Platform Openness Strategy

Yutec Sun*†

October 10, 2013

Abstract

This paper measures the importance of open access in building the customer base of app store platforms in the smartphone market. While iPhone and Android app stores attracted large number of mobile developers, it remains unclear why other competing platforms such as BlackBerry failed to duplicate the success of the app store strategy of the two platforms, despite having larger customer base on the consumer side. Among several reasons, I focus on the app store's openness to the participation of developers and the first mover advantage of the rival platforms. The main findings include that 1) more open access would have allowed BlackBerry's app store to attract greater number of developers than the rivals, 2) the earlier app store launch would have had little impact for both BlackBerry and iPhone, and 3) the open app store would have had significant impact on the platform's profits. These findings suggest evidence for the importance of the open access, relative to the first mover advantage, in the market outcome of the smartphone competition.

JEL Classification: L13, L86

Key words: two-sided platform, openness, app store

*Telecom-ParisTech, Department of Economics and Social Sciences, 46 rue Barrault, 75013 Paris, France.

†This draft is largely derived from the earlier version of my manuscript, *The Value of Branding in Two-Sided Platforms.*

1 Introduction

This paper measures the importance of open access in building the customer base of app store platforms in the smartphone market. In 2008, the smartphone operating system (OS) providers such as iPhone and Android launched an app store that provides a direct sales channel for mobile application developers within their own OS platforms. While the app stores of the two platforms successfully attracted large number of third-party developers, the incumbent platforms dominating the consumer smartphone demand at the time such as BlackBerry and Windows Mobile struggled to achieve as high developer participation as the two pioneering platforms. Despite the important strategic implication of the app store as evidenced in the history, it still remains unclear why the incumbent platforms failed to duplicate the success of the app store strategy of the two platforms.

There exist potentially several determinants for the success of the app store. First is the level of openness in the developer's access to the app store. Although all the app stores charged similar fees for the developer's access, there may have been significant difference in the cost of software development for each platform. For example, BlackBerry has lacked user-friendly software development tools compared to iPhone and Android, which tends to increase development time and costs, limiting the access to only highly profitable developers. Second is the consumer's demand for applications. If the consumers of iPhone and Android have higher valuation of applications, developers will have less incentive to participate in other platforms. Third factor is the timing of the app store launch, since the first mover platforms may have had an advantage in the larger developer bases. And lastly, rapid product innovations are likely to have contributed to the app store success.

This paper examines the U.S. market during 2007–2009 to measure the impact of each of these factors in the developer participation for three platforms: iPhone, Android, and BlackBerry. The smartphone market in this period provides a unique opportunity to observe variation in app store launch timings, in addition to the different growth rates of the developer participation across the three platforms. This paper adopts a structural framework of the consumer demand and the developer supply of applications to estimate the cost difference in the developer access to the app store across the platforms. The paper finds that the development cost was significantly high for the follower platforms including BlackBerry relative to the pioneer platforms.

By comparing market outcomes under counterfactual scenarios, the paper explores whether the fate of BlackBerry's app store could have been reversed by different platform strategies: launching the app store earlier, widening developer access to the app store, or accommodating better product technology. Assessing the importance of each platform strategy will shed light on the fundamental questions of *what makes an app* *store successful* and *how important platform openness and entry timing are to the success of an app store*. As BlackBerry has lost the platform war with iPhone and Android due in large part to the app store's failure, the findings will have important managerial implications for the platforms trying to build an ecosystem of consumers and developers, which applies to many software service providers (e.g., cloud computing services) or embedded operating systems (e.g., smart watches, smart TVs, or Google Glass).

The rest of the paper proceeds as follows. The next section presents some background on the smartphone industry. Section 3 describes the data for the smartphone demand and the application supply, and Section 4 builds a model framework for the consumer, the developer, and the handset providers. Estimation method is described in Section 5, and the estimation results are provided in Section 6. The counterfactual experiments are conducted in Section 7, and the limitations are discussed in Section 8, followed by the conclusion in Section 9.

2 Background

In the beginning of 2007, the smartphone market was dominantly supplied by four incumbent platforms: BlackBerry, Windows Mobile, Palm OS, and Symbian. Apple and Google entered the smartphone market in June 2007 and October 2008, respectively. Their shares of the consumer demand began to grow substantially since the launch of the mobile application stores in 2008. Figure 1 provides the total number of applications developed for each platform in log scale. Most of the applications were supplied to iPhone, Android and BlackBerry while fewer than 1,000 applications were available in the other app stores by the end of 2009.

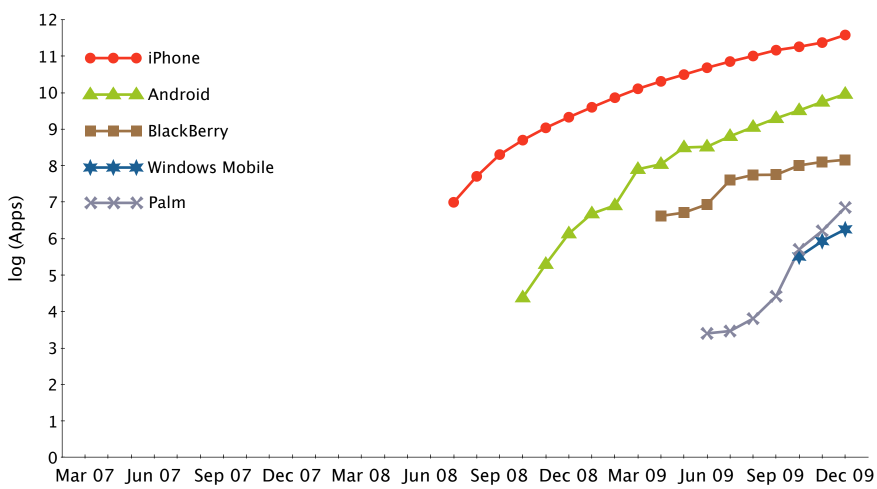

Figure 1: Log of total available applications for each platform

The app stores drastically lowered the cost of mobile software development. Prior to 2008, the primary distribution channels for third-party developers were mobile carrier's portals and on-device preloading through the deals with handset makers or mobile network operators. These channels were unavailable for most small-scale software firms due to the high costs associated with the traditional channels. The app stores dramatically reduced not only the financial costs but also the marketing costs by shortening the time-to-shelf from 68 days to 22 days and the time-to-payment from 82 days to 36 days on average (VisionMobile, 2010, pp.19-20).[1] By lowering the development costs, the app stores became a catalyst for the massive entry of third-party developers; according to a report of a mobile application directory service, there were about 55,000 mobile developers for iPhone and Android as of July 2010 (AppStoreHQ, 2010).[2]

3 Data

The data on smartphone handset demand were obtained from NPD group's monthly survey of smartphone and mobile phone consumers in the U.S. from January 2007 to December 2009. The data contained market shares and average selling prices to consumers at the handset-carrier-month level. Total 171 product models were observed during the 36-month period, yielding 3,045 observations. To represent the U.S. population properly, NPD weighted the survey samples based on a number of demographics including age, gender, region, and income. Total 13 handset makers produced smartphone models for six platforms: iPhone, Android, BlackBerry, Symbian, Windows Mobile, and Palm.[3] Observations for smartphones older than three years since launch were dropped because of the extremely small sales of these models. Furthermore, eight smartphone models with missing CPU speed information were excluded from the data. As a result, the final dataset contained total 2,737 observations for 152 smartphone models.

