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# Estimating Demand for Mobile Applications in the New Economy

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In 2013, the global mobile app market was estimated at over US$50 billion and is expected to grow to $150 billion in the next two years. In this paper, we build a structural econometric model to quantify the vibrant platform competition between mobile (smartphone and tablet) apps on the Apple iOS and Google Android platforms and estimate consumer preferences toward different mobile app characteristics. We find that app demand increases with the in-app purchase option wherein a user can complete transactions within the app. On the contrary, app demand decreases with the in-app advertisement option where consumers are shown ads while they are engaging with the app. The direct effects on app revenue from the inclusion of an in-app purchase option and an in-app advertisement option are equivalent to offering a 28% price discount and increasing the price by 8%, respectively. We also find that a price discount strategy results in a greater increase of app demand in Google Play compared with Apple App Store, and app developers can maximize their revenue by providing a 50% discount on their paid apps. Using the estimated demand function, we find that mobile apps have enhanced consumer surplus by approximately $33.6 billion annually in the United States, and we discuss various implications for mobile marketing analytics, app pricing, and app design strategies.

*Keywords*: mobile apps; demand estimation; Apple; Google; app characteristics; in-app purchases; in-app advertising; mobile analytics; mobile marketing
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## 1. Introduction

> The global market for mobile applications will soon be worth more than the market for traditional music. That's pretty significant when you think the market barely existed a couple of years ago, and now it's expected to grow to more than $US17 billion by 2012.
>
> (Patrick Mork, as quoted in Reardon 2010)

Mobile devices are changing the way that people communicate, work, and socialize. Much of the growing adoption and innovation in the industry is driven by mobile apps. Mobile apps are now being used worldwide to perform a variety of tasks—access social networks, read e-books, play games, listen to music, watch videos, and many other meaningful aspects of our lives. According to the International Data Corporation (2013), annual mobile application downloads on smartphones, tablets, and similarly specified mobile computing devices will increase from $87.8 billion in 2013 to $187 billion in 2017. Revenue from end users is forecast to increase from $10.3 billion in 2013 to $25.2 billion in 2017. The increasing availability of app-level data presents exciting opportunities for business analytics, especially mobile analytics.

Apps can be offered either for free or for a price. Some consumers are willing to pay more for additional features in higher quality apps, whereas some consumers only download free versions of apps with limited features. In a world where freemium is becoming common, some consumers purchase a paid version after trying the free version. This feature also lends itself to some interesting business analytics. App developers can use information on the price elasticity of different app categories to determine whether to offer an app for free and, if not for free, how much to charge it. Moreover, given that app stores often collect one-off or subscription fees for paid apps, it can be useful for them to obtain precise estimates of user demand. Knowledge of heterogeneous consumer intrinsic preferences toward mobile app characteristics can help app developers design and improve their app features, determine pricing strategies to better monetize their apps, and optimize their content and navigation. It can help advertisers understand what kinds of apps and app features consumers like to purchase and use.

There can be several other practical benefits from research on mobile-related business analytics. For app developers, revenues can be generated not just from the purchase of applications, but also from microtransactions within an app. The in-app advertisement option (IADV) is increasingly becoming the predominant way for app developers to monetize their apps. An in-app purchase option (IAP) provides a middle ground between offering an app at a premium price without any ads versus offering it for free but including ads. Mobile-related business analytics such as estimating demand for apps with the above features can help developers design apps that are more likely to engage users. Furthermore, leveraging mobile app analytics can help advertisers predict the most popular apps before they become popular and optimize merchandizing such as placement of product links and ads within the app accordingly. In addition, understanding mobile app audience demographics can help advertisers target ads based on the interests and composition of mobile app users.

Although much of the attention in academic research has been on examining user behavioral differences in the mobile channel versus traditional channels, important benefits lie in new products and services made available through these mobile platforms. Whereas prior work has studied the impact of the mobile web on users' multimedia content creation and consumption behavior (for example, Ghose and Han 2011, 2010), the value of mobile apps to consumers has not been quantified till date.

The first objective of this paper is the introduction of a theory-based structural model of consumer demand for mobile apps jointly with developer-side pricing equations that quantifies consumer preferences for different app features and different app categories. Mobile apps are usually categorized into two predetermined groups—*free* apps and *paid* apps—and grouped into predetermined categories in major app stores. Hence, consumer preferences toward apps in the same group are likely to be correlated. We address the potential hierarchical preference structure by building a random-coefficients nested logit demand model in a similar vein to the Berry et al. (1995; henceforth BLP) method. The second objective of this paper is to present results from counterfactual analyses that yield insights for app developers, app stores, and advertisers. Finally, we also aim to quantify the welfare impact from the availability of mobile apps. Motivated by an interest in analyzing the competition between Apple's iOS and Google's Android platforms, we examine the following questions in this paper:

1. What is the impact of different features of mobile app on demand in the two leading app platforms? What are the key drivers of app development costs?
2. What are the costs and benefits of in-app purchase and in-app advertisement options? What is the optimal discount price that maximizes revenues from app sales?
3. What is the level of substitution between different app categories? What is the difference in price elasticity between Apple and Google apps?
4. What is the increase in consumer surplus from the availability of mobile apps?

We use a panel data set consisting of the top 400 ranked apps' sales rank, price, and characteristic data from the two leading app stores—Apple App Store and Google Play—for four months in the United States. Our results show that demand increases with the app description length, number of screenshots, in-app purchase option, app age, version age, number of apps by the same developer, number of previous versions, offering both free and paid versions, app availability on multiple app stores, and the volume and valence of user reviews. On the contrary, app demand decreases with file size and the in-app advertisement option. Older and male consumers tend to be less sensitive to the price of apps than younger and female consumers, respectively. Notably, consumer preferences show strong correlation across apps from the same group (i.e., either within free apps or paid apps or within the same category). On the supply side, we find app file size is a major cost driver in app development, but that there are significant returns to scale in app development. Cost decreases with in-app purchase options, in-app advertisement, app age, and age restrictions. Compared with lifestyle apps, games, social, and utility apps have higher marginal costs, whereas media apps have lower marginal costs. These results are robust to a variety of alternate modeling specifications.

Interestingly, app developers tend to lower their up-front app prices when they provide an in-app purchase option within their apps. With regard to in-app advertisement, it adversely affects app demand. Our counterfactual experiments also show that in-app purchases and in-app advertisement bring the same level of change in revenues as one would get from offering a 28% price discount and increasing the price by 8%, respectively. A price discount strategy results in a greater increase of app demand in Google Play compared with Apple App Store. Our findings also suggest that app developers can maximize revenue from paid app sales by lowering the price by 50% in our context. 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 apps in both Apple and Android platforms enhanced consumer surplus in the United States by approximately $33.6 billion on an annual basis.

The remainder of this paper is organized as follows. We describe the related literature in §2. In §3, we describe the data. In §4, we describe the econometric models. In §5, we provide the results, and in §6, we discuss the managerial implications of the results.

## 2. 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.

### 2.1. Audience 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 in the mobile phone setting. For example, Danaher (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.

Furthermore, our study builds on an emerging stream of literature on mobile marketing. Shankar and Balasubramanian (2008) provide an extensive review of mobile marketing. Shankar et al. (2010) develop a conceptual framework for mobile marketing in the retailing environment and discuss retailers' mobile marketing practices. Sinisalo (2011) examines the role of the mobile medium among other channels within multichannel CRM (customer relationship management) communication. Spann et al. (2012) discuss the impact of weather and distance on coupon redemption. Danaher et al. (2012) evaluate the effectiveness of mobile phone promotions. Bart et al. (2014) study mobile advertising campaigns and find that they are effective at increasing favorable attitudes for higher (versus lower) involvement products. Hui et al. (2013) examine how mobile-phone-based in-store coupons can affect unplanned spending. A recent stream of work has investigated user behavior on the mobile Internet by mapping the interdependence between mobile content generation and usage (Ghose and Han 2011), documenting differences in search costs and location activities on mobile phones versus PCs (Ghose et al. 2013a) and quantifying the economic impact of tablets in the digital commerce market and examining its synergies with other channels—PCs and smartphones (Ghose et al. 2014).

Another emerging stream of work has started using randomized field experiments to causally measure cross-platform synergies between Web and mobile advertising (Ghose et al. 2013b); quantify how geographic distance between the user and a store and the rank of the offer on the mobile screen influence mobile coupon engagement rates (Molitor et al. 2013); investigate how ad creative characteristics such as format, USP (unique selling proposition), and message appeal account for differences in advertising effectiveness across smartphones, tablets, and PCs (Kleine et al. 2014); examine how user responses to targeted mobile offers varies based on location and time (Luo et al. 2013); and quantify how crowds influence users' propensity to respond to targeted mobile offers (Andrews et al. 2014).

To our knowledge, there are only a few papers that focus on economic and social aspects of mobile apps. Carare (2012) builds a reduced-form model and shows the impact of today's best-seller rank information on tomorrow's demand using Apple App Store data. Garg and Telang (2013) provide a methodology to calibrate the sales ranking and sales quantity relationship for apps using publicly available data from Apple App Store. Kim et al. (2013) demonstrate that the usage of an app is influenced by its structural positioning in the app network (or App-Net). Han et al. (2014a) quantify the intrinsic preference and satiation levels of different app categories using individual-level mobile app time-use data. Han et al. (2014b) examine whether addiction to mobile platform apps is socially rational. Bresnahan et al. (2014) examine platform choices by mobile app developers, including the decision to multihome. Liu et al. (2014) illustrate how the threat of competitors' entry influences the timing and quality of app entry. To our knowledge, no previous study has estimated a structural model of consumer demand in a mobile app setting using data on various app characteristics from the two major app stores—Apple App Store and Google Play. This paper thus makes a number of important contributions.

