user age and gender. $P_D^*(D)$ is a nonparametric empirical distribution observed from other data sources. Π is a matrix of coefficients that measure how the taste characteristics vary with observed demographics. Further, v_i is a vector capturing the additional unobserved consumer-specific preference towards app price and app characteristics. It follows a multivariate normal distribution. Σ is a scaling matrix. Similar to the literature in demand estimation (Berry et al. 1995, Nevo 2001), we assume that v_i has a standard normal distribution, and the vector Σ allows for each element of v_i to have a different standard deviation (Nevo 2000). This specification allows the observed demographics D_i and the unobserved factor v_i to determine the consumer-specific taste.

Combining equations (1) – (3) and defining the mean utility for app j, $\delta_{jt} = X_{jt}\bar{\beta} + \bar{\alpha}P_{jt} + \xi_{jt}$, we rewrite our model for u_{ijt} as follows:

$$u_{ijt} = \delta_{jt} + [P_{jt}, X_{jt}](\Pi D_i + \Sigma v_i) + \zeta_{igt} + (1-\rho)\varepsilon_{ijt}. \tag{4}$$

Our goal is then to estimate the mean utilities vector $(\bar{\alpha}, \bar{\beta})$, Π matrix of coefficients, the standard deviations in vector Σ, and the nesting coefficient ρ.

Each consumer i in market t chooses the app j that maximizes his/her utility. The aggregate market share for app j in market t is then the probability that app j gives the highest utility across all apps including the outside good. More specifically, following Grigolon and Verboven (2011), we compute the predicted market share of app j in market t as the integral of the nested logit expression over the standard normal

[1] We define a "market" as the combination of an "app store" and a "day".

random variable vector v_i:

$$s_{jt} = \int_v \frac{\exp\left(\left(\delta_{jt} + [P_{jt}, X_{jt}](\Pi D_i + \Sigma v_i)\right)/1-\rho\right)}{\exp\left(I_g/1-\rho\right)} \frac{\exp I_g}{\exp I} \phi(v), \tag{5}$$

where I_g and I are McFadden's (1978) "inclusive values" defined as

$$I_g = (1-\rho)\ln \sum_{k=1}^{J_g} \exp\left(\left(\delta_{jt} + [P_{jt}, X_{jt}](\Pi D_i + \Sigma v_i)\right)/(1-\rho)\right), \quad I = \ln\left(1 + \sum_{g=1}^{G} \exp(I_g)\right),$$

g refers to a group, and J_g is the number of apps in group g.

Supply-Side: Cost Function and App Pricing

We assume there are N app developers, each of which produces some subset, J_f apps of the J apps. The cost characteristics for each app are decomposed into an observable component (by the researcher), the vector w_{jt} for app j in market t and an unobserved component, ω_{jt}. Similar to Berry et al. (1995), we expect the observed app characteristics, the x_{jt}, to be part of the w_{jt}, and ω_{jt} to be correlated with ξ_{jt}. This is because, for example, large apps or high-quality apps might be more costly to produce. The marginal cost of app j in a market t, mc_{jt}, is written as

$$mc_{jt} = w_{jt}\gamma + \omega_{jt}, \tag{6}$$

where γ is a vector of parameters to be estimated.

Given the demand function in (4), the profit of app developer f, Π_j, is

$$\Pi_j = \sum_{j \in J_f} \left(P_{jt} - mc_{jt}\right) M s_{jt}\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right), \tag{7}$$

where mc_{jt} is given by (6), M is the total market size, and s_{jt} is the market share of app j given by (5). Similar to Berry et al. (1995), we assume each app developer chooses prices that maximize its profit given the characteristics of its apps and the prices and the characteristics of competing app developers. We assume no in-app purchase revenues.

Assuming the existence of a pure-strategy inferior equilibrium, the price vector satisfies the first order conditions as follows:

$$s_{jt}\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right) + \sum_{r \in J_f} (P_{rt} - mc_{rt}) \frac{\partial s_{rt}\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right)}{\partial P_{jt}} = 0. \tag{8}$$

The J first order conditions in (6) imply price-cost markups for each app. In vector notation, the first order conditions can then be written as

$$P = mc + \Delta\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right)^{-1} s\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right), \tag{9}$$

where $\Delta_{\mathrm{jrt}} = \frac{\partial s_{rt}}{\partial P_{jt}}$ if r and j are produced by the same app developer in a given market t and $\Delta_{\mathrm{jrt}} = 0$ otherwise. Note that prices are additively separable in marginal cost and the markup defined as

$$b\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right) = \Delta\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right)^{-1} s\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right), \tag{10}$$

Substituting in the expression for the marginal cost in (6), we obtain the cost function as follows:

$$P - b\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right) = w\gamma + \omega. \tag{11}$$

Since P is a function of ω, $b\left(P, X, \xi | \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho\right)$ is a function of ω. Also the correlation between ξ and ω generates a dependence between the markups and ω (Berry et al. 1995). Hence, the parameters in (11), γ, can be estimated if we assume orthogonality conditions between ω and appropriate instruments.

Estimation

We discuss how we identify the estimates of the parameters. As mentioned in the previous subsection, we build a structural model of user demand for mobile apps and jointly estimate it with supply-side equations.