Platform	Handset-Months	Avg Share (Platform)	Avg Share (Handset)	Avg Price ($)	Avg Apps	Total No. of Handsets
iPhone	87	0.0384	0.0137	276	25,372	7
Android	46	0.0184	0.0064	175	13,156	9
BlackBerry	965	0.0643	0.0024	142	730	28
Windows Mobile	1,108	0.0370	0.0012	154	31	70
Symbian	202	0.0035	0.0006	209	0	27
Palm	329	0.0134	0.0015	179	10	11
Total	2,737					152

Table 1: Descriptive statistics of smartphone handset data

The statistics on the third-party applications were found in reports from various online media.[4] Specifi-

[1]Apple charges $99 a year for application certification and distribution, and Android collects a one-time registration fee of $25. BlackBerry used to charge $200 as a registration fee, and additional $200 for submitting 10 apps to its app store, but it later announced it would waive both fees in 2010.

[2]The number also includes iPad developers.

[3]Maemo and other Linux-based platforms were not included due to the small number of observations.

[4]The sources include the websites tracking the app stores (e.g., 148Apps.biz, AndroLib.com, webOS Nation, and Distimo) and the

cally, these reports provided the monthly number of applications available for iPhone, Android, BlackBerry, Windows Mobile, and Palm.[5] This resulted in total 52 platform-month observations. Although the count measure does not take into account the quality of individual applications, there exists some evidence of the heterogeneity in the consumer preference for the mobile applications. The top five categories of applications ranked by total downloads were games, books, entertainment, education, and lifestyle in iTunes App Store, which accounted for over 50% of the total downloads in May 2011 (Malik, 2011). Since consumers tend to have widely varying personal tastes in these categories, large variety would be desirable as in other software markets such as video game software and online music stores. Hence, the total number of applications is considered as a reasonable approximation of the overall value of the available applications.[6]

The dataset was supplemented with handset characteristics, consumer price index, and market size information. The information on the handset characteristics was collected from pdadb.net, phonescoop.com, gsmarena.com, and manufacturers' websites. The consumer price index was used to deflate the price to the level of January 2007. Market size information was obtained from the Semi-Annual Wireless Industry Survey by Cellular Telecommunications Internet Association (CTIA). It reports the estimate of total U.S. mobile subscribers biannually, which was used as total market size in the analysis.

4 A Model of Two-Sided Platforms

This section describes the equilibrium framework of consumer demand, application supply, and smartphone pricing. Given this framework, a reduced-form model will be derived so that key model parameters can be estimated using the aggregate-level data on smartphone demand and application supply. I assume that in each time period, the game of smartphone pricing and app development/pricing is played in the following sequence:

1. Smartphone firms set prices under Bertrand competition.

2. App developers make a decision on developing software for smartphone OS platforms.

3. App developers set prices under monopolistic competition.

4. Consumers receive utility from their choice of a smartphone or an outside option; smartphone firms receive profits; app developers earn zero profit.

technology news media (e.g., PC World, Bloomberg, and Wired).

[5] Symbian's application store was excluded because the app store did not launch in the U.S. until the last period of the data.

[6] AppStoreHQ's report also suggests that a wide variety of apps were consumed by the smartphone users. It found that among the total 246,000 app installations for 5,000 randomly sampled Android users, there were 20,100 different applications (AppStoreHQ, 2011).

The smartphone vendors observe all the factors determining the developers' decisions and set the smartphone prices that maximize their own profits given the competitors' prices and the developers' best responses. The developers are assumed to incur fixed costs for software development in each period and earn zero economic profit in equilibrium under free entry.[7] The developers choose the price of apps that maximizes their own profits under monopolistic competition given the total number of users in each platform.

4.1 Consumer Demand of Smartphones

In each time period indexed by t, each consumer chooses a product j among $J_t + 1$ alternatives, where j indexes a smartphone if $1 \leq j \leq J_t$ and a traditional mobile phone if $j = 0$. The consumer is a subscriber of mobile phone service who owns either a traditional mobile phone or a smartphone. The consumer considers only the presently available smartphones and their applications when making a purchase decision, not taking into account future change in smartphone offerings and application supply.

Let U_{ijt} represent consumer i's utility of smartphone handset j at time t, and let g_j denote the OS of smartphone j. Then U_{ijt} is specified as

$$U_{ijt} = \beta_{g_j} + \vec{x}'_{jt}\theta_i + U^{SW}_{ijt} + \xi_{jt} + \epsilon_{ijt}, \tag{1}$$

where β_{g_j} represents consumer-perceived brand equity of platform g_j, $\vec{x}_{jt}$ is the vector of product characteristics of handset j at time t, ξ_{jt} is handset j's time-varying product quality unobserved to the econometrician at time t, and ϵ_{ijt} is consumer i's idiosyncratic taste for handset j at time t, which is assumed to follow an extreme value distribution. U^{SW}_{ijt} is the direct utility of third-party software applications available for handset j in platform g_j. θ_i is a vector of random coefficients following a normal distribution, which allows the researcher to account for the consumer's unobserved heterogeneous tastes for $\vec{x}_{jt}$. Combining the random coefficients with extreme-value distributed ϵ_{ijt} leads to a random coefficients logit specification.

I specify the application utility U^{SW}_{ijt} by adopting the representative consumer approach following the previous literature (Chou and Shy, 1990; Church and Gandal, 1992, 1993; Nair et al., 2004). Specifically, I use a constant elasticity of substitution (CES) utility function as

$$U^{SW}_{ijt}(x_{1gt}, ..., x_{N_{gt}gt}, z_{it}) = \left(\sum_{k=1}^{N_{gt}} \left(x_{kgt}\right)^a \right)^b + z_{it}, \quad a \in (0,1], b \in (0,1), \tag{2}$$

[7] Clements and Ohashi (2005), Nair et al. (2004), and Dubé et al. (2010) used similar assumptions on the software market to derive a reduced-form model of application supply.

where g is the index of the platform of smartphone j, N_{gt} is the cumulative number of applications available on platform g at time t, x_{kgt} is the demand for software k on platform g at time t, and z_{it} is a numéraire capturing the value of non-software purchases. This is the utility that representative consumer i would receive from consuming the variety of apps, $(x_{1gt}, ..., x_{N_{gt}gt})$. The aggregate demand obtained by this CES utility of the representative consumer is equivalent to the one generated by a discrete choice model of individual consumers (Anderson et al., 1992, Proposition 3.8).

The representative consumer consumes $\{x_{kgt}\}_{k=1}^{N_{gt}}$ that maximizes the CES utility under a budget constraint. Hence, equilibrium application demand $\{x^*_{kgt}\}_{k=1}^{N_{gt}}$ maximizes

$$\max_{\{x_{kgt}\}_{k=1}^{N_{gt}}} U_{ijt}^{SW}(x_{1gt}, ..., x_{N_{gt}gt}, z_{it}) \quad \text{s.t.} \quad \sum_{k=1}^{N_{gt}} \rho_{kt} x_{kgt} + z_{it} = y_i - p_{jt},$$

where ρ_{kt} is the price of application k, y_i is the income of consumer i, and p_{jt} is the price of smartphone j at time t. Then by the equilibrium assumption between application demand and supply, the indirect utility of apps is derived as $V_{ijt}^{SW} = y_i - p_{jt} + N_{gt}^{\gamma}$, where $\gamma \in (0, 1)$.[8] Instead of N_{gt}^{γ}, I use a log specification in order to incorporate heterogeneity in the consumer preference for the applications.[9]

After combining all the utility components and normalizing with respect to the income and the logit error scale, I obtain the indirect utility of smartphone j on platform g_j as

$$V_{ijt} = \beta_{g_j} + \vec{x}'_{jt}\theta_i - \alpha p_{jt} + \big[\gamma \log(N_{g_j,t}) - \sigma\big] I_{jt} + \xi_{jt} + \epsilon_{ijt}, \tag{3}$$

where $I_{jt} = 1$ if an app store is installed in handset j at time t and zero otherwise, and σ is a parameter that modulates the curvature of the log function of $N_{g_j,t}$. The indirect utility of the outside option is $V_{i0t} = \epsilon_{i0t}$.