### 2.2. 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 et al. 1995). 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), direct broadcast satellites and cable TV (Goolsbee and Petrin 2004), and elsewhere. We add to this literature by estimating consumer demand for mobile apps and by linking it to the literature on the economics of the Internet.

## 3. Empirical Background and Data Description

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 app. In March 2012, 3.1 billion apps were downloaded worldwide from two leading app stores—Apple App Store and Google Play (Xyologic 2012). We gathered mobile app profile and demand panel data from Apple App Store and Google Play from the U.S. market. We collected the data between September 5, 2012, and January 10, 2013 (four months). The data include 4,706 distinct apps in Apple App Store and 2,624 apps in Google Play. The total numbers of apps from the two app stores in the data may be different or some may be equal depending on their availability in each app store.

Our data set includes *daily* panel data on smartphone app sales rank, app prices, app characteristics, and user review data from Apple App Store and Google Play. The apps in the daily app data consist of both top-400 free apps and top-400 paid apps from each app store. The app ranking information is based on download data from sales charts in each app store. We capture an exhaustive list of app-related information provided to consumers when they browse in these app stores. The observed app characteristics in our sample include the following:

- app file size,
- app version,
- app age (days elapsed since app release),
- app version age (days elapsed since app version release),
- number of characters in the textual app description,
- number of screenshots,
- app age-restriction levels,
- app categories,
- app developer,
- number of apps provided by the same app developer,
- in-app purchase options, and
- in-app advertisement option.

We measure the file size of an app in megabytes (called *File Size*). As apps become more sophisticated, they increase in size, which means it takes longer for consumers to download and try those new apps. Hence, there can exist a relationship between file size and user demand. Moreover, app developers release new versions to address user requests for new features or functionalities and continually debug the app. The number of version updates is likely to be correlated with the quality of the app, and thereby eventually affect user demand. Because an older version of an app becomes unavailable after a new version is released, the demand for the new version may also be influenced by the previous versions. We create a variable that measures the number of distinct versions of an app (called *Number of Previous Versions*) and use it as a proxy for the level of functional maturity of an app. In addition, the decision to release a new version and terminate an old version is typically made by app developers endogenously. We use a series of version update indicator variables for a given app (called *App Version Updates*) as controls to alleviate concern of potential endogeneity.[1]

We also measure app age in two different ways. First, we measure the app age based on the number of days since the app was first released (called *App Age*). Although the first version release date of an app usually precedes the starting time of the sampling time window, we have information on the first version release dates of apps in our sample. It is conceivable that there exists a relationship between app age and demand due to increased awareness effects. Second, we measure the app age based on the number of days since the current version was released (called *Version Age*).

We use app developers' textual and visual descriptions 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 websites affects consumer purchase decisions. For example, Decker and Trusov (2010) use text mining to estimate the relative effects of product attributes and brand names on the overall evaluation of the products. Hence we posit that there is a relationship between app description length and app demand. Ghose et al. (2012) find that the information extracted from visual images of hotels (for example, whether the hotel is near the beach) influences consumer decisions on hotel reservation. Hence, we posit that there is a relationship between the number of screenshots about an app and the app demand.

We use app developers' self-rating with regard to age restriction. In both app stores, there are consistently four 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 corresponding levels, "+9" in App Store and "low maturity" in Google Play as corresponding levels, and so on.

[1] Some shocks such as user feedback and competing apps' new version releases may affect an app developer to change its app characteristics, and as a result some observed app characteristics are endogenously determined. By including *App Version Updates* controls, we allow for the observed app characteristics to be uncorrelated with unobserved app characteristics. The rationale for using these controls is that app characteristics change (e.g., file size, app description) when an app developer releases a new version of a given app. The *App Version Updates* controls will capture the impact of the unobserved shock on the observed app characteristics.

Since apps in different levels of age restriction mainly appeal to different segments of consumers, they can have different impacts on app demand. In accordance with Distimo's 2011 report on download volumes per app category (Koekkoek 2011), we classified apps in our data into the seven most popular categories, including games, entertainment, social, multimedia, utilities, education, and lifestyle.

We use app developer dummies (called *App Developers*) to incorporate the fact that app developers are different from each other in a number of ways, such as their development efficiency. We use app developer fixed effects (*App Developers*) to capture the time-invariant covariate of the development efficiency. We use a variable indicating the number of apps developed by the same developer (*Number of Apps by Developer*) to capture the time-varying covariate of development efficiency due to a learning process. As ongoing marginal costs arise from various maintenance tasks after app development, some of the maintenance costs of a given app can be shared by other apps built by the same developer.

For app developers, revenues can be generated not just from paid app downloads, but also from microtransactions within an app and in-app ad placements. The in-app purchase option (called *In-App Purchase Options*) provides additional features beyond the basic functionalities of an app and can allow users to purchase related goods or advanced features related to the app. Hence, in-app purchase modules can influence consumers' ex ante utility as well as app download decisions. On the contrary, the in-app advertisement option (called *In-App Advertisement*) may cause annoyance, because it displays distracting features such as animated banners, pop-ups, and floating advertisements. Therefore, providing an in-app advertisement can decrease the demand of an app. Moreover, the in-app purchase option and the in-app advertisement option provide app developers with incentives to lower their app sale prices. Hence, we use *In-App Purchase* and *In-App Advertisement* variables in the cost-side equation as well to capture their effects on price decrease.

We use a cross-chart listing indicator variable (called *Cross-Chart Listing*) to control for potential correlation across free and paid versions of an app. The *Cross-Chart Listing* variable takes a value of 1 if a given app appears both in the top-400 free app list and in the top-400 paid app list in a given day, and otherwise takes a value of 0. In a similar vein, we use a cross-platform listing indicator variable (called *Cross-Platform Listing*) to control for potential spillover effects (such as reputation spillover) across app stores. The *Cross-Platform Listing* variable takes a value of 1 if a given app appears both in Apple App Store and in Google Play at a given day, and otherwise takes a value of 0.

We also collected user reviews from each app store because it is well known from the literature that user generated product reviews affect sales. Consistent with prior work, we use the volume (called *User Review Count*) and the valence of the app rating (called *User Rating*) to control for word-of-mouth effects. Furthermore, we have aggregate-level information on user demographics such as age and gender for Apple App Store and Google Play, respectively, from the U.S. market. We also have aggregate-level market share data from app stores other than Apple 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* (%) | 0.007 | 0.039 | 0.012 | 0.054 | 0.002 | 0.009 |
| *Paid App Price* (US$) | 2.72 | 2.81 | 1.98 | 1.91 | 3.47 | 3.49 |
| *File Size* (megabytes)$^{(L)}$ | 2.37 | 1.44 | 3.08 | 1.18 | 1.65 | 1.32 |
| *Description Length* (characters)$^{(L)}$ | 7.05 | 0.79 | 7.15 | 0.66 | 6.95 | 0.89 |
| *Number of Screenshots* | 6.42 | 2.34 | 7.10 | 2.55 | 5.72 | 1.86 |
| *Age Restriction* (+4) | 0.65 | 0.66 | 0.72 | 0.68 | 0.58 | 0.61 |
| *Age Restriction* (+9) | 0.18 | 0.39 | 0.12 | 0.32 | 0.25 | 0.45 |
| *Age Restriction* (+12) | 0.13 | 0.34 | 0.12 | 0.32 | 0.15 | 0.36 |
| *Age Restriction* (+17) | 0.04 | 0.18 | 0.05 | 0.22 | 0.02 | 0.15 |
| *In-App Purchase* (1: yes, 0: no) | 0.47 | 0.50 | 0.41 | 0.49 | 0.53 | 0.50 |
| *In-App Advertisement* (1: yes, 0: no) | 0.66 | 0.47 | 0.52 | 0.50 | 0.80 | 0.40 |
| *App Age* (days)$^{(L)}$ | 5.76 | 1.21 | 5.77 | 1.40 | 5.74 | 0.97 |
| *Version Age* (days)$^{(L)}$ | 3.40 | 1.50 | 3.46 | 1.46 | 3.33 | 1.54 |
| *Number of Apps by Developer*$^{(L)}$ | 1.15 | 1.18 | 1.35 | 1.23 | 0.94 | 1.06 |
| *Number of Previous Versions* | 2.31 | 2.09 | 2.17 | 1.46 | 2.46 | 2.58 |
| *Cross-Chart Listing* (1: yes, 0: no) | 0.09 | 0.28 | 0.10 | 0.30 | 0.08 | 0.27 |
| *Cross-Platform Listing* (1: Yes, 0: No) | 0.32 | 0.47 | 0.32 | 0.47 | 0.32 | 0.47 |
| *Games* | 0.22 | 0.42 | 0.14 | 0.35 | 0.30 | 0.46 |
| *Entertainment* | 0.07 | 0.26 | 0.10 | 0.30 | 0.05 | 0.22 |
| *Social* | 0.39 | 0.49 | 0.40 | 0.49 | 0.38 | 0.49 |
| *Multimedia* | 0.12 | 0.33 | 0.15 | 0.36 | 0.10 | 0.30 |
| *Utilities* | 0.08 | 0.28 | 0.13 | 0.33 | 0.04 | 0.20 |
| *Education* | 0.07 | 0.26 | 0.05 | 0.23 | 0.09 | 0.28 |
| *Lifestyle* | 0.03 | 0.23 | 0.03 | 0.24 | 0.03 | 0.21 |
| *User Review Count*$^{(L)}$ | 7.69 | 2.72 | 6.04 | 2.21 | 9.36 | 2.10 |
| *User Rating* | 4.17 | 0.70 | 4.05 | 0.88 | 4.30 | 0.41 |
| Number of observations | 204,800 | | 102,400 | | 102,400 | |

*Note.* The sample period is from September 5, 2012, to January 10, 2013.
$^{(L)}$Logarithm of the variable.