Estimating the demand and supply jointly has the advantage of increasing the efficiency of the estimates, at the cost of requiring more structure (Nevo 2000). Our goal here is to estimate the mean and deviation of α_i and β_i and the mean of the nesting coefficient ρ in the demand side and the mean of γ in the supply side. We apply methods similar to those used in Berry et al. (1995) and Grigolon and Verboven (2011). In general, with a given starting value of $(\Pi^0, \Sigma^0, \rho^0)$, from the demand size, we look for the mean utility δ, such that the model-predicted market share is equal to the observed market share. As mentioned in the previous subsection 4.2, from the supply side, we compute the marginal cost *mc*. We then form a GMM objective function using the BLP's (1995) assumption that the supply and demand unobservables are mean independent of both observed app characteristics and cost shifters. Then we update the parameter value of $(\Pi^1, \Sigma^1, \rho^1)$ and use it as the starting point for the next-round iteration. This procedure is repeated until the algorithm finds the optimal values of parameters that minimizes the GMM objective function.

Specifically, we conduct the estimation in the following manner. We prepare the data including draws from the distribution of individual characteristics, v and D. For v, we draw from standard normal distribution. For D, we use empirical distribution of user age and gender. For each market we draw 1,000 individuals. For given values of Π, Σ, and ρ, we compute mean utility level δ that equates the predicted market shares to the observed shares and compute the marginal cost *mc* by subtracting the computed mark-ups from the price. And, for given Π, Σ, ρ, δ and *mc*, we compute the unobserved parameter for app characteristics, ξ, and the unobserved parameter for cost component, ω, then interact them with a set of instrumental variables, and finally compute the value of the GMM objective function. Since the mean utility parameters, mean cost components, and other control variables are linear parameters, we solve them as a function of the other (non-linear) parameters – Π, Σ, and ρ while we search for the value of the non-linear parameters that minimizes the objective function. Details are provided in Appendix A.

Instruments

It is critical to address price endogeneity in demand estimation. To separate the exogenous variation in prices (i.e., due to differences in marginal costs) and endogenous variation (i.e., due to differences in unobserved valuation), we use two sets of instruments. First, we use BLP-style instruments. Specifically, following BLP's (1995), we use the observed app characteristics (excluding price), the sums of the values of the same characteristics of apps offered by the same app developer, and the sums of the values of the same characteristics of apps offered by other app developers. The identifying assumption is that the location of apps in the characteristics space is exogenous, or at least determined prior to the revelation of the users' valuation of the unobserved app characteristics (Nevo 2000). Second, we use the average price of the same-category apps in the other app store as an instrument for price. This is similar in spirit to Hausman's (1996) approach. Similar to Ghose et al. (2012), the identification assumption is that, after controlling for category-specific means and demographics, app store-specific valuations are independent across app stores (but are allowed to be correlated within an app store). Hence, prices of the same-category apps in two app stores will be correlated due to the common marginal costs, but due to the independence assumption will be uncorrelated with app store-specific valuation. We performed an F-test in the first stage for each of the instruments. In each case, the F-test value was well over 10, suggesting our instruments are valid (i.e., the instruments are not weak). In addition, the Hansen's J-Test could not reject the null hypothesis of valid over-identifying restrictions. All instruments yielded similar results.

Inference of Market Share Data

Market shares are obtained from aggregating over consumers. We define a "market" as the combination of an "app store" and a "day." Correspondingly, the market share for each app is calculated based on the number of downloads for that app in that app store divided by the "total size of that market." Importantly, Apple apps are not compatible with Android. That is, one cannot use an Apple app on an Android, and vice versa. So with regard to market size, we define the total number of apps purchased in a certain market based on data from either Apple App Store or Google Play and from other minor app stores including mobile carrier's app stores, third-party app stores, mobile device-based app stores, etc. Figure 1 demonstrates that there are two markets at a given day, and we use both app-level panel data and app store-level aggregate level data to compute the market share of apps in each market. Hence, the outside good is defined as "no purchase from the two leading app stores but from other minor app stores during a given day" (see Appendix B). In our data, the market shares from these minor app stores are less than 5%.

Despite the fact that market share data for apps is a critical input for the estimation of our model, neither Apple App Store nor Google Play provides direct information on downloads for their apps. Instead, they both provide the sales rank of an app. For example, App Store provides a list of top 200 ranked apps along with the rank of each individual app. A long stream of literature has investigated the relationship between sales rank and actual sales quantity by either conducting experiments (Chevalier and Goolsbee 2003, Ghose, Smith and Telang 2006, Chevalier and Mayzlin 2006) or collaborating with the company to get access to the company's internal demand data (Brynjolfsson et al. 2003). We followed the latter approach. To get access to demand data, we collaborated with one of the app stores run by a major mobile carrier in the market. Similar to aforementioned papers, we assume that the relationship between app sales ranks and sales quantity follows the Pareto distribution. That is, a small number of so called 'killer apps' contribute to a large share of the market. Based on the estimates of parameters of the Pareto distribution, we infer the sales quantity of apps and finally calculate market shares of apps. Details are in Appendix B.