4.2 Application Supply

In each period, the developers first decide whether to develop applications for each platform. Once they choose to develop for a given platform, they set the price of each application under monopolistic competition, taking as given the total number of users in each platform. Let Π_{kgt}^{SW} be the developer's profit from application k on platform g at time t. Then ρ^*_{kt} is the equilibrium price of application k at time t that maximizes the

[8]For details on derivation, refer to Nair et al. (2004).

[9]The power function specification yielded similar estimation results but with poor model fit relative to the log specification estimated in Section 7. The full estimation result is available in the online appendix.

following profit function:

$$\Pi_{kgt}^{SW} = \left(\rho_{kt} - c^{SW}\right) B_{gt} x_{kgt}^{*} - FC_{gt},$$

where ρ_{kt} is the price of application k at time t, c^{SW} is marginal cost,[10] B_{gt} is the user installed base (i.e., the total current owners) of platform g at time t, x_{kgt}^{*} is the equilibrium demand for application k on platform g at time t, and FC_{gt} is the developer's fixed cost for providing an application which varies across platform-months. The fixed cost is decomposed as $FC_{gt} = e^{F_g \zeta_t \eta_{gt}}$, where the platform-specific fixed cost F_g includes financial and procedural costs that the developer incurs when developing and marketing applications on platform g. Hence F_g captures the degree of platform g's openness to the developer's participation. ζ_t and η_{gt} are common and platform-specific costs that vary over time, respectively.

Given the equilibrium prices ρ_{kt}^{*} and the free-entry assumption, equilibrium app supply N_{gt}^{*} is determined as[11]

$$\log N_{gt}^{*} = \kappa + \phi \log B_{gt} - F_g - \zeta_t - \eta_{gt}. \tag{4}$$

In this equation, the user installed base B_{gt} is a function of N_{gt}^{*} in equilibrium because the developers take into account the contemporaneous demand for the smartphones on platform g when making a development decision. Hence Equation 4 is an implicit function of the equilibrium app supply N_{gt}^{*}.

4.3 User Installed Base

To complete the specification of the application supply model, the installed base B_{gt} in Equation 4 needs to be defined since the data on the installed bases are unavailable to the researcher. Let M_t be the size of total mobile subscribers. To account for the replacement handset demand, I assume a homogeneous replacement cycle of $T = 24$ months.[12] Then the timing of smartphone replacement can be assumed to follow an exponential distribution with mean 1/24. By the memoryless property of the exponential distribution, the replacement rate is constant over time, and its value is $r \equiv P(T \leq 1) = 1 - e^{-1/24} \approx 0.04$. Then platform

[10] The marginal cost of application development is assumed to be homogeneous for lack of individual-level data on the developers, which greatly simplifies the equilibrium price ρ_k^{*} and thus the equilibrium app demand x_{kgt}^{*} as well. The simplifying assumption is considered to be a reasonable approximation because the biggest source of the marginal cost was the royalty paid to the platforms, which was homogeneous across the platforms.

[11] Details on the derivation are provided in Nair et al. (2004) and Dubé et al. (2010).

[12] The industry estimates the cycle to be between 18-24 months.

g's installed base at time t is

$$B_{gt} = (1-r)B_{gt-1} + rM_t s_{gt}, \tag{5}$$

where s_{gt} is the total market share of all smartphone handsets with OS g at time t.

4.4 Smartphone Supply

I assume that the smartphone handset producers set prices under Bertrand competition, taking into account the subsequent response of the app developers. Hence the smartphone vendors internalize the response of developers in their pricing decision.

To specify the smartphone producer's profit function, suppose the firm produces a single product indexed by j among J alternatives. Let p_j denote the price of handset j, N_g the total number of applications supplied to platform g among G operating systems, and c_j the marginal cost of handset j. $\boldsymbol{N}$ is a G-dimensional vector of app supplies, and $\boldsymbol{p}$ is a J-dimensional vector of prices. Let $D_j(\boldsymbol{p}, \boldsymbol{N})$ be the demand for product j as a function of prices and app supplies.[13] Then the producer of handset j chooses price p_j to maximize a per-period profit specified as

$$\Pi_j(\boldsymbol{p}, \boldsymbol{N}(\boldsymbol{p})) = (p_j - c_j)D_j(p_j, \boldsymbol{p}_{-j}, \boldsymbol{N}(\boldsymbol{p})), \tag{6}$$

given the prices of competing handsets $\boldsymbol{p}_{-j}$.[14] It is worth noting that the app supply itself is a function of prices in equilibrium; therefore, $\boldsymbol{N} = \boldsymbol{N}(\boldsymbol{p})$.

5 Estimating the Model of Two-Sided Platforms

The previous section specified the equilibrium model of two-sided platforms, i.e., the model of smartphone demand and application supply. In this section, I will describe empirical strategies for the key model parameters.

5.1 Identification

There are two main challenges in identifying the parameters of indirect network effects: γ in Equation 3 and ϕ in Equation 4. First, identifying the causal relationship can be difficult due to simultaneity between smartphone demand and application supply, which is likely to cause endogeneity bias. To control for the

[13] Other product characteristics are omitted deliberately to simplify the notation.
[14] The static pricing assumption is imposed due to the lack of data on smartphone marginal costs.

endogeneity of the application demand in Equation 3, I instrument for the number of apps, $\log N_{gt}$, with the average product attributes in own and rival platforms that are expected to be correlated with app supply through handset sales. The instruments are i) the average number of bluetooth-enabled devices in own platform, ii) the average number of app-enabled devices and average camera pixels in rival platforms, and iii) the log of average memory size in own platform interacted with a time trend and an app store dummy. I assume that these instruments are uncorrelated with unobserved product quality ξ_{jt} following Berry (1994) and Berry et al. (1995). As instruments for user installed base B_{gt} in the app supply model (Equation 4), I use the age of the latest OS versions and its quadratic term for each platform. This is because the maturity of OS is likely to be positively correlated with user installed bases but uncorrelated with unobserved app development costs, ζ_t and η_{gt}. However, if development costs have been declining in the mobile software industry, they might be negatively correlated with these instruments. I address this issue by including a time trend in the app supply model to control for the unobserved costs that are potentially serially correlated.

The second identification issue arises because correlated unobservables may cause a potential correlation between smartphone demand and application supply. Without addressing this issue, I may spuriously find indirect network effects between smartphone demand and application supply (Gowrisankaran et al., 2011). The unobservables potentially causing this spurious correlation problem include i) the increase in the unobserved product quality (ξ_{jt}) in the smartphone demand (Equation 3) and ii) the decline in unobserved app development costs (ζ_t and η_{gt}) in the app supply (Equation 4). However, the first drivers of the spurious correlation are unlikely to cause an identification problem for the smartphone demand model. The parameters of indirect network effects are identified because the applications have a universal impact on smartphone demand while the scope of the change in the unobserved quality is limited to a single product. Likewise, platform-specific cost changes are also unlikely to cause the identification problem because the developer's response to the size of user installed bases is universal across all the platforms in the app supply model.

Nevertheless, the estimation strategy may still have a risk of spurious correlation if there is a universal change in either unobserved smartphone qualities or unobserved app development costs across all products and platforms. To address this concern, I include a time trend both in the smartphone demand and the app supply models. Yet a change in a platform's brand equity may contribute to the spurious correlation bias to a certain extent if the improvement of the brand equity is highly correlated with the growth of its app supply. Hence, I include fixed effects for OS revisions to account for the improvement of platform brand equities.

The price coefficient in the demand model may be biased if potential price endogeneity is ignored. I use the instruments proposed by Berry et al. (1995), which include the sum of handset ages and the total number of app-enabled devices for a given firm. I also include a cost-related instrument, which is an indicator variable for whether each smartphone is sold via a corresponding mobile carrier's distribution channel. This is a proxy for mobile network carrier's subsidy, which is unobserved to the researcher.