Since neither app store provides information on the download of apps, we first calibrate the relationship between sales ranks and sales quantity using an additional panel data set in which we have information on ranks and the actual download of apps from a major third-party app store. Then we predict the download of apps in both Apple App Store and Google Play, and these predictions are used in actual demand estimation. Details on sales quantity imputation are provided in Online Appendix C (online appendix available at http://pages.stern.nyu.edu/~aghose/mobileapps_appendix.pdf). 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 boundaries of the market for an app. We discuss the market definition issue in detail in the Econometric Model section.

## 4. Econometric Model

In this section, we present a random-coefficients nested logit model to estimate the distribution of consumer preferences toward different mobile app characteristics, especially when the apps are categorized as free apps and paid apps and grouped into predetermined categories. 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 toward conducting counterfactual experiments and calculating consumer welfare gains in the next section.

### 4.1. Demand Side: Random-Coefficients Nested Logit Model

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

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

where $X_{jt}$ is a vector of observable characteristics of app $j$ in market $t$, and $\beta_i$ is a vector of the random coefficients (i.e., taste parameters) associated with those app characteristics.[2] Note that $P_{jt}$ is the price of app $j$ in market $t$, and $\alpha_i$ is a scalar for a random coefficient that captures consumers' heterogeneous tastes toward app price; $\xi_{jt}$ 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 evaluate the impact on demand as an app developer changes its pricing scheme. Moreover, we can assess the impact on demand when the developer provides various levels of price discount. In addition, we control for app versions, app developers, app platform, cross-chart correlation, cross-platform correlation, time trends, and the volume and valence of user reviews.

We use a three-level nested logit model to place the alternatives in nests. At the top level there are two nests: one for the free apps and one for the paid apps. This is because apps are usually grouped into two predetermined groups—free and paid—in major app stores including Apple App Store and Google Play. At the middle level there is one nest for each app category. This is also because apps are grouped into seven predetermined categories—games, entertainment, social, multimedia, utilities, education, and lifestyle. Last, at the bottom level there are apps of the same category from a given list (free or paid). The tree graph of the structure of apps is shown in Figure 1.

We assume that a mean-zero stochastic term represents an app-level taste shock. Note that $\bar{\varepsilon}_{ijt}$ is distributed extreme value or follows a more general "nested logit" distribution, which allows preferences to be correlated across apps in the same nest. Suppose we assign app $j$ to a top-level nest $g$, with the groups $g=0$ (outside goods), $g=1$ (free apps), and $g=2$ (paid apps), and a middle-level nest $h$, with the groups $h=1$ (games), $h=2$ (entertainment), $h=3$ (social), $h=4$ (multimedia), $h=5$ (utilities), $h=6$ (education), and $h=7$ (lifestyle). More specifically, following Cardell (1997), we decompose $\bar{\varepsilon}_{ijt}$ as follows:

$$\bar{\varepsilon}_{ijt} = \zeta_{ig(j)t} + \lambda_{g(j)}\zeta_{ih(j)t} + \lambda_{g(j)}\lambda_{h(j)}\varepsilon_{ijt}, \tag{2}$$

where $\lambda_{g(j)}$ and $\lambda_{h(j)}$ are nesting parameters ranged between 0 and 1, and $\zeta_{ig(j)t}$ and $\zeta_{ih(j)t}$ are random variables with the unique distribution with the property that if $\varepsilon_{ijt}$ is distributed extreme value, then $\bar{\varepsilon}_{ijt}$ is also distributed extreme value. The nesting parameters can be interpreted as the degree of preference correlation between apps of the same nest. So consumer preference toward apps in the same nest may be correlated. As $\lambda$ goes zero, consumers perceive apps of the same nest as perfect substitutes relative to apps in the other nest. As $\lambda$ goes to one, the within-group correlation goes to zero, thus the model reduces to the standard logit.[3] It should be also noted that because of consumer-specific random taste coefficients—$\alpha_i$ and $\beta_i$,—two apps in different nests could still have utilities that are more highly correlated than apps in the same nest.

We follow the BLP 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

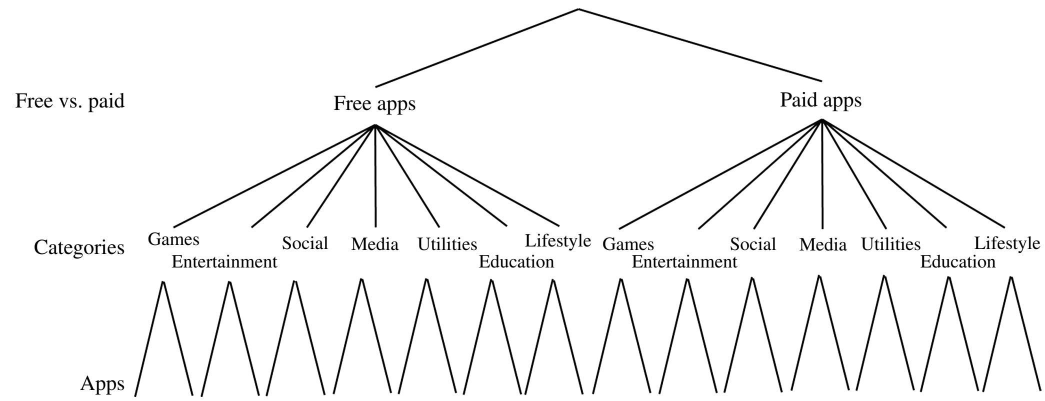
$$\begin{pmatrix}\alpha_i\\ \beta_i\end{pmatrix} = \begin{pmatrix}\bar{\alpha}\\ \bar{\beta}\end{pmatrix} + \Pi D_i + \Sigma v_i, \quad D_i \sim P_D^*(D),\ v_i \sim N(0, I). \tag{3}$$

The vector $(\bar{\alpha}, \bar{\beta})$, which is referred to as the mean utility of price and app characteristics, is common

[2] We define a "market" as the combination of an "app store" and a "day" (see §4.5 for details on market definition and market share computation).

[3] For simplicity, in our main model, we restrict the nesting parameters to be the same for all the nests at each level, although this is not necessary. We extend the main model to nest-specific nesting parameters in §5.2. We find the results remain qualitatively similar.

**Figure 1 Tree Diagram for a Nested Logit Model of Mobile App Choice**




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 at the app store level using other data sources (AdMob 2010); and $\Pi$ is a matrix of coefficients that measure how the taste characteristics vary with observed demographics. Furthermore, $v_i$ is a vector capturing the additional unobserved consumer-specific preference toward app price and app characteristics. It follows a multivariate normal distribution. $\Sigma$ is a scaling matrix. Following the demand estimation literature (BLP, Nevo 2001), we assume that $v_i$ has a standard normal distribution, and the vector $\Sigma$ allows for each element of $v_i$ to have a different standard deviation (Nevo 2000).[4] 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:

$$u_{ijt} = \delta_{jt} + [P_{jt}, X_{jt}](\Pi D_i + \Sigma v_i) + \zeta_{ig(j)t} + \lambda_{g(j)}\zeta_{ih(j)t} + \lambda_{g(j)}\lambda_{h(j)}\varepsilon_{ijt}. \tag{4}$$

Our goal is then to estimate the mean utilities vector $(\bar{\alpha}, \bar{\beta})$, $\Pi$ matrix of coefficients, the standard deviations in vector $\Sigma$, and the nesting coefficients $\lambda_{g(j)}$ and $\lambda_{h(j)}$.

Each consumer $i$ in market $t$ chooses the app $j$ that maximizes his/her utility.[5] 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, we compute the predicted market share of app $j$ in market $t$ as the integral over the distribution of demographic characteristics $D$ as well as over the standard normal random variable vector $v$ as follows:

$$s_{jt} = \int_v \int_D \frac{\exp((\delta_{jt} + [P_{jt}, X_{jt}](\Pi D_i + \Sigma v_i))/\lambda_{h(j)})}{\exp(I_{igh}/\lambda_{h(j)})} \cdot \frac{\exp(I_{igh}/\lambda_{g(j)})}{\exp(I_{ig}/\lambda_{g(j)})} \frac{\exp I_{ig}}{\exp I_i} P_D^*(D)\phi(\nu), \tag{5}$$

where the McFadden's (1978) "inclusive values" or "logsums" are defined by

$$I_{igh} = \lambda_{h(j)} \ln \sum_{j=1}^{J_{hg}} \exp((\delta_{jt} + [P_{jt}, X_{jt}](\Pi D_i + \Sigma v_i))/\lambda_{h(j)}),$$

$$I_{ig} = \lambda_{g(j)} \ln \sum_{h=1}^{H_g} \exp(I_{igh}/\lambda_{g(j)}),$$

$$I_i = \ln\left(1 + \sum_{g=1}^{G} \exp(I_{ig})\right),$$

where $G$ is the number of nests at the top level, $H_g$ is the number of subnests under nest $g$, and, finally, $J_{hg}$ is the number of apps in top-level nest $g$ and middle-level nest $h$. In our data, $J_{hg}$ is set to 400 in all nests.

