The Value of Branding in Two-Sided Platforms

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Abstract

This paper explores how mobile applications changed the value of branding in the early smartphone market. As the app stores became widely adopted by smartphone operating systems, the competition between the previously self-contained operating systems became a race for building a two-sided platform serving consumers and third-party developers. I examine whether the value of branding has been affected by the transition to the platform-based market, in which attracting a large number of developers can be more important driver of growth than building a strong consumer brand. Based on an equilibrium model of aggregate smartphone demand and application supply, I analyze the impact of the app stores on the brand value of three smartphone operating system platforms: iPhone, BlackBerry, and Android. The key findings are that 1) the app stores contributed to the growth in the value of the three platform brands and 2) platform openness to developer participation was a critical factor for achieving brand value growth in the market transition to two-sided platforms.

JEL Classification: L13, L15, L63, M31

Key words: two-sided platform, brand value, brand equity

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1 Introduction

This paper explores how the adoption of mobile application stores (app stores) changed the value of branding in the early smartphone industry. The app store, first introduced to the iPhone operating system (OS) in 2008, fundamentally changed how the OS platforms compete in the smartphone market (Menn, 2009; VisionMobile, 2011). The app stores transformed the previously self-contained OSs into a two-sided marketplace platform that directly connects smartphone end users and third-party developers.[1] This app store business model was widely adopted by the existing operating system providers, as it has become increasingly difficult to compete without the support of a large developer base even for the established brands that previously dominated the smartphone market.

The new emphasis on mobile applications raises a question about the importance of branding in two-sided platforms.[2] In markets characterized by hardware/software systems, relevant theories suggest that regardless of the difference in intrinsic benefits (e.g., brand or product quality), a platform attracting more developers can become dominant through a positive feedback mechanism, by which both hardware demand and software supply fuel the growth of each other simultaneously (Chou and Shy, 1990; Church and Gandal, 1992). The positive feedback may increase the value of branding for platforms adopting an app store because branding in a two-sided platform not only would directly contribute to increased consumer demand but also would indirectly do so by encouraging developer participation. On the other hand, numerous empirical studies on platform competition have found that brands without sufficient supply of complementary software lost their customers to the rivals despite offering a superior intrinsic value (Ohashi, 2003; Liu, 2010; Dubé et al., 2010), which likely reduced the return on brand investment for firms making a less successful transition to two-sided platforms. Hence, the prior literature is ambiguous about how the transition to two-sided platforms affected the value of platform brands in the smartphone market.

This paper fills this gap by analyzing the impact of app store adoptions on the value of the OS brands for smartphone vendors by using product-level data in the U.S. market from January 2007 to December 2009. This period encompasses the launch of app stores in five OS platforms including iPhone, Android, BlackBerry, Windows Mobile, and WebOS. Observing the periods before and after the app store openings helps identifying the impact that the app stores had on the value of each OS platform brands.

[1]The two-sided platform in this paper refers to the operating system platforms as a market intermediary between consumers and third-party software developers. While there may be a disagreement among researchers as to whether a market is two-sided or not, it is generally determined by a platform's decision rather than an intrinsic market characteristic (Rysman, 2009).

[2]The terms *brand equity* and *brand value* are strictly distinguished in this paper. I follow the convention of Goldfarb et al. (2009); brand equity refers to the intangible utility of a product associated with a brand name for consumers, and brand value denotes the incremental profit attributable to the brand name for firms, generated by the brand equity.

The brand value measurement in this paper follows the approach of Goldfarb et al. (2009). They propose an equilibrium framework in which brand value is defined as profit increment generated by a brand over and above the quality of search attributes, which are observable to consumers prior to purchase. This measurement approach involves simulation of a counterfactual experiment in which a focal platform loses its brand equity, i.e., the product quality that cannot be attributed to the search attributes. To account for the impact of the brand equity loss on both consumers and developers, I adopt the equilibrium framework of application demand and supply developed by Church and Gandal (1993) and Nair et al. (2004). It allows me to capture the indirect network effects between consumers and developers without observing individual-level data on applications or developers.

This paper analyzes the brand values of three main platforms: iPhone, BlackBerry, and Android. It finds that app stores contributed to the growth of brand values for all three platforms. However, it also finds that the contribution of the app stores varied across the platforms depending on two important platform characteristics: platform openness to the participation of developers and consumer preference for platform brands. iPhone's app store grew the brand value most effectively by leveraging its openness to developers even though its brand equity, i.e., consumer preference for its brand, was not yet commensurate with the traditional smartphone brands at the time. In contrast, while BlackBerry was estimated to be the most preferred brand among consumers, the app store's contribution to its brand value was the lowest due to the lack of openness to developers. On the contrary, despite having the lowest brand equity, Android's app store had an intermediate impact on the brand value relative to the other two platforms by virtue of its openness to developers. Hence, these findings suggest that platform openness was a critical factor for the brand value growth in the market transition to two-sided platforms.

The smartphone market offers a unique opportunity to explore the implication of the market transition to two-sided platforms, which sharply contrasts with other markets studied in the prior literature that were established originally as a two-sided market. Overall, my results suggest that brand equity of a one-sided platform can be leveraged by indirectly connecting existing customers with a new user group in a two-sided platform.

The outline of the paper is as follows. The next section discusses relevant studies on branding and indirect network effects. Section 3 provides a description of the data and a background on the smartphone market. Sections 4 and 5 discuss the model and the estimation strategy. Section 6 develops an approach to measuring the brand values of two-sided platforms. Section 7 presents the estimation results, and Section 8 provides an analysis of the brand values of the two-sided platforms. I discuss some limitations in Section 9 and then conclude in Section 10.