Finally, the price coefficient may be biased if consumers' forward-looking behavior is ignored.[15] To account for the consumer dynamics, I adopt a simple reduced-form approach rather than developing a fully structural model.[16] Specifically I use handset age (the number of months elapsed since launch) as a proxy variable to capture the option value of waiting for future products.[17] Approximating the future utility component with a simple reduced-form function has been proposed in the previous literature.[18] Though it is not perfect, Lou et al. (2011) found that this simple approach reduced the bias in the static demand model.

5.2 Estimation Method

I estimate the smartphone demand and the app supply models separately following Nair et al. (2004) and Song (2011). I estimate the smartphone demand using Berry et al. (1995)'s instrumental variables method based on the generalized method of moments (GMM) approach. The variables in the demand model include platform fixed effects, hardware attributes including price, fixed effects for network carriers and OS revisions, a time trend, and the age of handsets since launch.[19] The unobserved time-varying quality ξ_{jt} is assumed to be mean independent of these characteristics, such that GMM moment condition can be constructed as $G(\theta_0) = \mathrm{E}[\boldsymbol{Z}_{jt}\xi_{jt}] = \mathbf{0}$, where $\boldsymbol{Z}_{jt}$ is the vector of price and application instruments for handset j at time t, and θ_0 is the vector of true model parameters.

I obtain the GMM estimator by minimizing the objective function $g(\theta)'Wg(\theta)$, where $g(\theta)$ is the sample analog of $G(\theta)$, and W is an optimal GMM weight matrix. The estimation is done in a nested procedure. In the inner loop, the estimate of $\xi = \{\xi_{jt}\}_{j,t}$ is obtained for a given θ by matching each product's market share predicted at given parameter values with the observed share. The outer loop algorithm searches over θ that minimizes the objective function evaluated in the inner loop.[20] I use 200 Halton draws for Monte Carlo integration to compute the predicted market shares. For the weight matrix W, I use the heteroscedasticity

[15] The assumption of static consumer demand may be violated for two reasons. First, the consumer's dynamic purchase behavior may arise from the durable-good nature of smartphones and rapid technological innovations. Second, potential smartphone buyers are likely to compare the trade-off between purchasing a currently available product in the present and waiting for lowered price or improved quality that will become available in the future.

[16] Full-structural modeling approach would require information on ownership changes across all platforms over time. Without this information, identification will have to rely on strong assumptions on the replacement behavior.

[17] While more accurate proxy for the option value would also involve each age of all available handsets, including them all would be infeasible due to the large number of handsets. Hence I assume that the the age of a firm's own handset is a reasonable first-order approximation to the option value of waiting.

[18] See Geweke and Keane (2000), Carranza (2010), Lou et al. (2011), and Ching et al. (2011).

[19] Fixed effects for smartphone hardware manufacturers were estimated insignificant and thus are not reported in the paper.

[20] The convergence threshold for the inner and the outer loops are 10^{-13} and 10^{-8}, respectively.

and autocorrelation robust covariance estimator of Newey and West (1987).

6 Estimation Results

6.1 Consumer Demand

Table 2 presents the estimation results of the smartphone demand model in Equation 3. The first column (Logit) and the second column (Logit-IV) estimate the same simple logit model using ordinary least squares and instrumental variables regressions, respectively. From the second column to the last, I control for the endogeneity of prices and log(apps) using the same set of instruments throughout the columns.[21] Prices are normalized by Consumer Price Index to the hundreds of dollars in January 2007. In the third and the fourth columns (RCL I–II), I estimate random coefficients logit models instrumenting for prices and log(apps). Column RCL II includes fixed effects for major OS revisions. The coefficient estimates for all remaining product attributes are omitted from the table but are available in the appendix.

The first two columns, Logit and Logit-IV, yield different coefficient estimates for price and log(apps). Both coefficients become smaller as the potential endogeneity is controlled for in the Logit-IV column. This result is consistent with the concern that prices and apps may be positively correlated with unobserved product quality. On the other hand, the coefficient estimate for app store dummy (σ) indicates that having excessively small collection of apps may hurt smartphone sales.

	Logit		Logit-IV		RCL I		RCL II	
Observations = 2,737	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Price / CPI ($100)	-0.0005***	0.0001	-0.0046***	0.0006	-1.4441***	0.3508	-1.4105***	0.3554
log(Apps)	0.0016***	0.0002	0.0012***	0.0003	0.5712**	0.2221	0.4472**	0.2248
Appstore enabled (σ)	0.0100***	0.0012	0.0068***	0.0022	6.4193***	2.3050	5.7081**	2.2676
Standard Deviation of Random Coefficients								
Touchscreen					3.3643***	0.8504	4.0574***	0.8855
Appstore enabled					4.3522***	1.0446	4.5568***	1.0440
OS version F.E.	No		No		No		Yes	
R^2	0.5861		0.2527					
F	174.7265		96.9013					
$n\chi^2$			54.906		4.267		4.780	
p-value			<0.001		0.234		0.188	

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.
Utility for traditional mobile phones is normalized to zero up to logit error.

Table 2: Estimation of logit models of smartphone handset demand

Columns RCL I–II include random coefficients for two product attributes: touchscreen and app store

[21] For this reason, Column Logit-IV may have rejected the test of overidentifying restrictions.

dummy. I exclude the random coefficient for price because its estimate was negligible and insignificant.[22] Column RCL II adds fixed effects for two major OS revisions, iPhone OS 3.0 and Symbian 9, in order to address the spurious correlation problem driven by unobserved OS quality improvements. The inclusion of the OS revision fixed effects slightly reduces the coefficient of log(apps) from 0.571 to 0.447 in the RCL II column although it remains significant. The decrease in the log(apps) coefficient implies that if the model fails to account for the OS quality improvements, it would attribute their effects on smartphone demand to the consumer's valuation of apps, leading to the overestimation of the log(apps) coefficient.[23]

6.2 Application Supply

Table 3 reports the estimation results for the application supply model in Equation 4. The development cost for iPhone is normalized to zero. The first and the second columns estimate the app supply model by ordinary least squares (OLS I–II), and the third column (IV) uses instrumental variables regression to control for the endogeneity in log(installed base).

	OLS I		OLS II		IV	
Dep. Var: log(apps)	Parameter	Std. Error	Parameter	Std. Error	Parameter	Std. Error
log(Installed Base)	1.506***	0.341	1.224***	0.068	1.330***	0.103
Month	0.130***	0.033	0.161***	0.014	0.153***	0.018
Constant	-16.899***	4.459	-13.382***	1.005	-14.690***	1.274
log(Fixed Cost of App Development)						
Android	0.610	0.726				
BlackBerry	4.464***	0.224	4.343***	0.142	4.505***	0.198
Windows Mobile	5.213***	0.236	5.421***	0.154	5.469***	0.172
Palm	2.413**	1.004	3.234***	0.287	3.045***	0.320
Observations	52		52		52	
Instruments	No		No		Yes	
Overid test (p-value)	–		–		0.574	
R^2	0.972		0.971		0.969	
F	326.79		363.58		249.89	

***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.
iPhone's development cost is normalized to zero.

Table 3: Estimation of application supply model

In the OLS I column, the estimates for the log fixed costs of application development are high for Windows Mobile and BlackBerry, low for Android, and moderate for Palm. While Android has only slightly higher fixed cost than iPhone, the difference is insignificant. The positive and significant coefficient estimate of log(installed base) confirms the developers' positive valuation of the size of user installed bases. The strongly positive coefficient of the time trend, *Month*, is consistent with the conjecture that application development costs may have been in decline in the industry as the time trend variable captures the negative time-varying

[22]Estimation results with the random coefficient for price are available in the online appendix.
[23]Further inclusion of fixed effects for other OSs yielded a poor model fit with nonsignificant estimates.

costs of application development.