### 4.2. Supply Side: Cost Function and App Pricing

We assume there are $N$ app developers, indexed by $f$, each of which produces some subset $J_f$ apps of

[4] For simplicity, we assume that standard deviations in the vector $\Sigma$ are not correlated.

[5] A multiple discrete choice model is necessary if consumers download more than one app on the same day. We have calculated daily app download frequency per user in the United States by app store (Google Play and Apple App Store) and by app price type (free and paid) using external sources such as Xyologic and Distimo (leading mobile app consulting firms). We find the average daily app download frequency per user does not exceed 0.54 in any app store or price type. In particular, the daily average number of paid app downloads per user is typically less than 0.05. That an average individual user buys at most 0.54 apps per day suggests that a multiple discrete choice model may not be necessary in our app demand estimation. So we assume the conditional independence of the possible multiple purchases on the same day. Nonetheless, we empirically tested the validity of our assumption of a single discrete choice model by conducting model fit comparison with alternative multiple discrete choice models as robustness checks in §5.2.

the $J$ apps. The cost characteristics for each app are decomposed into an observable component (by the researcher), $w_{jt}$ for app $j$ in market $t$, and an unobserved component, $\omega_{jt}$; that is, we assume that marginal costs may not necessarily be zero in a mobile app setting, and we estimate the marginal costs using a list of observed app characteristics. The rationale for assuming nonzero marginal costs is that various maintenance tasks after app development incur ongoing costs. Such maintenance tasks typically involve (1) fixing crashes or errors reported by users of the app; (2) adding features requested by users after release; (3) user support, which incurs an ongoing cost that varies depending on the popularity of the app and how easy it is to use (for example, networking apps may require hosting and administrative costs); and (4) scaling costs. If an app becomes popular and uses a server or shared database, additional servers may be required or code may need to be optimized to scale more effectively to maintain high performance with more users (Crawford 2011). In addition, similar to Berry et al. (1995), we expect the observed app characteristics, the $x_{jt}$, to be part of the $w_{jt}$, and $\omega_{jt}$ to be correlated with $\xi_{jt}$.

We incorporate two unique features of mobile apps—*IAP* and *IADV*—into the marginal cost function. The IAP provides app developers with incentives to lower their app sales prices so that the app developers can increase their customer base at the expense of immediate app sales revenues in expectation that they can get additional revenues from future in-app purchases. Similarly, including ads in an app is another way to monetize apps. It also provides the app developers with incentives to lower their app prices. The majority of free apps are driven by in-app advertising. Hence, the marginal cost of app $j$ in market $t$, $mc_{jt}$, is written as

$$mc_{jt} = w_{jt}\gamma - \theta_1 IAP_{jt} - \theta_2 IADV_{jt} + \omega_{jt}, \qquad (6)$$

where $\gamma$, $\theta_1$, and $\theta_2$ are parameters to be estimated. Here $IAP_{jt}$ is an indicator variable identifying the availability of in-app purchase options in app $j$ at market $t$. It takes the value of 1 if the app has in-app purchase options and 0 otherwise. $IADV_{jt}$ is an indicator variable identifying the availability of in-app ad in app $j$ at market $t$. It takes a value of 1 if the app includes in-app advertising and 0 otherwise.

Note that we do not have revenue information from either in-app purchases or in-app advertisement in the current data set. In the absence of such revenue information, we assume that the total revenue of a given app from in-app purchase and in-app advertisement sales is proportional to the number of downloads of that app. Therefore, given the demand function in (4), the profit of app developer $f$, $\Pi_f$, is

$$\Pi_f = \sum_{j\in J_f}(P_{jt} - mc_{jt} - \theta_1 IAP_{jt} - \theta_2 IADV_{jt}) \cdot M s_{jt}(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \rho), \qquad (7)$$

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.

The price vector satisfies the first-order conditions as follows:

$$s_{jt}(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda) + \sum_{r\in J_f}(P_{rt} - mc_{rt} - \theta_1 IAP_{jt} - \theta_2 IADV_{jt})\frac{\partial s_{rt}(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda)}{\partial P_{jt}} = 0. \qquad (8)$$

The $J$ first-order conditions in (8) imply price-cost markups for each app. In vector notation, the first-order conditions can then be written as

$$P = mc + \theta_1 IAP_{jt} + \theta_2 IADV_{jt} + \Delta(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda)^{-1} \cdot s(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda), \qquad (9)$$

where $\Delta_{jrt} = -(\partial s_{rt}/\partial P_{jt})$ if $r$ and $j$ are produced by the same app developer in a given market $t$, and $\Delta_{jrt} = 0$ otherwise. Because of the missing revenue data from in-app purchases and in-app advertisement, we assume that the unit price of the in-app purchase option and the unit revenue from in-app advertisement (i.e., CPM) are independent of the app sales price. Thus, the first-order conditions in Equation (9) are the same as that without considering *IAP* and *IADV* in the revenue function, except that the price will be lower by $\theta_1 IAP_{jt}$ and $\theta_2 IADV_{jt}$.

Prices are additively separable in marginal cost and the markup defined as

$$b(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda) = \Delta(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda)^{-1} \cdot s(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda). \qquad (10)$$

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

$$P - b(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda) = w\gamma + \theta_1 IAP_{jt} + \theta_2 IADV_{jt} + \omega. \qquad (11)$$

Since $P$ is a function of $\omega$, $b(P, X, \xi \mid \bar{\alpha}, \bar{\beta}, \Pi, \Sigma, \lambda)$ is a function of $\omega$. Also the correlation between $\xi$ and $\omega$ generates a dependence between the markups and $\omega$ (BLP). Hence, the parameters in (11), $\gamma$, $\theta_1$, and $\theta_2$, can be estimated if we assume orthogonality conditions between $\omega$ and appropriate instruments.

### 4.3. 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 $\alpha_i$ and $\beta_i$ and the mean of the nesting coefficients, $\lambda_{g(j)}$ and $\lambda_{h(j)}$, in the demand side and the mean of $\gamma$ and $\theta$ 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 $(\Pi^0, \Sigma^0, \lambda^0)$, from the demand side, we look for the mean utility $\delta$, such that the model-predicted market share is equal to the observed market share. As mentioned in the previous §4.2, from the supply side, we compute the marginal cost, *mc*. We then form a generalized method of moments (GMM) objective function using the BLP (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 $(\Pi^1, \Sigma^1, \lambda^1)$ 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.[6]

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 the standard normal distribution. For $D$, we use the empirical distribution of user age and gender. We use the leading global mobile advertising network AdMob's (2010) comprehensive report on mobile metrics to capture demographic data by app store. We have access to the distributional information of age and gender.[7] For each market we draw 1,000 individuals. In the context of mobile apps, some consumers appear over time within a given app store, but not across different app stores. This is because multihoming is rare on the consumer demand side. For example, people usually own either Apple iPhone or Android-based phone, but not both. Thus, they use either Apple App Store or Google Play, respectively, not both at the same time. So we use different draws across app stores, but use same draws within an app store.

For given values of $\Pi$, $\Sigma$, and $\lambda$, we compute mean utility level $\delta$ that equates the predicted market shares to the observed shares and compute the marginal cost *mc* by subtracting the computed markups from the price. And, for a given $\Pi$, $\Sigma$, $\lambda$, $\delta$, and *mc*, we compute the unobserved parameter for app characteristics, $\xi$, and the unobserved parameter for cost component, $\omega$, and 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 (nonlinear) parameters—$\Pi$, $\Sigma$, and $\lambda$—while we search for the value of the nonlinear parameters that minimizes the objective function. Details are provided in Online Appendix B.

### 4.4. 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, 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 observed app characteristics are uncorrelated with unobserved app characteristics.

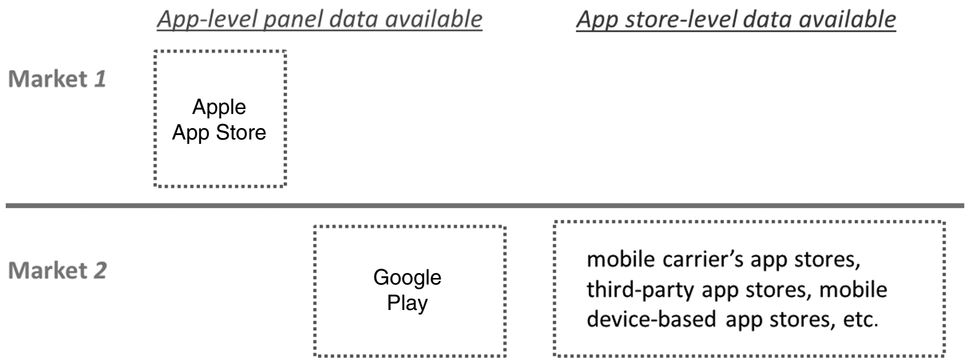
Some observed app characteristics and the app price can be correlated with each other when they are exposed to a common (unobserved) shock. As a result, there is a potential concern of endogeneity for these observed app characteristics. To address this concern, we have included a total of 39 indicator variables (called *App Version Updates*) that capture a series of major app version updates as additional controls in the demand equation. For example, the first indicator variable takes a value of 1 if there is a first major version update for a given app during our sampling period and 0 otherwise. The second indicator variable has a value of 1 if there is a second major version update and 0 otherwise, and so on. The rationale for using these controls is that when an app developer releases an updated version of a given app, some of the app characteristics (e.g., file size, app description) change as well. The version update indicator variables will capture the impact of the unobserved shock on the observed app characteristics. Thus, by controlling for these version updates in the demand equation, we alleviate the concern of endogeneity in observed app characteristics. As a result, we avoid violating the independence assumption between observed and unobserved app characteristics by using BLP-style instruments.