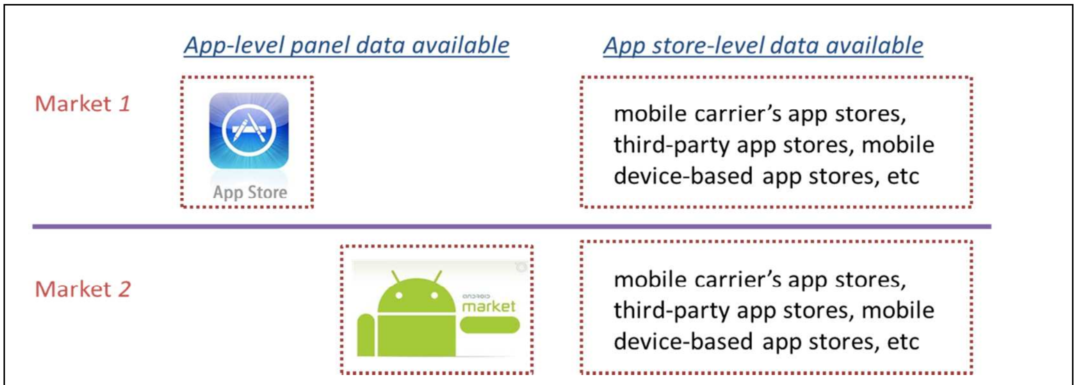

Figure 1. Defining a Market

Empirical Analysis Results and Counterfactual Experiments

In this section, we present our results from jointly estimating the demand and the pricing equation, present results on counterfactual analyses, and discuss the welfare impact from the introduction of mobile apps.

Estimate Results

The results of the estimates are in Table 2. The first two columns show results based on BLP-style instruments while the last two columns show results based on Hausman-style instruments. We find results remain qualitatively the same regardless of the use of the instrument set. Further, the first and the third columns show results based on user review count and its squared term, while the second and the fourth columns show results based on average user rating information. Because there is strong correlation between user review count and user rating in our data (i.e., 0.545, p-value < 0.001), we control each of the user review variables one at a time. We find results remain qualitatively the same regardless of the use of user review information.

In the first panel, estimates of the mean utility levels for each app characteristic are presented. App price has a negative impact on app demand, as one would expect. File size and app age have a positive impact on app demand. This result indicates that functionalities and maturity of apps play an important role in consumers' app purchase decisions. Also, app description length and number of screenshots have a positive impact on app demand. Thus it is important for app developers to provide customers with sufficient amount of textual and visual information about their apps in order to increase their app demand. In terms of age-restriction, compared to "general" (or 4+) apps, "low maturity" (or 9+) and "medium maturity" (or 12+) apps lower demand. This result indicates apps that contain simulated gambling, or include references to violence, sex, drugs, alcohol or tobacco in general have a negative impact on app demand. However, "high maturity" (or 17+) apps do not have a significantly negative impact on app demand as compared to "everyone" (or 4+) apps.

Table 2. Main Estimation Results

Variable	Coefficient (Std. Err.)^{I}	Coefficient (Std. Err.)^{II}	Coefficient (Std. Err.)^{III}	Coefficient (Std. Err.)^{IV}
		Means		
Price	-0.325*** (0.109)	-0.317*** (0.107)	-0.297** (0.118)	-0.288*** (0.106)
File Size$^{(L)}$	0.038*** (0.009)	0.026*** (0.007)	0.030*** (0.010)	0.027*** (0.008)
Description Length$^{(L)}$	0.039*** (0.014)	0.038*** (0.013)	0.020* (0.011)	0.025* (0.014)
App Age$^{(L)}$	0.014* (0.008)	0.017* (0.011)	0.023** (0.009)	0.023** (0.010)
Number of Screenshots	0.011** (0.004)	0.009** (0.004)	0.014** (0.005)	0.012** (0.006)
Age Restriction (+9)	-2.195*** (0.267)	-2.188*** (0.270)	-1.629*** (0.211)	-1.559*** (0.288)
Age Restriction (+12)	-0.138** (0.058)	-0.148** (0.061)	-0.214** (0.089)	-0.185** (0.090)
Age Restriction (+17)	-0.566 (1.050)	-0.584 (1.062)	-0.603 (0.482)	-0.632 (1.110)
Games	0.057** (0.027)	0.063* (0.037)	0.185*** (0.030)	0.178*** (0.059)
Entertainment	-0.164 (0.101)	-0.153 (0.119)	-0.020 (0.074)	-0.077 (0.130)
Social	0.133 (0.758)	0.142 (0.451)	0.095 (0.103)	0.100 (0.097)
Multimedia	-1.385*** (0.386)	-1.214*** (0.259)	-0.970*** (0.195)	-1.134*** (0.286)
Utilities	0.013 (0.027)	0.013 (0.049)	0.043 (0.037)	0.026 (0.025)
Education	-0.213*** (0.028)	-0.221*** (0.030)	-0.225*** (0.059)	-0.198*** (0.030)
Platform (1:Apple,0:Google)	0.194** (0.074)	0.184** (0.095)	0.202*** (0.049)	0.167*** (0.048)
User Review Count$^{(L)}$	0.075*** (0.024)		0.064** (0.030)	
User Review Count^2$^{(L)}$	-0.037*** (0.012)		-0.029** (0.012)	
User Rating		0.255*** (0.071)		0.293*** (0.086)
Nesting Coefficient	0.776*** (0.017)	0.727*** (0.032)	0.777*** (0.030)	0.742*** (0.022)
Constant	-5.932*** (0.306)	-5.813*** (0.652)	-5.598*** (0.093)	-5.620*** (0.083)
		Interaction Effects and Standard Deviation		
Price	0.035*** (0.010)	0.035*** (0.010)	0.035** (0.015)	0.036** (0.015)
Price × Age	0.014** (0.007)	0.014** (0.007)	0.016*** (0.002)	0.015*** (0.005)
Price × Gender	0.093*** (0.020)	0.098*** (0.013)	0.094*** (0.026)	0.096*** (0.024)
		Standard Deviations		
File Size$^{(L)}$	0.038** (0.017)	0.039** (0.017)	0.032** (0.015)	0.031*** (0.010)
Description Length$^{(L)}$	0.001 (0.021)	0.001 (0.020)	0.001 (0.024)	0.001 (0.022)
App Age$^{(L)}$	0.001 (0.017)	0.001 (0.017)	0.001 (0.022)	0.001 (0.020)
Number of Screenshots	0.001 (0.073)	0.001 (0.074)	0.001 (0.149)	0.001 (0.149)
Age Restriction (+9)	2.765** (1.392)	2.742** (1.376)	2.378** (0.988)	2.289** (1.067)
Age Restriction (+12)	0.105 (2.529)	0.096 (2.408)	0.088 (0.453)	0.084 (0.348)
Age Restriction (+17)	1.045** (0.554)	1.030** (0.589)	1.081** (0.483)	1.092** (0.483)
Games	0.006 (0.288)	0.006 (0.290)	0.006 (0.508)	0.006 (0.284)
Entertainment	0.274 (0.727)	0.283 (0.730)	0.323 (0.987)	0.324 (0.841)
Social	0.839*** (0.247)	0.840*** (0.248)	0.949*** (0.270)	0.905*** (0.259)
Multimedia	1.742*** (0.556)	1.809*** (0.582)	2.111** (1.083)	2.090** (1.022)
Utilities	0.003 (0.367)	0.003 (0.364)	0.002 (0.830)	0.003 (0.372)
Education	0.003 (0.164)	0.003 (0.164)	0.003 (0.186)	0.003 (0.142)