2 Related Literature

This paper contributes to the literature on two-sided platforms, indirect network effects, and branding. Despite the long history of research on indirect network effects and branding, there has been ambiguity about the value of branding in two-sided software platforms, which exhibit positive indirect network effects between both sides of the platform participants, namely consumers and developers. Some researchers have suggested that there is substitution between branding and apps in theoretical analyses of duopoly markets with indirect network effects. They found that markets with strong indirect network effects tend to standardize on a single platform regardless of horizontal differentiation (Church and Gandal, 1992; Chou and Shy, 1990) or vertical differentiation (Zhu and Iansiti, 2012; Sun and Tse, 2007). Numerous empirical studies have also attributed market concentration to indirect network effects in various two-sided markets such as personal computer operating systems (Shapiro and Varian, 1999, p.177), personal digital assistants (Nair et al., 2004), video cassette recorders (Ohashi, 2003), and video game consoles (Dubé et al., 2010; Liu, 2010; Lee, 2011; Corts and Lederman, 2009).

On the other hand, there exist a few studies that provide evidence that indirect network effects may complement the value of branding, although their focus is not on branding *per se*. Nair et al. (2004) observe that improvements in product quality can increase consumer demand via two channels: directly through increased consumer utility and indirectly through developers' enhanced profitability, which encourages software development. In a theoretical analysis of two-sided platform competition, Zhu and Iansiti (2012) find that if indirect network effects are moderate, superior quality is more important than larger user base for winning a dominant market share. Furthermore, the market dominance by a superior quality platform may be strengthened as indirect network effects become stronger. These findings suggest that branding may have become more valuable as the smartphone operating systems have changed from one-sided to two-sided platforms.

However, the impact of a platform's decision to become two-sided on the value of branding and platform competition is an open issue. This topic is closely related to the openness strategy in Rysman's (2009) survey of the literature on two-sided markets. The openness strategy discussed in his survey involves the choice of either compatibility between platforms or the number of sides of a platform (e.g., one-sided or multi-sided). While platform compatibility has attracted significant interest (Chen et al., 2009; Corts and Lederman, 2009; Lee, 2010), the latter issue has remained unexplored to the best of my knowledge. Moreover, branding studies have been scarce in the literature on two-sided markets. Technology products, particularly those exhibiting indirect network effects, have received less attention in the branding research compared to consumer packaged goods. Nevertheless, there is a rich literature on the measurement of brand equity that can be extended to the context of two-sided platforms.

Researchers have proposed various approaches to measuring the value of brands in markets of differentiated products. Keller and Lehmann (2006) categorize them by three distinct perspectives: customer based, financial market based, and company based approaches.[3] This paper employs the company-based perspective in measuring the value of the smartphone OS brands. The company-based view focuses on the value of a brand to firms and measures contemporaneous revenue or profit outcomes. Various measures under this perspective have been proposed: a price premium by Sullivan (1998), a revenue premium by Ailawadi et al. (2003), and a profit premium by Goldfarb et al. (2009). The revenue-premium measure has an advantage over the method based on a price premium because it captures the trade-off between price premiums and market shares. The profit-premium method proposed by Goldfarb et al. (2009) differs from Ailawadi et al. (2003) in that they adopt a structural modeling approach and consider marginal costs in estimating profit premiums.

This paper follows Goldfarb et al. (2009)'s profit-premium approach that views brand value as the extra profit that accrues to a firm due to its brand, which would not accrue otherwise. In other words, their brand value metric measures the difference in profits between an existing *branded* product and its hypothetical *unbranded* equivalent. For the unbranded product, they simulate a counterfactual scenario that manufacturers lose the brand equity down to the level of a reference brand. Using this approach, they measure the value of brands to retailers and manufacturers based on product-market data in an equilibrium framework. The measure of brand value encompasses drivers of brand equity discussed in the cognitive psychology (Keller, 1993) and the information economics literature (Wernerfelt, 1988; Erdem and Swait, 1998).

To extend Goldfarb et al. (2009)'s measurement approach to the context of two-sided platforms, I incorporate the two-sided platform framework developed by Nair et al. (2004). They derive an equilibrium model of aggregate software demand and supply, assuming monopolistic competition in the software market and free-entry of application developers. This has the advantage of summarizing the value of applications in a simple index, i.e., the number of applications available for each platform.

[3]The customer-based approach aims to evaluate brand equity based on consumer's perceived values. Among the examples of this approach are Kamakura and Russell (1993) and Sriram et al. (2007), both of whom estimated brand equity as an intangible value of a product offering for consumers based on actual purchase data. The financial-market based perspective views brand as a firm's asset that can be traded in financial markets and thus considers brand's long-term future performances as well as contemporaneous financial impact (Mizik, 2009).

3 Data

3.1 Description

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.[4] 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 handset-level data

The statistics on the third-party applications were found in reports from various online media.[5] Specifically, these reports provided the monthly number of applications available for iPhone, Android, BlackBerry, Windows Mobile, and Palm.[6] This resulted in total 52 platform-month observations. Although the count measure does not take into account the quality of individual applications, I argue that it is likely to be correlated with the aggregate quality.

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

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

[5]The sources include the websites tracking the app stores (e.g., 148Apps.biz, AndroLib.com, webOS Nation, and Distimo) and the technology news media (e.g., PC World, Bloomberg, and Wired).

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

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.

3.2 Smartphone Industry

3.2.1 Operating System Platforms

In the beginning of 2007, the smartphone market was dominated by four incumbent platforms: Research in Motion (RIM)'s BlackBerry, Microsoft's Windows Mobile, Palm Inc.'s Palm OS, and Nokia's Symbian. Figure 1 shows the unit sales of each platform as a share of total mobile phone sales averaged using three-month windows in the U.S. market.[7]

Apple entered the smartphone market by launching iPhone in June 2007. Google released its first Android handset, HTC Dream (also marketed as T-Mobile G1), in October 2008. Along with BlackBerry, iPhone achieved fast sales growth while Symbian, Palm, and Windows Mobile maintained status quo. Android started to gain significant market share in October 2009.