In OLS II, dropping Android's fixed cost improves the precision of the installed base coefficient estimate considerably (from 0.341 to 0.068) while it slightly reduces the log(installed base) coefficient. Without Android's fixed cost, all the parameters become significant at 1% level, but the fixed costs for other platforms are similar to those in the OLS I column.

The IV regression in the IV column yields fixed cost estimates similar to those obtained in the OLS II column. However, I obtain a slightly higher coefficient estimate for log(installed base) than the one in the OLS II column. This result is counterintuitive because the coefficient would be overestimated under potential endogeneity. One possible explanation is that as the observed factors explain most of the variation in the application supply as seen in the high R^2, the potential omitted-variable bias may not be as significant as in the smartphone demand estimation. Nonetheless, the IV regression yields similar fixed cost estimates as obtained in the OLS II column and does not reject the test of overidentifying restrictions at 10% level.

The estimation of the application supply model finds that iPhone and Android were the most open to developer participation while BlackBerry and Windows Mobile were the least accessible platforms. Palm was relatively favorable to developer participation although not as much as the two leading platforms.

7 Counterfactual Experiments

Once the parameters in the model of two-sided platforms are estimated, the next step is to compute the marginal cost c_j in the smartphone producer's profit function (Equation 6). I apply the approach of Nevo (2001) to the setting of two-sided platforms by accounting for the simultaneity between smartphone prices and application supplies.

Then, given the estimates of the demand and the supply model parameters and the marginal costs, I solve for equilibrium prices and application supplies under counterfactual app supply fixed costs and timing of app store launch. Because the equilibrium price-application pair can only be expressed as implicit functions, I develop a nested fixed point algorithm to solve for the equilibrium prices and application supplies simultaneously. The technical details of computing the marginal costs and the equilibrium solutions are provided in the online appendix.

Figure 2 compares the observed supplies for the BlackBerry app store with two counterfactual results. The first result is obtained by assuming that the BlackBerry app store had the same low development cost as iPhone's, while the second is based on the hypothesis that the BlackBerry app store was launched at the same time as Android. The two counterfactual app supplies display a contrasting result; while the early app store

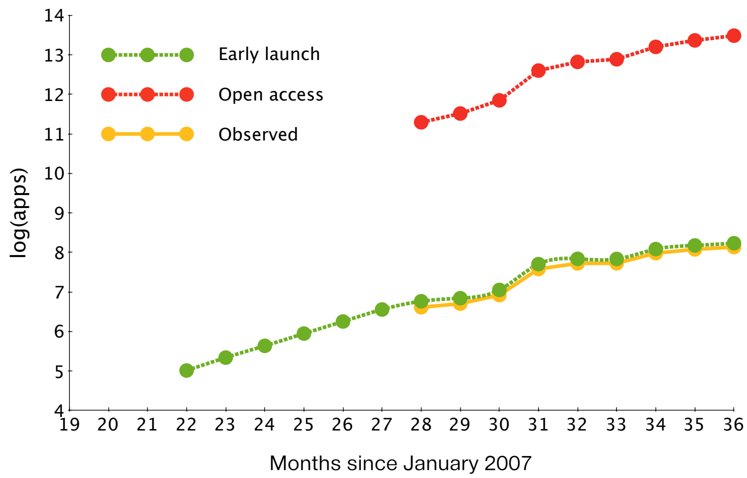

Figure 2: Total supply for BlackBerry's app store

launch has little impact on the original app supply, the reduced development cost leads to a large increase in the app supply. This implies that the increased consumer installed bases by the early app store launch has only limited effect for the developer's incentive to participate as long as there still remains a bottleneck in the developer access to the platform. This result is consistent with the relatively small supply observed in the BlackBerry app store because additional installed bases would have added little to BlackBerry, which was already owning the largest installed base in the consumer side.

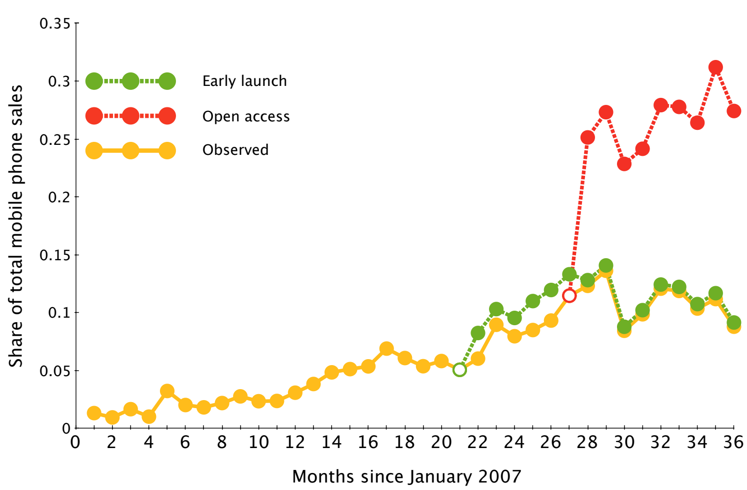

Figure 3: Share of BlackBerry smartphone sales

To measure the demand-side effect of removing the bottleneck in the developer access, Figure 3 compares the shares of the BlackBerry devices in the total mobile phone market. As expected, I find a similar pattern as in the previous figure. The early app store launch has a short-lived effect on the handset sales while the sales jumps dramatically with the open app store once the app store becomes available. This suggests that the open access can have a significant economic impact on the consumer demand due to the positive indirect network effects from the large supply of applications.

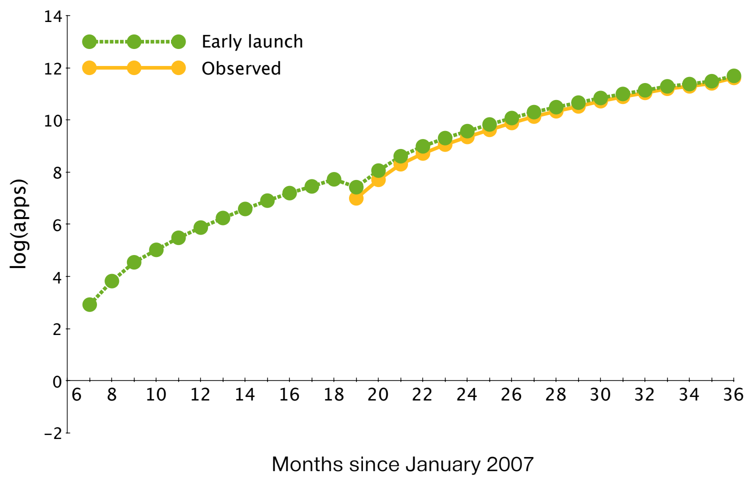

Figure 4: Total supply for iPhone's app store

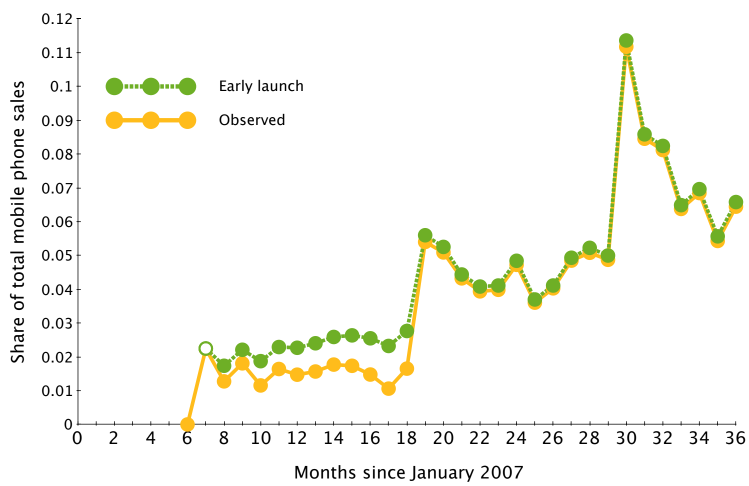

Figure 5: Share of iPhone smartphone sales

To further test the effect of the pioneering advantage, I consider how the app supply would have changed when the iPhone app store was launched at the time of market entry. This gives the platform a 12-month earlier start than the observed launch date, which may have important implication for the long-term outcome in the platform competition; it is of interest to see whether this strategy would have helped iPhone gain more dominant share in the application and the handset markets while delaying Android in achieving the growth in smartphone demand. Figures 4 and 5 show the app supply and the platform sales share under this