Cost Side Parameters								
File Size(L)	0.117***	(0.005)	0.118***	(0.006)	0.121***	(0.005)	0.120***	(0.006)
Description Length(L)	0.005	(0.005)	0.005	(0.005)	0.004	(0.005)	0.004	(0.005)
App Age(L)	0.129***	(0.006)	0.124***	(0.006)	0.118***	(0.010)	0.109***	(0.015)
Number of Screenshots	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Age Restriction (+9)	-0.020*	(0.012)	-0.018*	(0.011)	-0.024**	(0.012)	-0.020*	(0.012)
Age Restriction (+12)	-0.056***	(0.013)	-0.055***	(0.013)	-0.034**	(0.017)	-0.048***	(0.019)
Age Restriction (+17)	-0.180**	(0.079)	-0.180**	(0.077)	-0.174**	(0.078)	-0.169**	(0.072)
Games	-0.580***	(0.030)	-0.584***	(0.033)	-0.488***	(0.031)	-0.548***	(0.031)
Entertainment	-0.481***	(0.018)	-0.490***	(0.020)	-0.498***	(0.029)	-0.482***	(0.045)
Social	-0.388***	(0.029)	-0.380***	(0.030)	-0.497***	(0.042)	-0.320***	(0.053)
Multimedia	-0.182***	(0.020)	-0.184***	(0.021)	-0.234***	(0.028)	-0.205***	(0.030)
Utilities	0.004	(0.017)	0.004	(0.017)	0.006	(0.020)	0.006	(0.024)
Education	-0.528***	(0.022)	-0.530***	(0.022)	-0.438***	(0.020)	-0.464***	(0.023)
Platform(1:Apple,0:Android)	0.285***	(0.014)	0.253***	(0.035)	0.256***	(0.023)	0.250***	(0.029)
Apps by the Same Developer	-0.024***	(0.006)	-0.024***	(0.006)	-0.026***	(0.009)	-0.023***	(0.007)
Constant	0.715***	(0.039)	0.704***	(0.040)	0.978***	(0.120)	0.964***	(0.109)
GMM Objective Function		5.83e-4		5.76e-4		5.95e-4		5.76e-4

* Significant at 10% level. ** Significant at 5% level. *** Significant at 1 level.
I, III Based on user review count and its squared term II, IV Based on user review average rating only
† The unit of app price is in $10.
(L) Logarithm of the variable
The referent level for age restriction is +4 and the referent level for app category is lifestyle apps.

Further, compared to lifestyle apps, gaming apps have a positive impact on app demand while multimedia and education apps have a negative impact on demand. With regard to the user review controls, we find a positive sign for the linear form of the user review count variable and a negative sign for its quadratic form. This finding indicates the economic impact from the customer reviews is increasing in the volume of reviews but at a decreasing rate, as one would expect. We find average user rating has a positive impact on app demand. Moreover, apps on Apple iOS platform in general have a positive impact on app demand as compared to apps on Google Android OS platform. Lastly, we find the nesting parameter is very high and statistically significant (i.e., > 0.7 and p-value < 0.01). As it is close to one, this result implies that consumer preferences show strong correlation across apps from the same group (i.e., either within the free apps group or the paid apps groups), as one would expect.