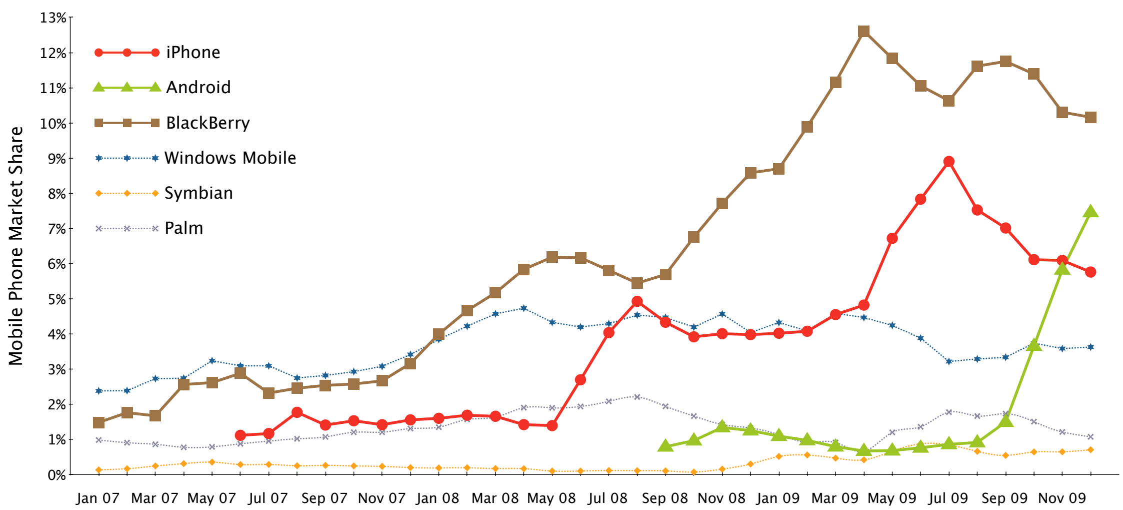

Figure 1: Three-month moving average unit sales of platforms as a share of total mobile phone sales

The unusual sales peaks in Figure 1 coincide with the release of flagship products. The sharp increase in the share of iPhone in July 2008 and July 2009 is due to the launch of iPhone 3G and iPhone 3GS, respectively. The rise of the Android's share during the last three months in the data is primarily driven by the participation of two manufacturing partners, Samsung and Motorola. BlackBerry's growth until early

[7] In Figure 1, the exact figures were smoothed by the three-month moving averages due to the confidentiality agreement with the data provider.

2009 is related to the introduction of the popular BlackBerry Bold, Curve, and Pearl series.

3.2.2 Application Market

The mobile application stores started to launch from the second half of the sample period. Figure 2 provides the cumulative number of applications supplied for each platform in log scale. iPhone, Android and BlackBerry had the majority of the applications, and the remaining platforms had fewer than 1,000 applications until the end of the 36 months.

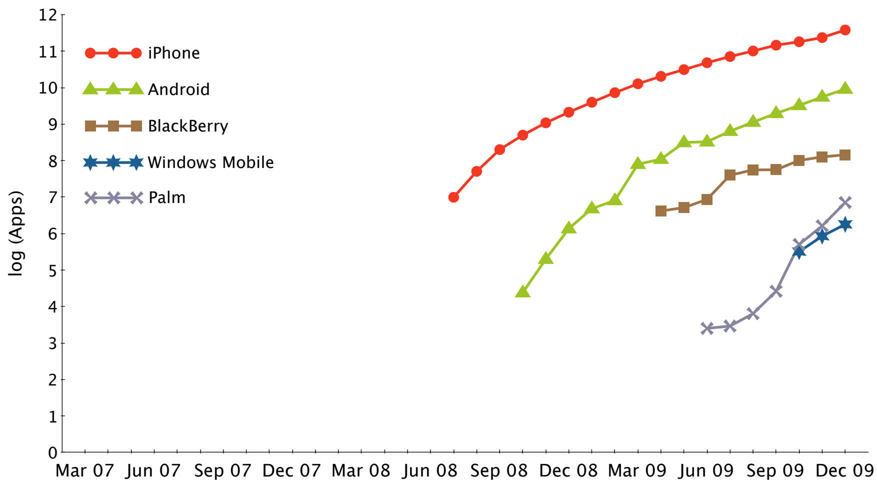

Figure 2: Log of total available applications for each platform

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).[8] 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, iPad, and Android combined as of July 2010 (AppStoreHQ, 2010).

The same report also found that a relatively limited number of developers were publishing apps for multiple platforms. Of the 55,000 developers, the multihoming developers were about 3.2% of iOS developers[9]

[8]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.

[9]iOS refers to a unified family of operating systems for iPhone, iPod Touch, and iPad.

and 13.8% of Android developers as of July 2010.

Another important feature of the application market is the consumer's preference for variety. The top five genres 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 needs for these genres, large variety would be desirable as in other software markets such as video game software and online music stores. 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). Hence, I argue that the total number of applications in my data is informative about how the variety of available applications affected consumer demand for smartphones.

4 The 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.[10] 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.

The smartphone firms 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.[11] The developers choose the price of apps that maximizes their own profits under monopolistic competition given the total number of users in each platform.

[10] Recall that smartphone demand data is given at product level and the app supply data is at platform level.

[11] 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.

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.

It is important to note that $\vec{x}_{jt}$ includes only the product attributes searchable to consumers prior to purchase, namely the search attributes. This allows the parameter of platform brand equity β_{g_j} to capture the utility component that is not associated with the searchable product attributes, which would be recognized by consumers only through the brand name associated with OS g_j. Hence β_{g_j} represents overall experience quality of OS g_j such as reliability, ease of use, and security of the smartphone OS.