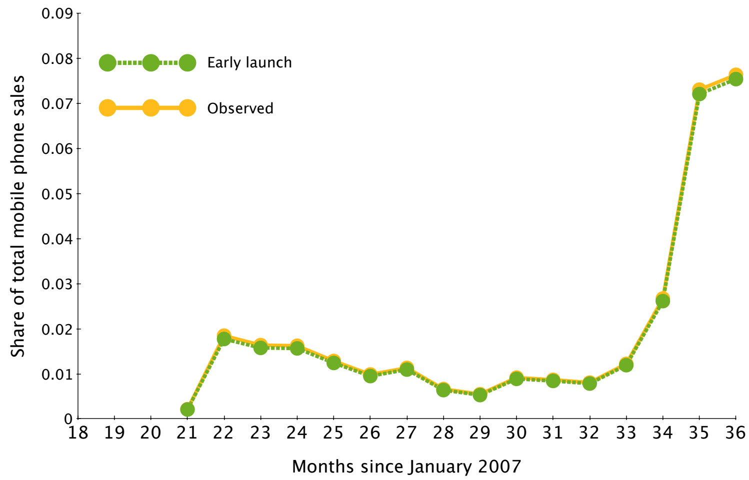

Figure 6: Share of Android smartphone sales

counterfactual scenario as well as the observed ones. The early launch, albeit producing a significant boost in the sales, has little impact on the original supply and demand. Likewise, the early launch is found to have no competitive effect on the sales of the Android platform as shown in Figure 6. From this, we can conclude that the pioneering advantage would have had contributed only to the contemporary demand with little impact on the long-term landscape of the platform competition. This provides an explanation that rationalizes Apple's decision to delay the opening of the app store until it accumulated enough user bases to attract the developers. Hence, at least in the early phase of the platform competition, building a more open ecosystem for the developers appears to have been more effective than providing an app store as early as possible to attract the developers.

8 Discussion

Some of the limitations in this paper can be addressed with richer data. More flexible consumer heterogeneity in the preference for apps can be incorporated in the model if data on consumer demographics or individual-level purchase history are available. Likewise, the simplifying assumptions on the developer's profit function can be relaxed with individual-level data on the developers.

This paper does not take into account the market's expectation about the long-run outcomes of the competition. Forward-looking consumers and developers may join the most popular platform that is expected to attract the largest installed bases in the future. If this is the case, then the effect of the change in BlackBerry's openness may have been underestimated since its earlier entry in the app store market may have indirectly affected the application supply via changed market expectation. Due to the lack of data on the developer market, a stronger assumption would be needed to incorporate the dynamics in the developer's participation model.

9 Conclusion

This paper examines the impact of two main factors on the participation of third-party developers in the application store of the smartphone platforms: a platform's openness to the developer's access and a pioneering advantage. It measures each platform's openness as a fixed cost of software development and finds that there exists wide variance in the openness across the platforms; while iPhone and Android were the most open platforms, BlackBerry and other incumbents had significantly high cost of access for the developers. Based on the estimates of the consumer preference and the platform openness, counterfactual experiments are conducted to understand the contribution of the platform openness and the timing of the app stores to the developer's participation in the platforms. The simulated experiment results show that the platform openness was the key driver in attracting the developers while the pioneering advantage had only limited and transitory effect on the application supply. BlackBerry's application supply would have increased dramatically if it had the same open app store as iPhone and Android. In contrast, an earlier app store launch would have a limited effect on BlackBerry's application supply. Similarly, iPhone's app supply would have remained almost unaffected by the launch of the app store by a full year earlier than observed. Hence, these findings shed light on why iPhone and Android achieved a success in building a two-sided platform and what was lacking in BlackBerry's app store in order to successfully attract the developers.

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A Full Estimation Results of Table 2

	Logit		Logit-IV		RCL I		RCL II		RCL III	
Observations = 2,737	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Price / CPI ($100)	-0.0005***	0.0001	-0.0046***	0.0006	-1.4441***	0.3508	-1.4105***	0.3554	-1.3091***	0.3258
log(Apps)	0.0016***	0.0002	0.0012***	0.0003	0.5712**	0.2221	0.4472**	0.2248	0.3931	0.2472
Appstore enabled (σ)	0.0100***	0.0012	0.0068***	0.0022	6.4193***	2.3050	5.7081**	2.2676	4.9551**	2.5094
Brand Equities										
iPhone	0.0018***	0.0010	0.0123***	0.0021	-6.4259***	1.0473	-7.0806***	1.0845	-6.9478***	1.0662
Android	-0.0098***	0.0011	-0.0058***	0.0018	-8.8064***	0.8023	-8.4591***	0.8353	-8.4195***	0.8249
BlackBerry	0.0020***	0.0005	0.0067***	0.0010	-6.0773***	0.5016	-6.0114***	0.5278	-6.1351***	0.4994
Windows	0.0003	0.0005	0.0045***	0.0010	-6.6524***	0.5333	-6.5931***	0.5589	-6.7356***	0.5195
Symbian	-0.0008	0.0006	0.0060***	0.0013	-6.8822***	0.7036	-7.7181***	0.6174	-7.7898***	0.5562
Palm	0.0005	0.0005	0.0061***	0.0012	-5.8483***	0.6533	-5.8406***	0.6710	-6.0588***	0.6251
Product Attributes Searchable to Consumers										
CPU (GHz)	-0.0009***	0.0001	-0.0005***	0.0002	-0.1214	0.0811	-0.1370*	0.0790	-0.1290	0.0792
Camera megapixel	0.0010***	0.0001	0.0020***	0.0002	0.6189***	0.1140	0.5976***	0.1116	0.5747***	0.1054
Screen size * Resolution	0.0001***	0.0000	0.0004***	0.0001	0.1228***	0.0419	0.1268***	0.0436	0.1376***	0.0442
Memory 500MB	0.0005	0.0006	0.0026***	0.0009	0.4278	0.5499	0.4441	0.5410	0.2848	0.5027
Memory 1GB	0.0016***	0.0006	0.0023***	0.0008	0.5008	0.4108	0.4847	0.4119	0.4755	0.3831
Handset age	-4E-5***	1E-5	-3E-5**	1E-5	-0.0261***	0.0066	-0.0251***	0.0067	-0.029***	0.0072
AT&T	0.0021***	0.0002	0.0008*	0.0004	0.8894***	0.1942	0.9137***	0.1916	0.9658***	0.1764
Verizon	0.0018***	0.0003	0.0004	0.0004	0.5185**	0.2113	0.5442***	0.2084	0.5981***	0.1960
T-Mobile	0.0017***	0.0003	0.0015***	0.0004	1.1267***	0.1766	1.122***	0.1750	1.1671***	0.1647
Sprint	0.0012***	0.0003	0.0014***	0.0004	0.9797***	0.1608	0.9952***	0.1594	0.991***	0.1485
Touchscreen	0.0112***	0.0008	0.0113***	0.0012	-0.2680	0.8464	-0.7352	0.8900	-0.8827	0.9073
Keyboard	0.0011***	0.0002	0.0023***	0.0003	0.6021***	0.1384	0.5827***	0.1385	0.5341***	0.1317
3G data	0.0015***	0.0002	0.0019***	0.0003	0.5712***	0.1321	0.5569***	0.1299	0.5504***	0.1213
Bluetooth 2.0	-0.0005**	0.0003	0.0008*	0.0005	0.5175**	0.2347	0.4619**	0.2276	0.3987*	0.2157
Month	1E-5	1E-5	-0.0003***	3E-5	-0.0748***	0.0216	-0.0743***	0.0225	-0.0651***	0.0215
OS Version Fixed Effects										
iPhone 3.0							1.5949**	0.6352	1.4221**	0.5922
Android 2.0									0.0057	0.7621
BlackBerry 4.2+									-0.0534	0.2044
BlackBerry 5.0									-0.7684*	0.4576
Windows 6.1									-0.2692	0.2556
Windows 6.5									-0.7433	0.6299
Symbian 9							1.0567*	0.6094	0.8589	0.5705
Palm WebOS									0.2984	0.9458
Standard Deviation of Random Coefficients										
Touchscreen					3.3643***	0.8504	4.0574***	0.8855	3.8063***	0.8836
Appstore enabled					4.3522***	1.0446	4.5568***	1.0440	4.1204***	1.1297
R^2	0.5861		0.2527							
F	174.7265		96.9013							
$n\chi^2$			54.906		4.267		4.780		6.893	
p-value			$<$0.001		0.234		0.188		0.075	