The second panel presents the effect of demographics on the mean utility levels. Recall that the mean price coefficient is negative. Thus the positive estimate of interaction between app price and consumer age suggests that while the average consumer is sensitive to the price of apps, older consumers tend to be less price sensitive than younger consumers, as one would expect. Similarly, the positive estimate of interaction between app price and consumer gender (1: male, 0: female) indicates that male consumers tend to be less price sensitive than female consumers. In the third panel, the standard deviation captures the effects of heterogeneity around the mean utility level for each app characteristic due to the unobserved demographics. The effects are statistically significant for file size, age-restriction levels (+9 and +17), and social and multimedia categories. This result indicates that the heterogeneity in the coefficient is partly explained by the standard deviations, suggesting it is important to incorporate customer taste heterogeneity in our empirical data.

Finally, in the fourth panel, the estimates of the cost-side parameters are presented. We find the coefficient on file size is positive and statistically significant, thus it seems a substantial cost shifter in mobile app development. This suggests that the marginal cost for an app increases as the app developer adds additional features into the app or/and improve the functionality of the app, as one would expect.

Also, we find app age has a positive impact on cost. This finding suggests that mature apps still incur costs for continuous updates, fixing bugs, etc. However, app description length and number of screenshots do not have impact on app cost. Moreover, we find as compared to lifestyle apps, in most other app categories the marginal cost is smaller. App developers in general incur less cost for their apps on Apple iOS platform as compared to apps on Google Android OS platform. Lastly, the coefficient on the number of apps provided by the same developer is significantly negative, indicating returns to scale in app development seem substantial.

Counterfactual Experiments

A key advantage of structural modeling is that it allows for normative policy evaluation. To measure explicitly the economic impact of strategic policies, we conducted several counterfactual experiments. Specifically, we simulated the following two sets of scenarios.

Counterfactual Experiment I: Effects of Price Discount

One of the popular ways app developers earn more revenue is to offer a significant price discount. Distimo (2012b) reported that when apps are on sale the average revenue rose by 41% in the Apple App Store for iPhone when looking at those apps that were already among the 100 ranked apps. Moreover, the revenue during the whole sales period increased by 22%. In the Google Play on the first day of price reduction the revenue increased by 7%, and during the wholesale period increased by 29%. Distimo (2012) also found that the maximal sales occurred when the price was cut in half or the application was offered in tier 1 ($0.99) or tier 2 ($1.99).

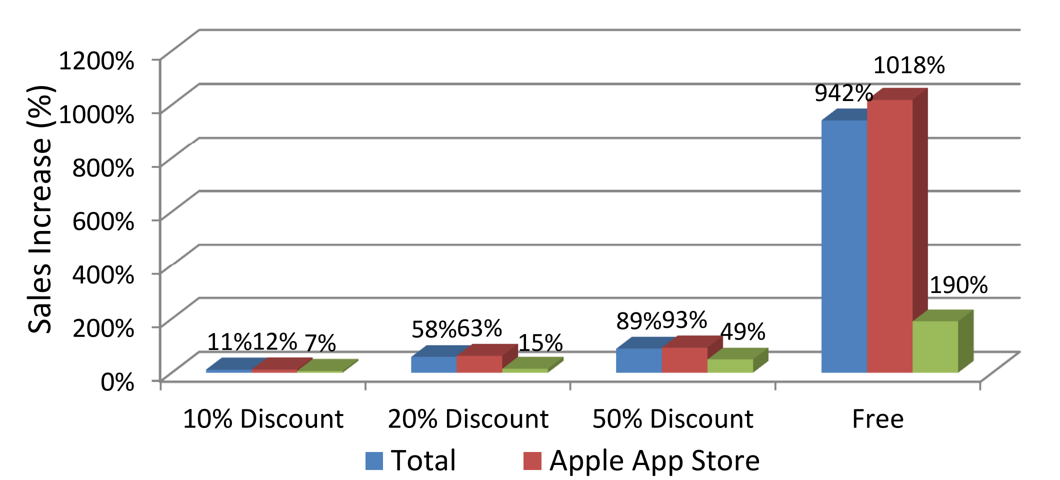

Figure 2. Effects of Pricing Strategies on App Demand

To examine how price reduction for paid apps will affect app demand, we conducted the following counterfactual experiments. We assumed price reduction by 10%, 20%, 50%, and finally changed it to free, and examined subsequent demand changes, respectively. We repeated this experiment one at a time for each app in our sample, then calculated the percentage changes in sales for that app before and after the price reduction. Our findings show that the overall increase of app demand is highest for free pricing schemes in all app stores, as one would expect. Figure 2 demonstrates comparison of the effects of different pricing strategies on app demand across Apple App Store and Google Play. It suggests price discount strategies in general seem to be more effective in Apple App Store as compared to Google Play to increase app demand. This may reflect the fact that the average app price is higher in Apple App Store than that in Google Play (i.e., $5.59 vs. $0.44, respectively). Moreover, our findings show that as we increase the amount of price discount the effects also increase non-linearly. For example, we find as compared to 10% price discount strategy, 20% discount strategy will increase the demand by approximately 5 times (i.e., 11% to 58%). Moreover, free app strategy will further increase the demand by approximately 85 times (i.e., 11% to 942%).