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

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

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 $\gamma \in (0, 1)$.[12] Instead of N_{gt}^{γ}, I use a log specification in order to incorporate heterogeneity in the consumer preference for the applications.[13]

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 following profit function:

$$\Pi_{kgt}^{SW} = \Big(\rho_{kt} - c^{SW}\Big) B_{gt} x^*_{kgt} - FC_{gt},$$

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

[13] 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.

where ρ_{kt} is the price of application k at time t, c^{SW} is marginal cost,[14] 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[15]

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

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.[16] 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 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.

[14] 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.

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

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

5 Estimating the Model of Two-Sided Platforms

The previous section developed 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 to estimate the key parameters of the model. The discussion of smartphone pricing is reserved for the next section where I present the framework of brand value measurement.

5.1 Identification

There are two main challenges for 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 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., 2010). The unobservables potentially causing this spurious correlation problem include i) improvements of brand equity (β_g) and unobserved product quality (ξ_{jt}) in smartphone demand (Equation 3), and ii) declines of unobserved app development costs (ζ_t and η_{gt}) in 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 brand equity and unobserved quality is limited to a single platform or 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. To alleviate this concern, 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.[17] To account for the consumer dynamics, I adopt a simple reduced-form approach rather than developing a fully structural model.[18] 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.[19] Approximating the future utility component with a simple reduced-form function has been proposed in the previous literature.[20] 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

[17] 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.

[18] 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.

[19] 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.

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

platform brand dummies, hardware attributes including price, fixed effects for network carriers and OS revisions, a time trend, and the age of handsets since launch.[21] 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.[22] I use 200 Halton draws for Monte Carlo integration to compute the predicted market shares. For the weight matrix W, I use the heteroscedasticity and autocorrelation robust covariance estimator of Newey and West (1987).

6 Measuring the Brand Value of Two-Sided Platforms

6.1 Framework

This section outlines the framework for measuring the brand value of two-sided platforms from the perspective of smartphone handset producers. As mentioned in Section 4, the smartphone 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 to 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, c_j the marginal cost of handset j, and β_g the brand equity of OS platform g built into product j. $\boldsymbol{\beta}$ and $\boldsymbol{N}$ are G-dimensional vectors of brand equities and app supplies, respectively, and $\boldsymbol{p}$ is a J-dimensional vector of prices. Let $D_j(\boldsymbol{\beta}, \boldsymbol{p}, \boldsymbol{N})$ be the demand for product j as a function of brand equities, prices, and app supplies.[23] Then the producer of handset j chooses price p_j to maximize a per-period profit specified as

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

[21] Fixed effects for smartphone hardware manufacturers were estimated insignificant and thus are not reported in the paper.
[22] The convergence threshold for the inner and the outer loops are 10^{-13} and 10^{-8}, respectively.
[23] Other product characteristics are omitted deliberately to simplify the notation.

given brand equities $\boldsymbol{\beta}$ and prices of competing handsets $\boldsymbol{p}_{-j}$. It is worth noting that the app supply itself is a function of brand equities and prices in equilibrium, i.e., $\boldsymbol{N} = \boldsymbol{N}(\boldsymbol{\beta}, \boldsymbol{p})$.

The two-sided market framework requires that the app supply is in an equilibrium relationship with the handset demand. Hence equilibrium pair $(\boldsymbol{p}^*, \boldsymbol{N}^*)$ satisfies not only that $\boldsymbol{p}^*$ simultaneously maximizes Equation 6 for all $j = 1, ..., J$, but also that $\boldsymbol{N}^*$ satisfies the equilibrium condition in Equation 4 given $\boldsymbol{p}^*$.

Suppose product j is the only product available in platform g. Then brand value can be expressed as

$$\Pi_j(\beta_g, \boldsymbol{\beta}_{-g}, \boldsymbol{p}^*, \boldsymbol{N}^*) - \Pi_j(0, \boldsymbol{\beta}_{-g}, \tilde{\boldsymbol{p}}^*, \tilde{\boldsymbol{N}}^*),$$

where $(\boldsymbol{p}^*, \boldsymbol{N}^*)$ is the observed market equilibrium of prices and application supplies, and $(\tilde{\boldsymbol{p}}^*, \tilde{\boldsymbol{N}}^*)$ is a new equilibrium pair under the counterfactual scenario that platform g's brand equity is lost $(\beta_g = 0)$. The loss of brand equity in the two-sided market causes not only the firms to adjust their prices but also the developers to respond accordingly, resulting in the new equilibrium pair $(\tilde{\boldsymbol{p}}^*, \tilde{\boldsymbol{N}}^*)$. The brand value measure therefore represents the profit premium for handset maker j in equilibrium that can be attributed solely to platform g's brand equity. Hence the brand value measure takes into account the changes in not only consumers' brand choices but also smartphone producers' pricing strategies and the developers' application supplies in equilibrium.

The reaction of the application developers is the characteristic that distinguishes the platform-centric smartphone market from the traditional one-sided smartphone market prior to the arrival of the app stores. I measure the impact of the transition from one-sided to two-sided platforms on brand values by taking the following difference:

$$\Big[\Pi_j(\beta_g, \boldsymbol{\beta}_{-g}, \boldsymbol{p}^*, \boldsymbol{N}^*) - \Pi_j(0, \boldsymbol{\beta}_{-g}, \tilde{\boldsymbol{p}}^*, \tilde{\boldsymbol{N}}^*)\Big] - \Big[\Pi_j(\beta_g, \boldsymbol{\beta}_{-g}, \boldsymbol{p}_0^*, \boldsymbol{N}_0^* = \boldsymbol{0}) - \Pi_j(0, \boldsymbol{\beta}_{-g}, \tilde{\boldsymbol{p}}_0^*, \tilde{\boldsymbol{N}}_0^* = \boldsymbol{0})\Big].$$

In the above expression, $(\boldsymbol{p}^*, \boldsymbol{N}^*)$ and $(\tilde{\boldsymbol{p}}^*, \tilde{\boldsymbol{N}}^*)$ are the equilibrium pairs with all the app stores present, and $(\boldsymbol{p}_0^*, \boldsymbol{N}_0^*)$ and $(\tilde{\boldsymbol{p}}_0^*, \tilde{\boldsymbol{N}}_0^*)$ are the equilibrium pairs under the counterfactual scenario that eliminates the entire app suppliers from all platforms. Hence the first bracketed term captures the brand value for a two-sided platform, while the second bracket represents the counterfactual brand value for a one-sided platform that has no applications. With this measurement approach, I evaluate the app stores' impact on the value of the platform brands.