Second, we use the average price of same-category apps by the "same app developer" in the other app

[6] An alternative BLP estimation method (Dubé et al. 2012) is useful for larger-scale data.

[7] According to AdMob's (2010) report, 73% of Android users (i.e., Google Play users) are male, compared with 57% of iPhone users (i.e., Apple App Store users). The average age of Google Play users (35) is similar to that of Apple App Store users (37). Apple and Google Play users are fairly evenly split across age groups. There are six age groups: 17 or younger, 18–24, 25–34, 35–44, 45–54, and 55 or older. We use weighted averages calculated using the midpoint of each segment. For example, 15 years was assumed for the "17 or younger" segment, and 65 was assumed for the "55 or older" segment.

**Figure 2** **Defining a Market**




store and the price of the same app by the "same app developer" in the other app store as instruments for price. This is similar in spirit to Hausman's (1997) approach. Similar to Ghose et al. (2012), the identification assumption is that, after controlling for app developers and consumer demographics, app-store-specific valuations are independent across app stores (but are allowed to be correlated within an app store). Hence, prices of same-category apps by the "same app developer" and prices of the same app by the "same app developer" in different app stores will be correlated because of the common marginal costs, but due to the independence assumption will be uncorrelated with app-store-specific valuation. The rationale for assuming that marginal costs of same-category apps by the same developer across two app stores are correlated to each other is that (1) same-category apps by the same developer share similar cost components and (2) multihoming (i.e., hosting an app at more than one app store) is quite popular on the supply side in the mobile app context. App developers use modules to create a new mobile app. When they develop a new app within a given category (i.e., gaming apps), they tend to reuse the existing modules of the same app category. Thus, the development and maintenance costs of the same-category apps tend to be correlated to each other.[8]

In addition, we assume that shocks in one app store do not necessarily affect demand in the other app store. This is because although multihoming is popular on the supply side, it may be rare on the consumer demand side. For example, people do not usually own both the Apple iPhone and Android-based phone simultaneously. Rather, at any given point in time, they typically own either of the two, and use either Apple App Store or Google Play. 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 $J$-test could not reject the null hypothesis of valid overidentifying restrictions. All instruments yielded similar results.

### 4.5. 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, because Apple apps are not compatible with Android Apps, we treat Apple App Store and Google Play as different markets. Moreover, Apple's iOS users can only purchase apps from Apple App Store. However, Android users can purchase apps not only from Google Play, but also from other Android-based app stores such as third-party app stores. So with regard to market size, for Apple apps, we define the total number of apps purchased in a given market based on data only from Apple App Store. However, for Google Play apps, we define the total number of apps purchased in a given market based on data not only from Google Play, but also from other Android-based app stores including third-party app stores, mobile carrier's app stores, and mobile device manufacturer-based app stores (excluding Apple App Store). Figure 2 demonstrates there are two markets on a given day, and we use both app-level panel data and app store-level aggregate data to compute the market share of apps in each market. Hence, the outside good is defined as "no purchase during a given day" for Apple users and as "no purchase from Google Play but possibly from other

[8] Furthermore, multihoming costs become increasingly lower due to evolving hybrid and Web-oriented mobile architectures. Mobile app development is moving away from native architecture (OS/device specific) and becoming increasingly device agnostic through hybrid and Web-oriented mobile architectures to reach out to a larger customer base (Sharma 2012, Hyrynsalmi et al. 2012). For example, certain mobile application development platforms, like Antenna AMP, offer cross-platform suites that enable a single app shell to be executed on multiple mobile devices, using device- and OS-specific client apps. Thus, to the extent that multihoming is popular on the supply side, the development and maintenance costs of a given app (of a given app developer) across multiple app stores will be correlated with each other.

app stores during a given day" for Android users (see Online Appendix C for details).

Despite the fact that market share data for apps are 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, Apple App Store provides a list of the top 400 ranked apps along with the rank of each individual app. A stream of literature has investigated the relationship between sales rank and actual sales quantity by either conducting experiments (Chevalier and Goolsbee 2003, Ghose et al. 2006) or collaborating with a company to get access to the company's internal sales data (Brynjolfsson et al. 2003, Garg and Telang 2013). We followed the latter approach. To get access to demand data, we collaborated with a major third-party app store in the market. Similar to the aforementioned papers, we assume that the relationship between app sales ranks and sales quantity follows the Pareto distribution. Based on the estimates of parameters of the Pareto distribution, we infer the sales quantities of apps and finally calculate market shares of apps. Details are provided in Online Appendix C.

## 5. Empirical Results

In this section, we present our results from jointly estimating the demand and pricing equations, show robustness to several alternative specifications, present results on counterfactual analyses, and discuss the welfare impact from the introduction of mobile apps.

### 5.1. Estimation Results

The results of the estimates are in Table 2. The first column shows results based on BLP-style instruments, whereas the second column shows results based on Hausman-style instruments. We find results remain qualitatively the same regardless of the use of the instrument set.

In the first panel, estimates of the mean utility levels for each app characteristic are presented. We find a 10% price discount results in 5% increase in app demand, with a greater increase of app demand in Google Play compared with Apple App Store (7% and 3%, respectively). Longer wait times to download a sophisticated app adversely affect consumer's app purchase decisions. We find a 10% increase in file size results in 1.1% decrease in app demand. We find a 10% increase in description length results in a 2.3% increase in app demand, and adding one more screenshot increases app demand by 4.2%. Thus, it is important for app developers to provide customers with sufficient amount of textual and visual information about their apps to increase their app demand. In terms of age restriction, compared with "general" (or 4+) apps, "low maturity" (or 9+), "medium maturity" (or 12+),

**Table 2 Main Estimation Results**

| Variable | Coefficient (std. err.) BLP-style instruments | Coefficient (std. err.) Hausman-style instruments |
|---|---|---|
| | Mean effects | |
| *Price* | −0.215 (0.039)*** | −0.225 (0.037)*** |
| *File Size*$^{(L)}$ | −0.037 (0.005)*** | −0.038 (0.008)*** |
| *Description Length*$^{(L)}$ | 0.049 (0.008)*** | 0.054 (0.009)*** |
| *Number of Screenshots* | 0.022 (0.003)*** | 0.019 (0.009)** |
| *Age Restriction* (+9) | −0.455 (0.310) | −0.302 (0.847) |
| *Age Restriction* (+12) | −0.233 (0.062)*** | −0.195 (0.054)*** |
| *Age Restriction* (+17) | −0.119 (0.047)** | −0.127 (0.038)*** |
| *In-App Purchase Options* | 0.384 (0.139)*** | 0.379 (0.120)*** |
| *In-App Advertisement* | −0.128 (0.051)** | −0.134 (0.039)*** |
| *App Age*$^{(L)}$ | 0.105 (0.044)** | 0.109 (0.045)** |
| *App Age Squared*$^{(L)}$ | 0.035 (0.019)* | 0.044 (0.021)** |
| *Version Age*$^{(L)}$ | 0.208 (0.080)** | 0.193 (0.077)** |
| *Version Age Squared*$^{(L)}$ | 0.052 (0.061) | 0.063 (0.051) |
| *Number of Apps by Developer*$^{(L)}$ | 0.173 (0.030)*** | 0.166 (0.025)*** |
| *Number of Previous Versions* | 0.033 (0.015)** | 0.036 (0.017)** |
| *Cross-Chart Listing* (1: yes, 0: no) | 0.563 (0.052)*** | 0.589 (0.048)*** |
| *Cross-Platform Listing* (1: yes, 0: no) | 0.032 (0.014)** | 0.030 (0.015)** |
| *User Review Count*$^{(L)}$ | 0.374 (0.132)*** | 0.367 (0.102)*** |
| *User Review Count Squared*$^{(L)}$ | 0.007 (0.003)** | 0.007 (0.004)* |
| *User Rating* | 1.935 (0.042)*** | 1.694 (0.043)*** |
| *Platform* (1: Apple, 0: Android) | 1.146 (0.049)*** | 1.198 (0.050)*** |
| *Nesting Coefficient* (Level 1) | 0.236 (0.041)*** | 0.215 (0.028)*** |
| *Nesting Coefficient* (Level 2) | 0.310 (0.063)*** | 0.306 (0.090)*** |
| *Constant* | −14.078 (0.365)*** | −14.639 (0.438)*** |
| | Interaction effects | |
| *Price* | 0.028 (0.005)*** | 0.024 (0.010)** |
| *Price* × *Age* | 0.113 (0.023)*** | 0.108 (0.030)*** |
| *Price* × *Gender* | 0.010 (0.005)** | 0.018 (0.005)*** |
| | Unobserved heterogeneity: Distribution of parameters across users | |
| *File Size*$^{(L)}$ | 0.024 (0.004)*** | 0.026 (0.005)*** |
| *Description Length*$^{(L)}$ | 0.002 (0.010) | 0.002 (0.006) |
| *Number of Screenshots* | 0.003 (0.026) | 0.003 (0.040) |
| *Age Restriction* (+9) | 0.022 (0.010)** | 0.022 (0.010)** |
| *Age Restriction* (+12) | 0.007 (0.047) | 0.005 (0.053) |
| *Age Restriction* (+17) | 0.002 (0.019) | 0.004 (0.013) |
| *In-App Purchase Options* | 0.012 (0.004)*** | 0.013 (0.003)*** |
| *In-App Advertisement* | 0.003 (0.006) | 0.003 (0.007) |
| *App Age*$^{(L)}$ | 0.021 (0.015) | 0.019 (0.018) |
| *Version Age*$^{(L)}$ | 0.007 (0.024) | 0.012 (0.035) |
| | Cost-side parameters | |
| *File Size*$^{(L)}$ | 0.004 (0.001)*** | 0.005 (0.001)*** |
| *Description Length*$^{(L)}$ | −0.076 (0.337) | 0.021 (0.206) |
| *Number of Screenshots* | −0.011 (0.080) | −0.025 (0.048) |
| *Age Restriction* (+9) | −0.204 (0.020)*** | −0.171 (0.032)*** |
| *Age Restriction* (+12) | −0.123 (0.047)*** | −0.172 (0.041)*** |
| *Age Restriction* (+17) | −0.232 (0.095)** | −0.260 (0.082)*** |
| *In-App Purchase Options* | −0.263 (0.025)*** | −0.245 (0.049)*** |
| *In-App Advertisement* | −0.530 (0.270)** | −0.492 (0.230)** |
| *App Age*$^{(L)}$ | −0.219 (0.106)** | −0.237 (0.142)* |
| *Version Age*$^{(L)}$ | −0.162 (0.519) | 0.013 (0.380) |
| *Number of Apps by Developer*$^{(L)}$ | −0.207 (0.058)*** | −0.185 (0.083)** |
| *Games* | 0.161 (0.008)*** | 0.137 (0.018)*** |
| *Entertainment* | −0.018 (0.041) | −0.008 (0.056) |
| *Social* | 0.612 (0.027)*** | 0.584 (0.053)*** |
| *Media* | −0.085 (0.006)*** | −0.083 (0.007)*** |
| *Utilities* | 0.145 (0.061)** | 0.132 (0.043)*** |
| *Education* | 0.183 (0.150) | 0.226 (0.150) |
| *Platform* (1: Apple, 0: Android) | 0.800 (0.372)** | 0.992 (0.467)*** |
| *Constant* | −0.547 (0.094)*** | −0.562 (0.034)*** |
| GMM objective function | 4.15e−5 | 3.58e−5 |