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.
Utility for traditional mobile phones is normalized to zero up to logit error.

Table 4: Estimation of logit models of smartphone handset demand

Dependent variable: log(Installed Base)

(N=52)	Coefficient	Std. Error	t	p-value
Age of OS	0.394	0.069	5.67	$<$0.001
(Age of OS)^2	-0.010	0.002	-3.58	0.001
BlackBerry	0.011	0.429	0.03	0.979
Windows	-0.896	0.405	-2.21	0.032
Palm	-0.579	0.222	-2.61	0.012
Month	0.029	0.020	1.46	0.150
Constant	11.675	0.762	15.32	$<$0.001
R^2	0.76			
F	276.91			
p-value (Hansen's test)	0.574			

iPhone's development cost is normalized to zero.

Robust estimate of the standard error is used.

Table 5: First-stage regression results for application supply estimation

A Computation of Marginal Costs

Let g_j be the OS platform of handset $j \in J$, $A_{g_j} = \{k \in J : g_k = g_j\}$ be the set of all handsets in the platform of handset j, and $\bar{A}_{g_j} = \{k \in J : g_k = g_j, N_{g_k} > 0\}$ be the subset of A_{g_j} that contains only the handsets with a positive number of apps. For a firm owning a set of handsets F, the profit function is specified as

$$\pi = \sum_{k \in F} (p_k - c_k) s_k.$$

Then the marginal cost is derived from the FOC:

$$\frac{\partial \pi}{\partial p_j} = s_j + \sum_{k \in F} (p_k - c_k) \frac{ds_k}{dp_j} = 0, \quad \text{where} \quad \frac{ds_k}{dp_j} = \int \frac{\partial s_{ik}}{\partial p_j} + \sum_g \frac{\partial s_{ik}}{\partial \log N_g} \frac{\partial \log N_g}{\partial p_j} F(d\nu_i).$$

Note that

$$\frac{\partial s_{ik}}{\partial \log N_g} = \begin{cases} \gamma s_{ik}(1 - \sum_{l \in A_g} s_{il}) & \text{if } k \in A_g, \\ -\gamma s_{ik} \sum_{l \in A_g} s_{il} & \text{if } k \notin A_g, \end{cases} \quad \text{and} \quad \frac{\partial \log N_g}{\partial p_j} = \frac{\phi \partial \log B_g}{\partial p_j} = \frac{\phi r M}{B_g} \sum_{l \in A_g} \frac{\partial s_l}{\partial p_j}.$$

The second term is obtained from the application supply equation $\log N_g = \kappa + \phi \log B_g - \log F_g$ and the installed base equation $B_{gt} = r M_t \sum_{l \in A_g} s_{lt} + (1 - r) B_{gt-1}$, where $s_{lt} = \int s_{ilt} F(d\nu_i)$.

Define matrices dS/dN and dN/dP such that

$$\left[dS/dN\right]_{k,g} = \gamma \Big(s_k \, 1\{k \in A_g\} - \sum_{l \in A_g} \int s_{ik} s_{il} \Big), \quad \left[dN/dP\right]_{g,j} = \frac{\phi r M}{B_g} \sum_{l \in A_g} \frac{\partial s_l}{\partial p_j}.$$

Then the marginal cost is $c = p + (\Omega_1 + \Omega_2)'^{-1} S$, where S is the vector of market shares, $\Omega_2 = dS/dN \cdot dN/dP$, and

$$[\Omega_1]_{k,g} = \begin{cases} \int \frac{\partial s_{ik}}{\partial p_j} & \text{if } k, g \in F, \\ 0 & \text{otherwise.} \end{cases}$$

B Fixed Point Algorithm for Equilibrium Application Supply

In the outer optimization loop, I obtain the equilibrium prices by finding iteratively the best response of each firm to the prices of rival's handsets. For optimization, I use the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method, which is one of the widely used quasi-Newton methods. At each hill-climbing step of the outer loop, I solve for the equilibrium application supply for all the platforms by finding a fixed point of Equation 4. The following proposition is useful for implementing the fixed point iteration.

Proposition. *Let X be a subset of $\boldsymbol{R}^G$ such that $X_g = (\kappa + \phi \log \underline{B}_g - \log F, \kappa + \phi \log \bar{B}_g - \log F)$ for $g = 1, ..., G$, where $\underline{B}_g$ and $\bar{B}_g$ are the lower and the upper bounds of platform g's installed base B_g, i.e., $\underline{B}_g = 0$ and $\bar{B}_g = M$. Let $T : X \to X$ be a G-dimensional operator with $T = (T_1, ..., T_G)$ such that $T_g(\log \boldsymbol{N}) = \kappa + \phi \log B_g(\log \boldsymbol{N}) - \log F_g$, where $\log \boldsymbol{N} = (\log N_1, ..., \log N_G)$. If $\phi\gamma < 1$, then T has a unique fixed point in X and is a contraction mapping of modulus $\beta < 1$.*

Recall that γ and ϕ are the parameters that capture the indirect network effects on the consumer and the developer sides, respectively. Hence the proposition implies that the sequence of N_g generated by applying the operator T recursively will converge to a unique fixed point, unless the indirect network effects are strong to the extent that a change in application demand or supply is multiplied by the response of the other side of the platform.