6.2 Measurement Procedure

Once the parameters in the model of two-sided platforms are estimated, the next step in measuring brand values is to compute the marginal cost c_j in the smartphone producer's profit function (Equation 6). Nevo (2001) and Goldfarb et al. (2009) use the first-order condition to recover the marginal costs. I apply their approach to the setting of two-sided platforms by taking into account the simultaneity between smartphone prices and application supplies.

Given knowledge of the demand system $D(\cdot)$ and the marginal costs, I solve for equilibrium prices and application supplies under counterfactual brand equity $\boldsymbol{\beta}$. 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.

7 Estimation Results

7.1 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.[24] Prices are normalized by Consumer Price Index to the hundreds of dollars in January 2007. From the third to the fifth columns (RCL I–III), I estimate random coefficients logit models instrumenting for prices and log(apps). In Columns RCL II and RCL III, I include fixed effects for major OS revisions. The coefficient estimates for searchable product attributes are not reported in 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.

Columns RCL I–III include random coefficients for two product attributes: touchscreen and app store dummy. I exclude the random coefficient for price because its estimate was negligible and insignificant.[25]

[24] For this reason, Column Logit-IV may have rejected the test of overidentifying restrictions.
[25] Estimation results with the random coefficient for price are available in the online appendix.

Observations = 2,737	Logit Estimate	s.e.	Logit-IV Estimate	s.e.	RCL I Estimate	s.e.	RCL II Estimate	s.e.	RCL III 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
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 2: Estimation of logit models of smartphone handset demand

Including the random coefficients changes the ordering of the brand equity estimates obtained in the Logit-IV column; while iPhone has higher brand equity than BlackBerry in Logit-IV, the rank of iPhone's brand equity falls to the third place in RCL I. The change in the iPhone brand equity suggests that it had relatively more sales than other platforms from those consumers with high valuation of a touchscreen and an app store. On the other hand, with the inclusion of the random coefficients, all the signs of the brand equities become negative. However, this does not imply that the brand equities are nonexistent because they are identified only up to relative levels and the mean utility for outside option is normalized to zero.

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 estimates of both fixed effects are large and significant at 10% level while they decrease iPhone's brand equity from -6.42 to -7.08 and Symbian's from -6.88 to -7.71. This indicates that both iPhone and Symbian considerably improved their brand equities by releasing major OS software upgrades, which appears to be consistent with the growth of their market shares as shown in Figure 1. Despite the change in brand equities, the brand equity ranking remains unchanged among the three platforms in focus; BlackBerry has the highest brand equity while Android has the lowest, and iPhone is ranked in between the two.

In addition, the inclusion of the OS revision fixed effects 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.

The brand equity estimates in the RCL II column are robust to the inclusion of additional OS revision fixed effects in RCL III. Even though I include six additional fixed effects for major revisions of other platforms, they do not significantly alter the brand equity estimates obtained in the RCL II column. The RCL III result also shows that although the added fixed effects decrease the log(apps) coefficient further from 0.447 to 0.393, all of their estimates are insignificant, and the model rejects the test of overidentifying restrictions at 10% level (p = 0.075). This contrasts with the RCL II result, which has the p-value of 0.188. Hence I use the brand equity estimates in RCL II to compute the brand values in Section 8.

7.2 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 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 overall estimation results of the application supply model show 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. Given the estimates, the next section analyzes how consumer brand equities and app development costs contributed to generating different outcomes for the brand values of iPhone, BlackBerry, and Android.

8 Analysis of Brand Values

8.1 Brand Values

In this section, I estimate the brand values of iPhone, BlackBerry, and Android. As described in Section 6, I measure the brand values by taking the difference in profits between the observed equilibrium and a counterfactual equilibrium under the scenario that the brand equity is lost to the level of a baseline brand. Nokia's Symbian is chosen as the baseline brand for the analysis because its lowest brand equity (excluding Android) offers a natural benchmark for the brand value measurement. This requires a different approach to measuring Android's brand value, which is discussed later in this section.