*Notes*. The referent level for age restriction is +4. The referent level for app category is lifestyle apps. Coefficients for fixed effects of time (day), app developers, and app version updates are omitted due to brevity.
$^{(L)}$Logarithm of the variable.
*Significant at 0.1; **significant at 0.05; ***significant at 0.01.

and "high maturity" (or 17+) apps lower demand. This result indicates that apps that contain simulated gambling or include references to violence, sex, drugs, alcohol, or tobacco in general have a negative impact on app demand.

Interestingly, in-app purchase and in-app advertisement options have different effects on app demand. Whereas the IAP increases app demand, the IADV decreases it. This difference is attributable to the fact that the IAP provides benefits through additional features and functionalities, whereas the IADV can cause annoyance on the demand side. App age and version age have a positive impact on app demand. And the app age has a positive curvilinear effect. This result indicates that the maturity of apps play an important role in consumers' app purchase decisions. We find a 10% increase in app age and version age results in 1.7% and 0.5% increases in app demand, respectively. The number of apps developed by the developer has a positive effect on app demand. This result suggest that if the developer has created a large number of high-quality apps in the past, then consumers might trust the app from this developer, and this will influence the demand for the app also. Furthermore, the number of previous versions has a positive effect on app demand. This result indicates that quality updates are an important driver for demand in a mobile app setting; hence the demand for the new version may also be influenced by the demand from the previous versions.

Cross-chart listing has a positive effect on app demand. This result suggests that when an app appears both in the free top 400 and the paid top 400 lists, the demand becomes higher compared to when the same app appears only in one of these two lists. This is possibly because if an app developer releases both the free and paid versions, consumers can try the free version first and then migrate to the paid version. As a result, it generates a positive cross-chart listing correlation in consumers' ex ante utility.[9] We find that cross-platform listing has a positive effect on app demand as well. This result indicates that if an app developer releases its app in both platforms (Apple App Store and Google Play), consumers become more aware of the app, and consequently some spillover effects generate positive cross-platform correlation in consumers' ex ante utility.

With regard to the user reviews, both the volume and the valence of user rating have a positive impact on app demand, as one would expect. The volume of user reviews has a positive curvilinear effect on app demand. Furthermore, apps on the Apple iOS platform in general have a positive impact on app demand as compared with apps on the Google Android OS platform. Last, we find that each nesting parameter is small and statistically significant. Because it is close to zero, this result implies that consumer preferences show strong correlation across apps from the same group at a top level (i.e., within the same list, free or paid) and at a middle level (i.e., within the same category).

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 although the average consumer is sensitive to the price of apps, older consumers tend to be less price sensitive than younger consumers. 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 distribution of parameters across users 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 level (+9), and in-app purchase options. This result indicate 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 that file size has a positive impact on cost, and thus it seems to be a cost driver in mobile app development. However, app description length and number of screenshots do not have impact on app cost. In terms of age restriction, compared with "general" (or 4+) apps, "low maturity" (or 9+), "medium maturity" (or 12+), and "high maturity" (or 17+) apps cost more to develop. We find in-app purchase options and in-app advertisement are major cost inhibitors in the mobile app setting. This result suggests that both in-app purchases and in-app advertising provide the app developers with incentives to lower their app sales prices because they impact app demand. Furthermore, app age has a negative impact on cost. Ongoing marginal costs for app developers arise from various maintenance-related tasks after app development. Thus, this finding suggests that developers of mature apps incur lower costs for periodic updates and fixing bugs through a learning process. Also, the number of apps provided by the same developer has a negative impact on cost, indicating returns to scale in app development seem substantial. We find that, compared with lifestyle apps, in the games, social, and utilities app categories, the marginal cost is large. On the contrary, in the media apps category, the marginal cost is smaller. Last, app

[9] Under our three-level nested logit model, a free version and a paid version of the same app cannot appear in the same (bottom-level) choice set. Therefore, they cannot be double counted in the demand model.

developers in general incur lower costs for their apps on the Apple iOS platform compared with apps on the Google OS platform.

### 5.2. Robustness Checks

We implemented a series of robustness checks and found our results are robust to these modifications.

**5.2.1. Separate Estimation for Each App Store.** We estimate our main model by pooling the data from both app stores, with one platform dummy variable indicating the app store. Having only one dummy variable might not be able to fully capture the differences of the demand between these two platforms. This is because consumers' self-selection into a platform in the first place (Apple iOS or Google Android) may attract different types of consumers. For example, Google Android users might be more tech savvy, and Apple users might be less so, which might be correlated with their preferences for apps. To address this concern, we estimate our model specification separately for Apple App Store and for Google Play (for details, see Tables A.1 and A.2 in Online Appendix A). The results indicate that, overall, our key coefficient estimates remain qualitatively the same between two app stores in terms of the sign and the statistical significance. We compare the effects of different pricing strategies on app demand by using expected own price elasticities. We find that the app demand is more price elastic in Google Play than in Apple App Store (expected own price elasticities are −3.731 and −1.973, respectively). Our counterfactual experiments on the effects of price discounts in §5.3 also demonstrate that Google Play users are more price sensitive than Apple users. This finding is consistent with numerous trade press reports that Apple device users are less price sensitive than device users on other platforms such as Android and Windows.

**5.2.2. Multiple Discrete Choice Model.** App users can sometimes download multiple apps on the same day. This can happen if there are some complementarities in the functionalities of those apps. A multiple discrete choice model is necessary if consumers download multiple apps in a given day. Hence, we relax the assumption that consumers can purchase only one app per day, the one with the highest utility. We extend our single discrete choice, nested logit model to a multiple discrete choice setting using Fan's (2013) approach. The key difference between the single discrete choice model (our main model) and the multiple discrete choice models is that the sum of "market shares" in a given market can be larger than 1 in the multiple discrete choice model. "Market penetration" is therefore a better term and is used in the multiple discrete choice model. We consider two alternative multiple discrete choice models—a two discrete choice model and a three discrete choice model. In the two discrete choice model, the probability that a consumer downloads app $j$ is the sum of the probability that $j$ is the first choice and the probability that $j$ is the second choice (Fan 2013). In a similar vein, in the three discrete choice model, the probability that a consumer downloads app $j$ is the sum of the probability that $j$ is the first choice, the probability that $j$ is the second choice, and the probability that $j$ is the third choice.

**Table 3** **Model Fit Comparison Results**

| | Single choice model | Two choice model | Three choice model |
|---|---|---|---|
| | In-sample model prediction (market share) | | |
| RMSE | 0.00551 | 0.02138 | 0.05306 |
| MSE | 0.00003 | 0.00046 | 0.00282 |
| MAD | 0.00124 | 0.00376 | 0.00387 |
| | Out-of-sample model prediction (market share) | | |
| RMSE | 0.02122 | 0.04898 | 0.05620 |
| MSE | 0.00045 | 0.00240 | 0.00316 |
| MAD | 0.00132 | 0.00402 | 0.00439 |

We conduct a model fit comparison of the single discrete choice model (our main model) with the aforementioned alternative multiple discrete choice models. We use both in-sample and out-of-sample data and measure root mean square error (RMSE), mean square error (MSE), and mean absolute deviation (MAD). We allow the data to determine which model provides the best description of the data. Table 3 provides the model fit comparison results. We find that the single choice model provides the best performance in both in- and out-of-sample predictions. This result lends support to the validity of our assumption of the single discrete choice model in our empirical context. Note that because the fit of the three choice model is worse than that of the two choice model and that of the two choice model is worse than that of the single choice model, we show below results from the $k$ discrete choice models when $k$ is up to three. In general, as we increase the number of app purchases per day from one to two to three and even beyond that, we find that the fit of the model deteriorates.[10] Furthermore, we find the estimation results from multiple discrete choice models remain qualitatively consistent with the single choice model. Table A.3 in Online Appendix A provides estimation results on multiple discrete choice models.