Counterfactual Experiment I: Substitution Patterns across App Categories

We looked into how price changes in one app category will affect the demand for other app categories. Table 3 shows relative percentage changes in column-app-category compared to the row-app category with respect to a 50% price cut in the row-app-category. For example, we cut the price in half for a game app and found that the demand for game app category increases 0.146% while the demand for utility category drops 0.158%. Thus the relative percentage change is computed as -108% (i.e., -0.158/0.146*100), implying the game apps and the utilities apps substitute to each other. Meanwhile, we also conducted similar analyses for apps from other categories. Other findings suggest that the game apps in general substitute to other app categories such as education and lifestyle apps among others.

Table 3. Substitution Patterns Across App Categories

	Games	Entertainment	Social	Multimedia	Utilities	Education	Lifestyle
Games	100%	-39%	-61%	-55%	-108%	-94%	-88%
Entertainment	-5%	100%	-10%	-8%	-19%	-16%	-15%
Social	-8%	-2%	100%	-17%	-15%	-6%	-7%
Multimedia	0%	0%	0%	100%	0%	0%	0%
Utilities	-7%	-4%	-11%	-12%	100%	-9%	-9%
Education	-3%	-4%	-6%	-5%	-11%	100%	-8%
Lifestyle	-4%	-5%	-8%	-6%	-13%	-11%	100%

We assumed 50% price reduction for apps in each row (app category).

From the above set of counterfactual experiments, the basic findings are as follows: (i) price discount strategy is more appropriate for apps in Apple App Store to increase app demand, (ii) effects of price discounts increase non-linearly, and (iii) the substitution effects between game apps and other apps such as utility and education apps are strong.

Welfare Estimation

Previous studies show that product variety increase social welfare (e.g., Brynjolfsson et al. 2003, Ghose et al. 2006). Also, competition lowers the prices (e.g. Brynjolfsson and Smith 2000), which also increase the social welfare. Hausman and Leonard (2002) break the total welfare impact from the introduction of a new product into two components: (1) the variety effect resulting from the availability of the new product and (2) the price effect resulting from changes of prices of existing products. Only the variety effect becomes relevant in our empirical context because there are no existing apps before the launch of the app store. Hence, we focus on the welfare impact resulting from the availability of mobile apps.

Assuming that there is no income effect (i.e., does not vary as a result of the price change), according to McFadden (1981) we integrate analytically the extreme value distribution of ε_{ij}, then the customer welfare in the random coefficient logit model is calculated as (Song 2007):

$$CW_t = \sum_{i=1}^{ns} \frac{\log\left(\sum_{j=1}^{J} \exp\left(\delta_{jt} + \alpha_i p_j\right) q_{jt}\right)}{\alpha_i} \tag{12}$$

where ns is the number of consumers in the market and q_{jt} is the quantity of app j sold at time t. We divide the changes in indirect utilities by α_i (i.e., marginal utility of income) to measure monetary changes.

We calculate the consumer surplus for the smart phone users in South Korea. The number of smartphone users in South Korea reached 26 million as of April 2012, allowing over half of the population to surf the web and download mobile applications on the go. Using the estimated demand function and inferred sales quantity of apps, we find that the availability of top ranked apps in both Apple and Android platforms enhanced consumer surplus in South Korea by approximately $160 million over the time period of our study.

In addition, it is important to note that Equation (4) suggests that we computed consumer surplus gains from downloading of apps into one's mobile devices beyond and above not downloading at all. Given that people can download Web apps (or PC apps) instead of mobile apps into their desktops or/and laptops, a more realistic baseline level to compute the consumer surplus of mobile apps against will be downloading Web apps. Since we do not have Web app sales information, we attempt to adjust the above consumer surplus estimate using the ratio of number of mobile apps and Web apps in the market. According to MobiThinking (2012), there are approximately 400,000 active mobile apps and about 4,800 Web apps from various app stores. Keeping this in mind, the adjusted consumer surplus is reduced to approximately $158 million over the 4 month period in the South Korean market.

Conclusions

In the domain of mobile telecom services, emerging markets, especially those in east Asia have often served as a crystal ball for mature markets such as the US and Western Europe. It started off with innovations in variable pricing of mobile data services, first introduced in the South Korean market in the early part of the prior decade. A similar trend has now caught on in the US too. A fundamental innovation brought forth by the advent of the mobile internet has been the widespread adoption of mobile phone based applications (apps). Various factors have been contributing to that growth including advancements in network technologies, the lowering of mobile data usage cost, the growing adoption of smart phones around the world, and a continuous increase in application usability. Mobile apps are also a democratizing experience in the same way that blogs were on the Web ten years ago. The barriers to building and distributing a compelling mobile app are falling and the ways for mobile app developers to monetize these apps are increasing, creating a more and more vibrant ecosystem for digital innovation. As consumers increasingly use mobile apps in both emerging and mature markets, it is important to understand the underlying drivers of user demand for mobile apps. In this paper, we estimate a structural model of user demand in a mobile app setting, present results on counterfactual analyses, and quantify the consumer surplus from the availability of such mobile apps.