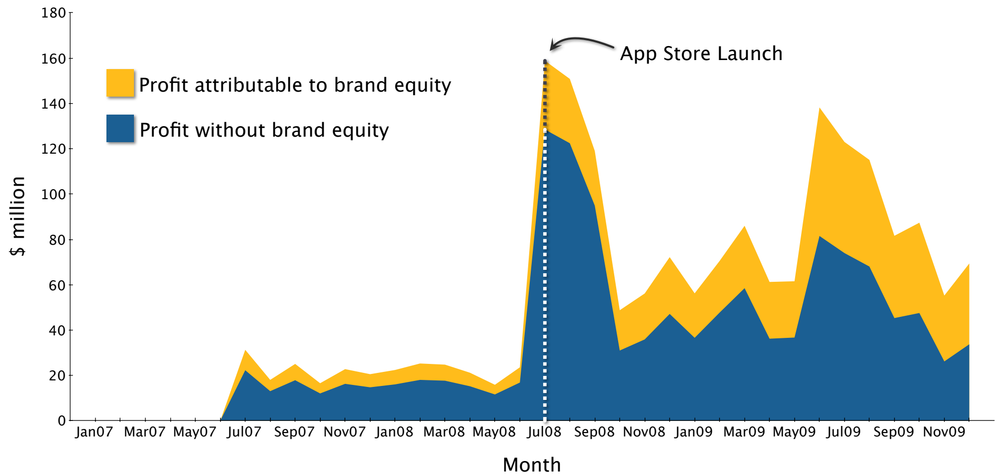

Figure 3: The value of iPhone brand

Figure 3 displays two profit curves; the upper curve is the original profit estimate for Apple in the observed equilibrium, and the lower curve is the counterfactual profit with iPhone's brand equity replaced by the reference brand's. The gap between the two curves represents iPhone's brand value, i.e., the profits generated by iPhone's brand equity over time. With the arrival of the app store in July 2008, iPhone's brand value starts to grow over time both in absolute size and in relative proportion to the original profit. This result suggests that iPhone's app store may have had a positive impact on its brand value.

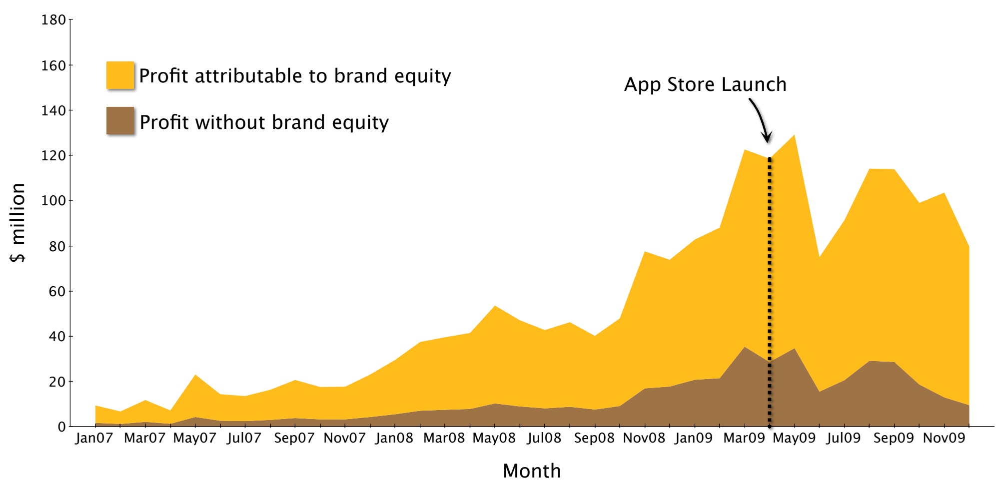

Figure 4: The value of BlackBerry brand

The same plot is obtained for BlackBerry in Figure 4. First, the overall size of the brand value is larger than iPhone's, whether in absolute size or in relative proportion to total profits. This result is not surprising because BlackBerry has the highest brand equity among the three platforms. The second key difference from the previous figure is that BlackBerry's brand value appears to be relatively unaffected by the app store although there is marginal growth in the brand value after the app store launch. Considering the high development cost for the BlackBerry apps, their contribution to the brand value may have been limited by the platform's lack of accessibility for the BlackBerry developers.

In contrast to the two platforms, Android's brand value needs to be computed in a different way because its brand equity estimate is even lower than the benchmark brand's. Hence I increase Android's brand equity to the level of Symbian's because there is no such alternative reference as a generic brand in the consumer packaged goods market. Even though measuring Android's brand value needs a counterintuitive approach, it still deals with the same question of how much consumer brand equity is worth to Android smartphone producers, for brand value is fundamentally a relative construct.

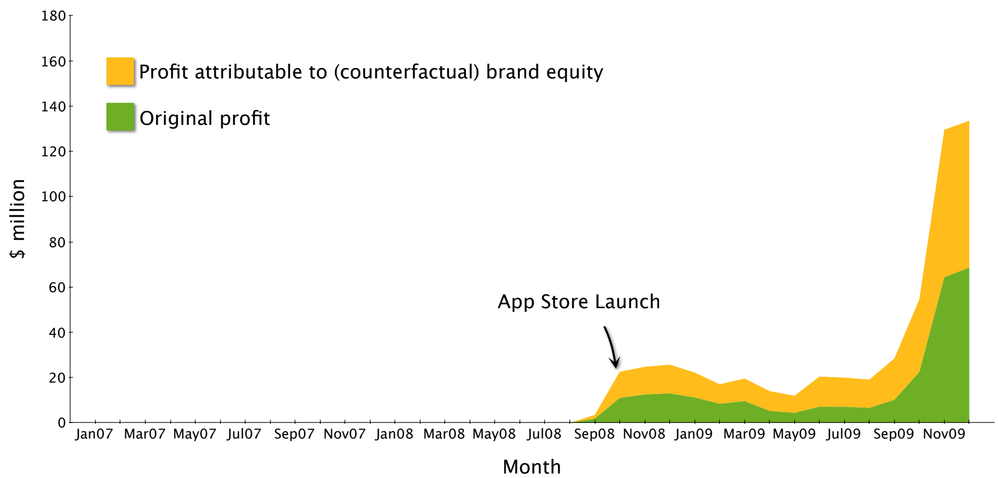

Figure 5: The value of Android brand

Therefore, the gap between the two curves in Figure 5 represents Android's forgone brand value that would have accrued to Android's OEMs (original equipment manufacturers) if the platform had Symbian's brand equity.[26] While Android is estimated to have overall smaller brand value than the other two platforms, its brand value is relatively large in proportion to the total (counterfactual) profit. However, because Android had an app store almost with the market entry, it is difficult to assess without further analysis how much of the brand value can be attributed to the app store.