[10] In general, latent-class models allow for more flexible function forms, and thus improve model fit at the expense of an increase in the number of parameters to be estimated. In our context, as we increase the number of app purchases per day from one to $k$, we impose additional restrictions on choice probability equations without incorporating additional parameters into the model. Hence, depending on the nature of the observed data, it is possible for multiple choice models to have a worse fit than a single choice model.

**5.2.3. Group-Specific Nesting Coefficients Model.** We relax the assumption of the same nesting coefficient for all the nests at each level. To be specific, we allow the degree of preference correlation among free apps to be different from that among paid apps, and also allow the degrees of preference correlation across categories to be different from each other. Our findings indicate that, overall, our main results remain qualitatively the same regardless of the use of separate nesting coefficients (for details, see Table A.4 in Online Appendix A). With regard to nesting coefficients, we find that the top-level nesting coefficients (i.e., 0.228 and 0.240) are quite similar to the top-level nesting coefficient in the main model (i.e., 0.236). Furthermore, the middle-level nesting coefficients are also similar to the middle-level nesting coefficient in the main model. This suggests that the benefit of having separate nesting coefficients compared to just one nesting coefficient at each level seems less significant in our empirical context.

**5.2.4. Pure Characteristics Model.** The pure characteristics model provides an alternative way of estimating consumer demand by eliminating the idiosyncratic logit error term $\varepsilon_{ij}$ from the utility function. Instead, consumer preferences are only related to product characteristics by relying solely on the unobserved product characteristics and unobserved variation in taste parameters to generate stochastic choices (Berry and Pakes 2007, Song 2007). We find the results remain qualitatively the same; that is, the signs of the estimates for the mean utility and the standard deviations (i.e., the individual specific deviation from that mean) for each app characteristic are similar to those in the main model (for details, see Table A.5 in Online Appendix A).

**5.2.5. Tablet Apps from Apple App Store.** The rapid adoption of tablets has driven the widespread use of tablet apps. As an additional robustness check to see whether our results are driven by some smartphone-specific idiosyncrasies, we examine a data set of tablet apps from the Apple App Store that has similar information on app sales rank, app prices, app characteristics, and user review data from the U.S. market. Our findings indicate that the main results remain qualitatively the same (for details, see Table A.6 in Online Appendix A). One key difference is that a 10% price discount results in a 1.9% increase in Apple tablet app demand, compared with a 3.0% increase in Apple smartphone app demand in the U.S. market. This suggests that tablet users are less price sensitive than smartphone users. This finding is consistent with media reports that tablet users generally have more disposable income.

## 5.3. Counterfactual Experiments

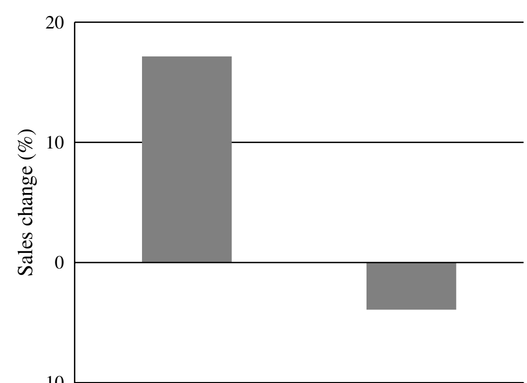
A key advantage of structural modeling is that it allows for normative policy evaluation. To generate insights for businesses interested in mobile analytics, we conducted several counterfactual experiments. Specifically, these counterfactuals demonstrate the (i) direct and indirect effects of in-app purchase and in-app advertising; (ii) effects of app pricing strategies on app demand, price elasticity comparison across app stores, and optimal discount prices that maximize revenues from app sales; and (iii) substitution patterns across app categories.

**5.3.1. Counterfactual Experiment I: Effects of In-App Purchase Options and In-App Advertisement.** In-app purchase and in-app advertisement options are increasingly popular monetization options for app developers. According to Koekkoek (2011), half of the revenue of the top 200 grossing apps in the Apple App Store for iPhone is generated from in-app purchases. This proportion is even higher in Google Play, where 65% of the revenue from the top-grossing apps is generated by in-app purchases.

The IAP provides additional features beyond the basic functionalities of an app. Thus, providing IAPs directly increases the demand of an app beyond its indirect effect on app demand due to price decrease on the supply side. In a similar vein, the IADV is likely to cause annoyance and hence decrease app demand. Here we conduct counterfactual experiments to distinguish the direct effect of the IAP on app sales from the indirect effect of the IAP due to price decrease. We repeat the same counterfactual experiments for the IADV as well. In our simulation setup, we allow for the IAP (or the IADV) in apps that previously did not offer such options and examined subsequent changes in demand. We repeated this experiment for each app without the IAP (or the IADV) in our sample and then calculated the percentage changes in market shares for that app before and after the IAP (or the IADV).

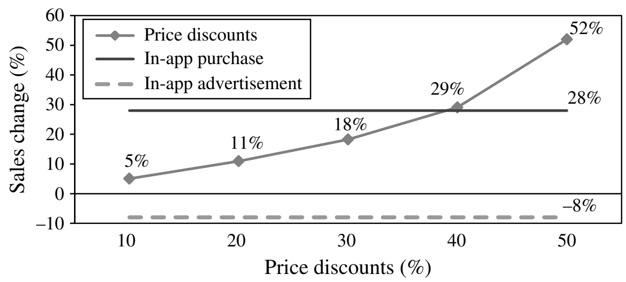
Figure 3 demonstrates the direct effects of the IAP and the IADV on app demand. Our findings suggest

**Figure 3** Direct Effects of In-App Purchases and In-App Advertisement on App Demand




| | In-app purchase | In-app advertisement |
|---|---|---|
| Direct effect | 17% | −4% |

**Figure 4** Economic Impacts of Direct Effects of In-App Purchase and In-App Advertisement Options




that the direct effect of the IAP results in an increase in app demand by 17% due to additional functionalities beyond its indirect effect due to price decrease. In the case of the IADV, we find that the direct effect of advertising annoyance causes a decrease in app demand by 4%, as one would expect besides its indirect effect due to an increase in revenues from in-app advertisement. Since we do not observe any revenue data from in-app purchases and in-app advertisement, we computed the equivalent amounts of price discount to the direct effects of in-app purchase and in-app advertisement options, respectively. Figure 4 shows that, on average, the direct effect on the increase in market share from having an in-app purchase option is equivalent to offering a 28% price discount. In other words, offering additional features in apps leads to the same increase in revenues as lowering app prices by 28%. Similarly, an in-app advertisement leads to the same decrease in revenues as raising app prices by 8%.

**5.3.2. Counterfactual Experiment II: Effects of Price Discount, Price Elasticity Comparison Across App Stores, and Optimal Discount Amount.** Besides in-app purchase and in-app advertisement options, app developers can earn more revenues through significant price discounts. Spriensma (2012) reported that when apps are on sale, the average revenue rose by 41% in Apple iPhone App Store when looking at those apps that were among the top 100 ranked apps. Moreover, the revenue during the whole sales period increased by 22%. In Google Play, on the first day of price reduction, the revenue increased by 7%, and during the whole sale period increased by 29%.

To examine how price reduction for paid apps will affect app demand, we conducted the following counterfactual experiments. We assumed price reductions of 10%, 20%, 30%, 40%, and 50%, and examined subsequent respective demand changes. We repeated this experiment for each app, one at a time, in our sample and calculated the percentage changes in market shares for that app before and after the price reduction. Our findings show that, overall, a decrease in price has a greater impact on app demand in Google Play than Apple App Store. Figure 5 demonstrates a comparison

**Figure 5** Effects of Pricing Strategies on App Demand

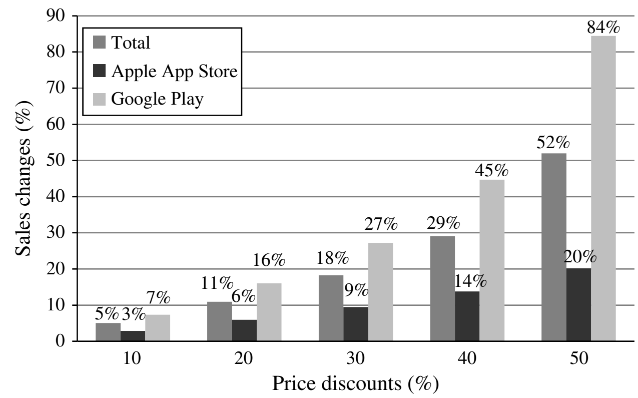
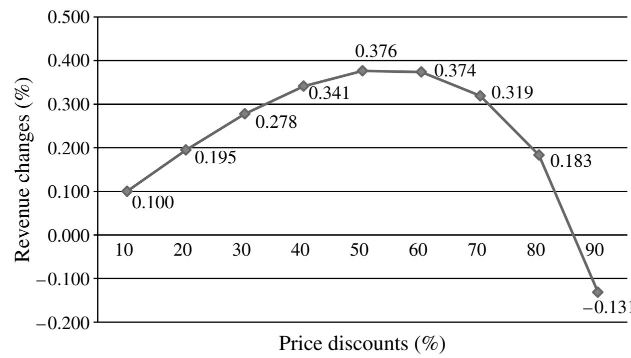



**Figure 6** Optimal Price Discount to Maximize App Sales Revenues




of the effects of different pricing strategies on app demand across Apple App Store and Google Play. For example, a 50% price discount results in a 20% increase in app demand in Apple App Store compared with an 84% increase in Google Play.[11] This result may reflect the fact that Google Play users are intrinsically more price sensitive than Apple users. This finding is very consistent with numerous trade press reports that Apple device users are less price sensitive than device users on other platforms such as Android and Windows.