Proof. It suffices to show that $\|T_g(\boldsymbol{N}) - T_g(\boldsymbol{N'})\| < \beta\|N_g - N'_g\|$ for $\beta \in (0,1)$. Suppose $N_g \geq N'_g$ for all $g = 1, ..., G$ without loss of generality. Then by definition,

$$\begin{aligned}
\|T_g(\boldsymbol{N}) - T_g(\boldsymbol{N'})\| &= \|\phi \log B_g(\boldsymbol{N}) - \phi \log B_g(\boldsymbol{N'})\| \\
&= \phi \left\| \int_{\boldsymbol{N'}}^{\boldsymbol{N}} \sum_k \frac{\partial}{\partial N_k} \log B_g(\boldsymbol{\nu}) \mathrm{d}\boldsymbol{\nu} \right\| \\
&\leq \phi \int_{\boldsymbol{N'}}^{\boldsymbol{N}} \left\| \sum_k \frac{\partial}{\partial N_k} \log B_g(\boldsymbol{\nu}) \right\| \mathrm{d}\boldsymbol{\nu}.
\end{aligned}$$

Since

$$\begin{aligned}
\frac{\partial}{\partial N_k} \log B_g(\boldsymbol{N}) &= \frac{1}{B_g} \frac{\partial}{\partial N_k} M\Big[rS_g + (1-r)B_{gt-1}\Big] \\
&= \frac{Mr}{B_g} \sum_{j \in A_g} \frac{\partial s_j}{\partial N_k} = \begin{cases} \frac{Mr}{B_g}\gamma \sum_{j \in A_g} s_j (1 - \sum_{l \in A_g} s_l) & k = g \\ -\frac{Mr}{B_g}\gamma \sum_{j \in A_g} s_j \sum_{l \in A_k} s_l & k \neq g \end{cases} \\
&= \begin{cases} Mr\gamma s_g(1-s_g)/B_g & k = g \\ -Mr\gamma s_g s_k / B_g & k \neq g \end{cases},
\end{aligned}$$

$$\begin{aligned}
\sum_k \frac{\partial}{\partial N_k} \log B_g(\boldsymbol{N}) &= \frac{Mr\gamma}{B_g}\Big(s_g(1-s_g) - \sum_{k \neq g} s_g s_k\Big) \\
&= \frac{Mr\gamma}{B_g} s_g \Big(1 - \sum_k s_k\Big) \leq \gamma \frac{rMs_g}{B_g} \leq \gamma.
\end{aligned}$$

Hence,

$$\|T_g(\boldsymbol{N}) - T_g(\boldsymbol{N'})\| \leq \phi\gamma \|\boldsymbol{N} - \boldsymbol{N'}\|,$$

which implies that T_g is a contraction mapping of modulus $\beta < 1$ if $\phi\,\gamma < 1$. Since the operator T maps X to itself, it has a fixed point in X. The uniqueness follows from the fact that T is a contraction mapping with $\beta < 1$. □

C Estimation Results for Alternative Specifications

Table 6 provides estimation results for alternative specifications based on the random coefficients logit model in Table 2. Column I adds the random coefficient for price to the specification of RCL II in Table 2. The standard deviation of the price random coefficient has high standard error, and Column I rejects the test of overidentifying restrictions at 10% level (p-value=0.091). From Column II to Column IV, I allow the coefficient of log(Apps) to vary by the three platforms: BlackBerry, Android, and iPhone. When I include

Observations = 2,737	I Est.	I s.e.	II Est.	II s.e.	III Est.	III s.e.	IV Est.	IV s.e.
Price / CPI ($100)	-1.414	0.888	-1.330	1.253	-1.332	1.089	-1.308	1.999
log(Apps)	0.447	0.225	-0.005	0.987	0.043	0.834	-0.218	0.992
Appstore enabled (σ)	5.712	2.355	1.439	8.631	2.098	7.699	-0.391	7.396
log(Apps)*iPhone							-0.005	0.863
log(Apps)*Android					0.275	0.276	0.165	0.304
log(Apps)*BlackBerry			0.074	0.303	0.056	0.271	0.139	0.268
Product Attributes Searchable to Consumers								
CPU (GHz)	-0.137	0.088	-0.164	0.076	-0.163	0.081	-0.170	0.073
Camera megapixel	0.598	0.114	0.602	0.120	0.597	0.112	0.599	0.112
Screen size * Resolution	0.127	0.044	0.115	0.042	0.114	0.043	0.114	0.046
Memory 500MB	0.443	0.634	0.470	0.569	0.473	0.611	0.476	0.560
Memory 1GB	0.485	0.412	0.497	0.433	0.552	0.424	0.536	0.438
Handset age	-0.025	0.007	-0.026	0.007	-0.026	0.007	-0.026	0.007
AT&T	0.913	0.194	0.952	0.196	0.956	0.190	0.968	0.212
Verizon	0.544	0.211	0.584	0.207	0.575	0.211	0.600	0.204
T-Mobile	1.122	0.183	1.135	0.177	1.150	0.181	1.154	0.170
Sprint	0.995	0.164	0.999	0.168	0.995	0.162	0.996	0.159
Touchscreen	-0.716	4.153	0.259	4.409	-0.144	4.359	1.235	3.727
Keyboard	0.583	0.139	0.583	0.159	0.592	0.146	0.584	0.136
3G data	0.557	0.138	0.556	0.157	0.569	0.156	0.563	0.141
Bluetooth 2.0	0.462	0.239	0.381	0.246	0.385	0.238	0.360	0.275
Month	-0.074	0.023	-0.069	0.022	-0.069	0.022	-0.067	0.024
Brand Equities								
iPhone	-7.078	1.212	-5.079	6.509	-5.684	5.421	-3.751	2.077
Android	-8.459	0.866	-7.349	3.383	-9.937	4.853	-8.087	3.669
BlackBerry	-6.009	0.835	-6.026	0.776	-6.045	0.824	-6.044	0.651
Windows	-6.591	0.797	-6.683	0.721	-6.699	0.769	-6.713	0.700
Symbian	-7.717	0.668	-7.775	0.642	-7.785	0.651	-7.800	0.682
Palm	-5.838	0.907	-5.980	0.850	-5.987	0.892	-6.027	0.827
OS Version Fixed Effects								
iPhone 3.0	1.594	0.642	1.479	1.610	1.848	1.499	1.221	3.391
Symbian 9	1.058	0.631	0.960	0.648	0.963	0.629	0.937	0.620
Standard Deviation of Random Coefficients								
Touchscreen	4.032	5.076	2.391	7.588	2.977	6.156	-0.032	98.968
Appstore enabled	4.564	1.846	2.807	4.919	3.327	4.771	1.984	4.667
Price	0.027	5.199	-0.006	22.808	-0.011	13.036	-0.001	66.072
$n\chi^2$	4.773		6.869		6.711		7.437	
p-value	0.091		0.032		0.034		0.024	

Utility for traditional mobile phones is normalized to zero up to logit error.

Table 6: Estimation of alternative models of smartphone handset demand

BlackBerry-specific log(Apps) coefficient in Column II, the coefficients of log(Apps) and app store dummy become smaller in magnitude and lose significance. Furthermore, the brand equities of iPhone and Android as well as all the random coefficients become highly insignificant, and the model strongly rejects the overidentification test. I find similar results when I subsequently include additional indirect network effects parameters that are Android- and iPhone-specific in Column III and Column IV. As expected, the estimation results in Columns II–IV appear to be consistent with the observation that the data lack the variation needed for identifying the heterogeneous indirect network effects.

D Alternative Specification of Application Demand

Observations = 2,737	Estimate	s.e.
Price / CPI ($100)	-1.257	0.339
(Apps)$^{\gamma}$	0.006	0.006
γ	0.574	0.086
Product Attributes Searchable to Consumers		
CPU (GHz)	-0.179	0.069
Camera megapixel	0.602	0.104
Screen size * Resolution	0.086	0.035
Memory 500MB	0.363	0.503
Memory 1GB	0.584	0.370
Handset age	-0.026	0.006
AT&T	1.000	0.180
Verizon	0.598	0.203
T-Mobile	1.179	0.173
Sprint	0.976	0.151
Touchscreen	-4.704	2.054
Keyboard	0.595	0.129
Wifi	0.009	0.164
3G data	0.603	0.138
Bluetooth 2.0	0.349	0.190
Month	-0.066	0.021
Brand Equities		
iPhone	-7.457	1.174
Android	-8.335	0.720
BlackBerry	-6.095	0.550
Windows	-6.791	0.542
Symbian	-7.125	0.709
Palm	-6.094	0.665
Standard Deviation of Random Coefficient		
Touchscreen	6.374	1.709
$n\chi^2$	10.039	
p-value	0.039	

Table 7: Smartphone demand estimation with alternative application demand function