Table 4 compares the brand values before and after the adoption of the app stores by each platform. The table reports median, interquartile, and interdecile ranges for the brand value estimates measured by annual average amounts in millions of dollars.[27] I estimate the distribution of the brand values using 500 Monte

[26]The OEM firms were HTC, Motorola, and Samsung.
[27]Median brand values are reported instead of mean values in the table because of its robustness to extreme values in the simulated

Value of Brand	Pre-App Store	Post-App Store	Both Periods	% Growth
iPhone				
Median	80.2	462.7	299.8	517.1%
25%, 75% percentiles	[6.8, 128.5]	[106.1, 675.1]	[67.0, 445.8]	[476.1, 601.6]
10%, 90% percentiles	[-98.9, 164.0]	[-433.4, 859.7]	[-293.1, 569.2]	[407.8, 758.9]
Android*				
Median	–	238.3	238.3	–
25%, 75% percentiles		[42.3, 547.7]	[42.3, 547.7]	
10%, 90% percentiles		[-65.2, 955.3]	[-65.2, 955.3]	
BlackBerry				
Median	280.1	830.2	600.4	293.4%
25%, 75% percentiles	[240.6, 337.8]	[708.7, 989.7]	[513.9, 719.0]	[281.9, 303.0]
10%, 90% percentiles	[208.0, 414.4]	[606.5, 1,226.1]	[439.5, 883.6]	[271.1, 311.3]

Based on 500 Monte Carlo estimation results.
Symbian is the benchmark brand for computing brand values.
*Forgone brand values of Android for HTC, Motorola, and Samsung combined.

Table 4: The growth of brand values since the adoption of the app stores (in millions of dollars/year)

Carlo samples from the asymptotic distribution of the model estimates. Then for each platform, I compute the growth rate as a ratio of the brand values between the two periods. The brand value estimation results confirm the previous findings that both iPhone and BlackBerry grew the value of their brands considerably after the launch of the app stores. The brand value estimates tend to have relatively large standard errors because of the limited number of observations for each platform brands, especially iPhone and Android. Nevertheless, the Monte Carlo results confirm the positive and significant growth of iPhone and BlackBerry's brand values with sharper confidence intervals.

But more important in Table 4 is the difference between the growth rates of iPhone and BlackBerry's brand values. iPhone, despite having smaller brand value than BlackBerry, achieved 517% growth while BlackBerry's brand value grew only 293%. Considering the low development cost of the iPhone apps, this result suggests that platform openness to developers may have been the key factor for the brand value growth since the adoption of the app stores.

The value of the Android brand in Table 4 represents the forgone brand value combined across all the OEMs. Android had only one month of sales prior to the app store opening, which is omitted in the table because Android's first-month sales do not appear to have been of a full month in the data judging from the negligible volume.

distribution of the brand values.

8.2 Impact of App Stores on Brand Values

Given the brand value estimates, I examine the impact of the app stores on the brand values by conducting a counterfactual experiment in which none of the platforms adopted an app store.

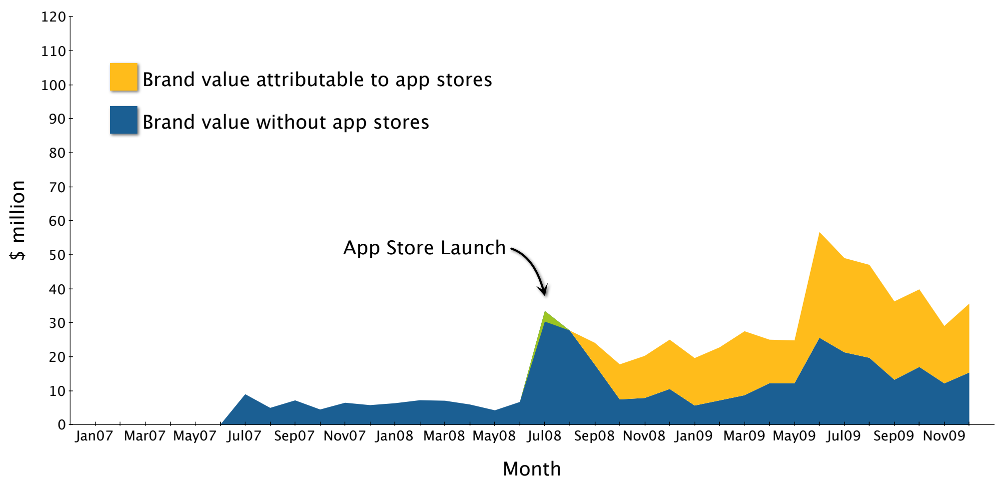

Figure 6: App stores' impact on iPhone's brand value

Figure 6 compares iPhone's brand values in two market equilibria. The upper curve represents iPhone's brand value in the observed equilibrium, and the lower curve corresponds to the brand value in a counterfactual equilibrium where there exists none of the app stores in the market. Hence the area between the two curves captures iPhone's brand value that can be attributed to the app store.

Immediately after the launch of iPhone's app store, it has a slightly negative impact on the brand value because the consumers had negative valuation of the app store that had few apps available. Nonetheless, after a couple of months, the app store begins to contribute to the brand value substantially, both in absolute size and in relative proportion. Hence, the app store accounts for most of the growth in iPhone's brand value during the post app store period.