We conducted additional counterfactual experiments to search for the optimal price discounts in terms of maximizing app sales revenues. Notice that we have computed the revenue change by comparing app sales revenues before and after lowering the price. Figure 6 shows that app developers can maximize their revenue by providing a 50% discount on their paid apps.

**5.3.3. Counterfactual Experiment III: Substitution Patterns Across App Categories.** Last, we looked into how price changes in one app category will affect the demand for other app categories. Table 4 shows

[11] We also examined the price discount effect for apps with the same price in both app stores. Our findings continue to show that a decrease in price has a greater impact on increase in app demand in Google Play than Apple App Store.

**Table 4 Substitution Patterns Across App Categories**

| | Games (%) | Entertainment (%) | Social (%) | Multimedia (%) | Utilities (%) | Education (%) | Lifestyle (%) |
|---|---|---|---|---|---|---|---|
| Games | 28 | −4 | −1 | −3 | −2 | −2 | −1 |
| Entertainment | −2 | 21 | −1 | −1 | −2 | −3 | −1 |
| Social | −4 | −6 | 11 | −7 | −5 | −5 | −4 |
| Multimedia | −2 | 2 | −1 | 22 | −2 | −1 | −2 |
| Utilities | −2 | −1 | −1 | −3 | 25 | −2 | −1 |
| Education | −1 | −3 | −1 | −1 | −4 | 24 | −3 |
| Lifestyle | −2 | −1 | −3 | −2 | −2 | −1 | 24 |

changes in the column app categories' market shares with respect to a 30% price cut in the row app categories. We performed this experiment one at a time for each app in a given app category, and then calculated the average percentage changes in market shares at the category level. For example, when we lowered the price by 30% for a social networking app, we found that the demand for the social networking app category increased 11%, whereas the demand for multimedia apps dropped 7%, implying the social networking apps and the multimedia apps acts as substitutes for each other. We also conducted similar analyses for apps from other categories. Our findings suggest that social apps in general substitute to other apps. In particular, the substitution effects between social apps and multimedia apps are strong.

From the above set of counterfactual experiments, the basic findings are as follows: (i) the in-app purchase option and in-app advertisement bring economic benefits equivalent to offering a 45% price discount and 13% price discount, respectively; (ii) price discount strategy is more appropriate for apps in Google Play to increase app demand, and the optimal price discount is 50% discount; and (iii) social apps in general substitute to other apps.

### 5.4. Welfare Estimation

Previous studies have shown that product variety increases consumer welfare (Brynjolfsson et al. 2003, Ghose et al. 2006). Also, competition lowers product prices (e.g., Brynjolfsson and Smith 2000), which also increases the 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 setting 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 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 $\varepsilon_{ij}$, and then the customer welfare in the random-coefficients nested logit model is calculated as

$$CW_t = \sum_{i=1}^{ns} \frac{\ln(1+\sum_{g=1}^{G}\exp(I_{ig}))}{\alpha_i}, \qquad (12)$$

where $I_{ig}$ is a group-specific inclusive value at the top level as defined in Equation (5), $ns$ 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 $\alpha_i$ (i.e., marginal utility of income) to measure monetary changes.

We next calculate the consumer surplus for mobile users in the United States. There were 224 million active mobile app users in the United States as of February 2013 (Gordon 2013), allowing over 70% of the population to surf the Web and download mobile apps. Using the estimated demand function and inferred sales quantity of apps, we find that the availability of top-ranked apps in both Apple and Google platforms enhanced consumer surplus in the United States by approximately \$11.3 billion 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 compared to not downloading apps at all. Given that people can download Web apps (instead of mobile apps) into their desktops or 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 approximately 4,800 Web apps from various app stores. Keeping this in mind, the adjusted consumer surplus is approximately \$11.2 billion over the time period of our study, which translates into \$33.6 billion annually in this market.[12]

[12] The adjusted consumer surplus during our four-month sampling period is derived by multiplying the unadjusted consumer surplus, \$11.3 billion, by the number of active mobile apps, 400,000, and then

## 6. Managerial Implications and Conclusions

A fundamental innovation brought forth by the advent of the mobile Internet has been the widespread adoption of mobile apps. 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 vibrant mobile ecosystem. Apps are transitioning from being a tool to being a medium that people express themselves through. As consumers increasingly use mobile devices, it becomes 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.

We show that demand increases with the app description length, number of screenshots, in-app purchase option, app age, version age, number of apps by the same developer, number of previous versions, cross-chart listing, cross-platform listing, and volume and valence of user reviews. On the contrary, app demand decreases with file size and in-app advertisement option. Older and male consumers tend to be less sensitive to the price of apps than younger and female consumers, respectively. On the supply side we show that app file size is a major cost driver in app development, but that there are significant returns to scale in app development. Cost decreases with in-app purchase, in-app advertisement, app age, and age restrictions. Compared with lifestyle apps, games, social, and utility apps have higher marginal costs, whereas media apps have lower marginal costs.

We show that app developers tend to lower their upfront app prices when they provide an in-app purchase option within their apps. This finding is consistent with a recent report (Cutler 2012) that shows when consumers spend on paid apps, they are less likely to spend inside an app because paid apps serve as an economic substitute for in-app purchases. With regard to in-app advertisement, although it adversely affects app demand, we found that it is worth adding in-app advertisement because advertisement revenues can be larger than the loss from consumer avoidance of ad-loaded apps.

When a developer offers a price discount on an app with an in-app purchase option, there is a delicate balance that has to be achieved. On the one hand, the sale price has to be low enough to trigger enough downloads to make up for the lost revenue. On the other hand, future purchases from within the downloaded app should be high enough to make up for the lost revenue from offering the price discount in the first place. We show that app developers can maximize their revenue from paid app sales by offering a 50% price discount. Thus, this finding provides a good benchmark for app developers as they grapple with the conundrum regarding how much discount to offer on the sale price of an app. We presented follow-up analyses on pricing strategies and showed that a price discount results in a greater increase of app demand in Google Play compared with Apple App Store. We found social apps act as a substitute for many other apps, and, in particular, the substitution effects between social apps and multimedia apps are strong. In addition, we showed that the availability of mobile apps enhanced consumer surplus by approximately \$33.6 billion in the United States on an annual basis.

Data availability issues suggest that some caution is warranted in the demand and welfare estimation. For example, some consumers may first narrow down the entire set of apps to a smaller set and then make a decision from the consideration set. We do not have user-level app purchase data and therefore are unable to model this issue accordingly. Moreover, including the consideration stage into a random utility framework is not trivial because the consideration sets are neither observed nor identifiable with certainty (Ben-Akiva and Boccora 1995). Thus, we cannot separately empirically identify a consideration set and user demand for apps because of limitations in our data. Future work may consider using a model of the underlying consideration formation and structurally estimate demand with data on individual-level user browsing patterns.

Our app-level data cannot distinguish whether multiple downloads of an app originate from a single user through multiple mobile devices (i.e., a smartphone and a tablet) or whether they are from multiple users. Future research can consider a multivariate probit model (Manchanda et al. 1999) to model possible interdependency across apps when an average consumer purchases multiple apps per day, provided they have data on individual-level data and the number of apps is not too large. We do not observe app usage data. Future research can consider a unified model of the demand for app usage with discrete app purchase choices, provided they have individual-level data on app usage. Furthermore, our data set does not contain price menu information of in-app purchases. Future research may consider examining how app developers set their price menu of in-app purchases and determine the in-app advertisement price, and how they affect consumer demand and cost function equations. Notwithstanding these limitations, to the extent that prices and product characteristics of mobile apps affect market outcomes, the increasing size of the mobile app industry may have profound implications for the future direction of mobile commerce and mobile customer analytics.

dividing this value by the total number of mobile and Web apps, 404,800. Then the annualized, adjusted consumer surplus is derived by dividing the aforementioned adjusted consumer surplus by 4, and then multiply the value by 12.

This paper presents the first formal model of app-level demand estimation that is based on observing users' app downloading behavior. Such analysis is a step toward enabling different kinds of mobile analytics. Mobile analytics is of interest to managers for several reasons, such as optimizing app content and navigation, improving app merchandizing such as placement of ads and product links within apps, and performing customer analytics. Understanding how customers interact with the mobile channel is vital to the success of a brand's mobile strategy.

Mobile analytics provides firms with insights into customer engagement, behavior, and loyalty, revealing the content and media they find most compelling. It can help them track in-app ad responses, searches and purchases with the app, session duration and frequency of usage, and so on. Analyzing which platform (Apple or Android) and device (smart phone, tablet, or PC) are giving them the best performance on the above metrics helps brands figure out how to optimally allocate resources. For example, companies like Flurry and Localytics have analytics packages that let publishers see the devices that users have and the features that their devices incorporate. Having this information helps them infer, for example, whether adding a feature to their app that makes use of a user's microphone should be done over some other feature incorporating the user's camera. Brands have realized that mobile apps offer a viable channel to promote their brand, reach consumers, and sell products. Recent reports from the U.S. 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 into apps. The results from our paper highlighting key determinants of app demand and development costs can help firms understand how to manage marketing in mobile app platforms.

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