Our results show that demand increases with the file size, app age (time since release), app description length, and number of screenshots. In terms of age-restriction, compared to “everyone” (or 4+) apps, “low maturity” (or 9+) and “medium maturity” (or 12+) apps lower demand. Compared to lifestyle apps, gaming apps have a positive impact on app demand while multimedia and education apps have a negative impact on demand. Notably, we find consumer preferences show strong correlation across apps from the same group (i.e., either within free apps or paid apps). We incorporate consumer heterogeneity in the model and find that older and male consumers tend to be less sensitive to the price of apps than younger and female consumers, respectively. In the supply-side we find app file size and app age are major cost component in app development. Also, our findings suggest there exist significant returns to scale in app development. Our counterfactual experiments show price discount strategy results in a greater increase of app demand in Apple App Store compared to Google Play and the effects of price discounts increase non-linearly. Our findings also indicate strong substitution effects between game apps and other apps such as utility and education apps. In addition, our results show that the availability of top ranked apps in both Apple App Store and Google Play enhanced consumer surplus approximately $158 million in South Korea over the time period of our study.

Data availability issues suggest that some caution is warranted in the demand and welfare estimation. For example, we do not have information on in-app ads. As the presence of in-app ads provides app developers with incentives to lower their price, we can include it in the supply-side app pricing function as an additional cost parameter. Moreover, we do not have in-app purchase option data. In addition, we do not have information on consumers’ mobile internet rate plans (i.e., fixed monthly fees with unlimited internet access, usage-based fees, etc), and hence cannot impute the one time transmission charges incurred when consumers download apps using their phones. Also, our data cannot distinguish whether multiple downloads of an app is from a single user through his multiple mobile devices (i.e., a smartphone and a tablet) or from each of multiple users downloads the app once. It is possible that demand function for apps will vary when user-level sales data is employed. Furthermore, the mobile app store in our data is based on apps built upon Apple App Store and Google Play in South Korea. It is likely that the magnitude of the surplus will vary across platforms and countries. Notwithstanding these limitations, our analysis documents increased consumer surplus from the availability of mobile apps. To the extent that prices and product characteristics of mobile apps affect market outcomes, the increasing size of the mobile app store may have profound implications for the future direction of mobile commerce.

Recent media reports document that 91% of top brands have a presence in at least one of the major mobile app stores. This is a significant increase compared to 18 months ago when only 51% of the brands published or licensed an application. Brands have realized that publishing applications in the various app stores offers a viable channel to promote their brand, reach consumers, and sell products. This is especially true of companies in emerging markets who actively use app stores as a way to market their products. One of the trends driving the growth in in-app advertising is the growing amount of time mobile users are spending on casual gaming and social media activity using their smartphones in emerging markets. Recent reports from the US market also show that time spent in mobile apps has now exceeded mobile Web usage, so it makes sense that there is a systematic reallocation of advertising dollars. Given the tremendous reach of apps on smartphones, advertisers who are not marketing within apps are probably missing a big opportunity In addition to the heavy usage mobile apps receive, another reason why marketers would want to invest marketing dollars in apps is that these ads can produce strong results because it can provide more information about a user than browser-based use can, potentially enabling them to better target their efforts. The results from our paper highlighting differences in elasticity of demand across different categories of apps can shed some light on some of these questions and help understand how firms can manage their brand marketing in mobile application platforms. We hope our paper paves the way for future research in this important area.

Appendix A. Estimation Steps

Step 1. Solving for mean utility level of apps δ

With initial values of parameters Π, Σ, and ρ, we solve for the mean utility levels $\delta_{\cdot t}$ $(\cdot)$ that set the predicted market shares of an app equal to the observed market shares of that app. We predict the market share of each app in each market as a function of app characteristics, prices, and unknown parameters. As mentioned in Section 4.1, assuming that $\bar{\varepsilon}_{ijt}$ follows a more general "nested logit" distribution, we can calculate the predicted-market share of app j in market t using equation (5). We approximate the integral over υ_i in (5) by simulating R draws over the density of υ as follows:

$$s_{jt} = \frac{1}{R}\sum_{i=1}^{R} \frac{\exp\left(\left(\delta_{jt} + [P_{jt}, X_{jt}](\Pi D_i + \Sigma \upsilon_i)\right)/1-\rho\right)}{\exp\left(I_g/1-\rho\right)} \frac{\exp I_g}{\exp I}. \tag{A1}$$

We then use the contraction mapping method by BLP (1995) to obtain the approximation to $\delta_{\cdot t}$ $(\cdot)$.

Step 2. Solving for mean level of marginal cost mc

Given the initial values of parameters Π, Σ, and ρ and the estimated δ, we compute the marginal cost mc by subtracting the computed mark-ups from the price as follows:

$$mc = P - \Delta(P, X, \xi | \delta, \Pi, \Sigma, \rho)^{-1} s(P, X, \xi | \delta, \Pi, \Sigma, \rho). \tag{A2}$$

Note that the markups depend only on the parameters of the mean utility level δ, non-linear demand parameters Π, Σ, and ρ, and the equilibrium price vector P.

Step 3. Solving for Π, Σ, ρ, $\bar{\alpha}$, $\bar{\beta}$, and γ

To account for the endogeneity of price, we use a GMM estimator and form an objective function by interacting the unobservable parameters for app characteristics and marginal costs, ξ and ω, with a set of instrumental variables and cost shifters, Z. For given Π, Σ, ρ, δ, and mc, first we compute the unobservables as follows:

$$\xi_{jt} = \delta_{jt} - \left(X_{jt}\bar{\beta} + \bar{\alpha}P_{jt}\right) \quad \text{and} \quad \omega_{jt} = mc_{jt} - w_{jt}\gamma. \tag{A3}$$

Defining $T(\theta) = [\xi, \omega]$, we search for the value of θ that minimizes the GMM objective function as follows:

$$\hat{\theta} = \underset{\theta=\{\theta_1,\theta_2\}}{\operatorname{argmax}} T(\theta)' Z \Phi^{-1} Z' T(\theta) \tag{A4}$$

where θ_1 contains the linear parameters, $\bar{\alpha}$, $\bar{\beta}$, and γ, and θ_2 contains the non-linear parameters, Π, Σ, and ρ. Φ is a consistent estimate of $E[Z'T(\theta)T(\theta)'Z]$.The time required to this search can be reduced by using the first order conditions, with respect to θ_1, to express θ_1 as a function of θ_2, as follows:

$$\hat{\theta}_1 = (X'Z\Phi^{-1}Z'X)^{-1}X'Z\Phi^{-1}Z'\delta(\hat{\theta}_2). \tag{A5}$$

Now the non-linear search is limited to θ_2. We use Nedler-Mead Simplex algorithm to approximate the parameter values for θ_2. Then using the estimated θ_2, we estimate compute θ_1 using (A5).

Appendix B. Market Share Computation

While demand data on apps is unavailable, most app stores provide details on the rank of an app. Researchers have investigated the relationship between sales ranks and actual sales (Brynjolfsson et al. 2003, Chevalier and Goolsbee 2003, Chevalier and Mayzlin 2006). To infer app demand for Apple App Store and Google Play, we collaborated with one of the app stores run by a major mobile carrier in the market to calibrate the relationship between sales rank and download of apps. The company launched its mobile app store in 2010. Consumers can download either free or paid apps from the company's app store. Similar to other major app stores like Apple App Store, app developers including large companies and individuals can register their apps to the company's app store. Our dataset spans 46 weeks encompassing 4,977 registered apps including education, games, lifestyle, multimedia, utilities, etc.

Following Chevalier and Goolsbee (2003) and Brynjolfsson et al. (2003) among others, we assume that the relationship between sales quantity and sales rank follows Pareto distribution with shape and scale parameters (i.e., a and b, respectively):

$$Sales\ Quantity = b * (Sales\ Rank)^{-a} + \varepsilon. \tag{B1}$$

Prior studies show that shape parameters typically range between 0.6 and 1.2, and decrease over time (Brynjolfsson et al. 2010, Chevalier and Mayzlin 2006, Ghose, Smith, and Telang 2006, Brynjolfsson et al. 2003, Chevalier and Goolsbee 2003). Consistent with previous findings, we found the shape parameter of 0.753. Assuming that the shape parameter remains the same across app stores in the market, we use this shape estimate in our market share calculation for Apple App Store and Google Play. However, the scale parameter of an app store may greatly vary by the market share of the app store. Without knowing scale parameters of each app store in the market, we assume the scale parameter of an app store is proportional to the aggregate-level market share of app stores in the market.

An app store market typically consists of two major app stores like Apple App Store and Google Play along with several minor app stores including mobile carriers' app stores and third-party app stores. According to Korea Communications Commission (2011), in the market of our setting, the market shares of Apple App Store, Google Play, and minor app stores are 64.9%, 32.7%, and 2.4%. Importantly, as Apple apps are not compatible with Android Apps, we treat Apple App Store and Google Play as different markets. This is because the iPhone/iPad and the Android phones/devices use different operating systems. Hence, we compute the market share of app j in App Store as follows:

$$\text{Market Share}_j^{\text{Apple}} = \frac{\widehat{\text{Sales}}_j}{\sum_{k\in\text{Apple Rank}\le 200}\widehat{\text{Sales}}_k + \sum_{k\in\text{Apple Rank}>200}\widehat{\text{Sales}}_k + \sum_{k\in\text{Minor App Stores}}\widehat{\text{Sales}}_k} \tag{B2}$$

where $\widehat{\text{Sales}}_j$ refers to the unscaled estimate of sales quantity of app j. However, we can only infer $\sum_{k\in\text{Apple Rank}\le 200}\widehat{\text{Sales}}_k$ in the denominator. To estimate other components in the denominator, based on the estimated shape parameter (i.e., 0.753), we infer the ratio between the sum of unscaled sales quantity of top 200 apps and that of the rest of apps as 11.52: 7.28. We compute $\sum_{k\in\text{Apple Rank}>200}\widehat{\text{Sales}}_k$ as $\frac{7.28}{11.52} * \sum_{k\in\text{Apple Rank}\le 200}\widehat{\text{Sales}}_k$. Given that the market share ratio between App Store and all minor app stores is 64.9: 2.4, we infer $\sum_{k\in\text{Minor App Stores}}\widehat{\text{Sales}}_k$ as $\frac{2.4}{64.9} * \left(1 + \frac{7.28}{11.52}\right)\sum_{k\in\text{Apple Rank}\le 200}\widehat{\text{Sales}}_k$. Similarly, we compute the market share of app j in Google Play as follows:

$$\text{Market Share}_j^{\text{Google}} = \frac{\widehat{\text{Sales}}_j}{\sum_{k\in\text{Google Rank}\le 200}\widehat{\text{Sales}}_k + \sum_{k\in\text{Google Rank}>200}\widehat{\text{Sales}}_k + \sum_{k\in\text{Minor App Stores}}\widehat{\text{Sales}}_k}. \tag{B3}$$

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