The impact of the app store on BlackBerry's brand value is shown in Figure 7. As in Figure 6, BlackBerry's brand value benefited from the app store after the early period of the app store launch. Despite the large brand value, however, BlackBerry's app store had a much smaller impact on the total brand value in comparison to iPhone's app store. Considering that BlackBerry had both the highest brand equity and development cost, I conclude that it was the lack of openness to developers rather than the lack of brand equity that limited the growth of BlackBerry's brand value. Hence the result suggests the importance of platform openness to developer participation for growing brand value in the market transition to two-sided platforms.[28]

[28] As a side note, BlackBerry's brand value was growing significantly prior to the introduction of the app store. During this period,

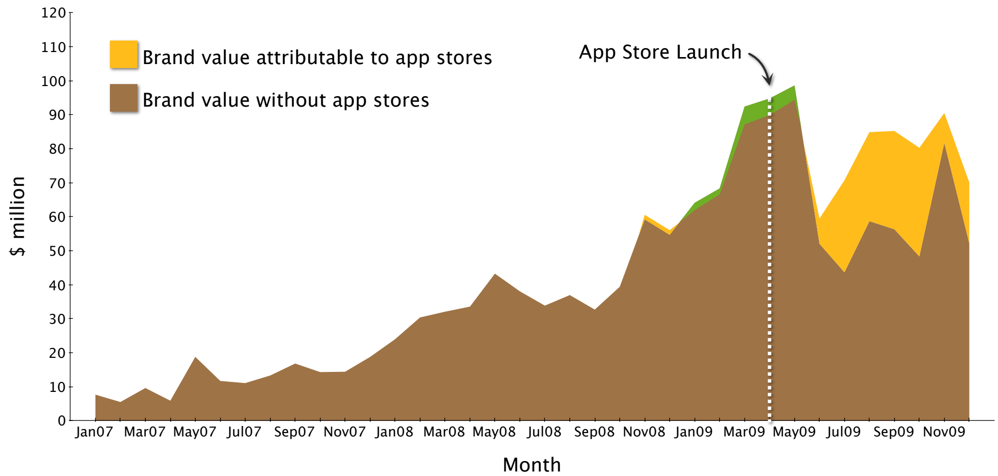

Figure 7: App stores' impact on BlackBerry's brand value

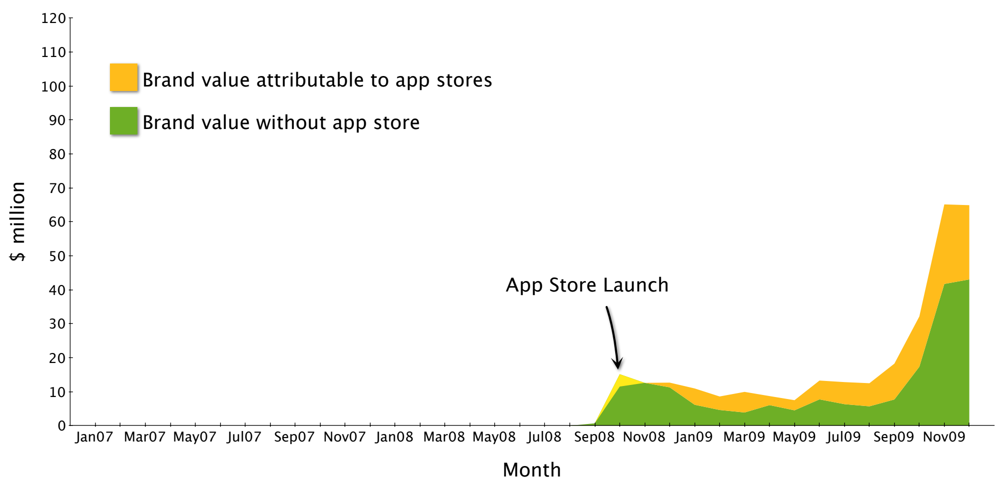

Figure 8: App stores' impact on Android's brand value

I obtain the opposite result for Android in Figure 8. Although Android's overall (foregone) brand value is relatively small, a large part of the brand value is attributable to the app store similarly as in iPhone's case. In comparison to BlackBerry, Android's app store appears to have made a greater impact on the brand value throughout the entire period. Hence, this result adds support to the importance of platform openness for growing existing brand value, if any, by leveraging the network between the two sides via the app store.

Table 5 summarizes the change of brand values due to the app stores taking into account only the periods after each app store was launched. This allows me to consider how the brand values would have changed had it not been for the developer's participation. As in the previous table, the brand values are converted

RIM introduced a number of blockbuster product series including BlackBerry Pearl, BlackBerry Bold, and BlackBerry Curve. Hence BlackBerry appears to have increased its brand value by a more traditional branding strategy.

	Brand Value w/o App Stores	Brand Value w/ App Stores	Change of Brand Value	% Increase of Brand Value
iPhone				
Median	195.4	462.7	173.7	96.0%
25%, 75% percentiles	[18.1, 378.1]	[106.1, 675.1]	[27.0, 319.7]	[37.2, 181.7]
10%, 90% percentiles	[-222.5, 556.7]	[-433.4, 859.7]	[-224.1, 461.9]	[0.4, 270.3]
Android*				
Median	155.3	238.3	58.6	48.2%
25%, 75% percentiles	[31.0, 327.2]	[42.3, 547.7]	[-0.2, 204.0]	[14.8, 92.3]
10%, 90% percentiles	[-47.5, 524.9]	[-65.2, 955.3]	[-16.4, 497.0]	[-2.6, 146.8]
BlackBerry				
Median	712.4	830.2	110.3	15.9%
25%, 75% percentiles	[602.9, 871.5]	[708.7, 989.7]	[75.0, 150.9]	[10.2, 21.6]
10%, 90% percentiles	[519.0, 1,048.9]	[606.5, 1,226.1]	[30.9, 192.1]	[4.4, 26.9]

Symbian is the benchmark brand for computing brand values.

*Forgone brand values of Android for HTC, Motorola, and Samsung combined.

Table 5: The contribution of app stores to brand values (in millions of dollars/year)

into annual average amounts in millions of dollars, and Android's brand values represent the forgone brand values for the three handset manufacturers.

The results in Table 5 are consistent with the previous figures. First, the app stores helped growing the brand values for all three platforms. The growth rate of the brand values ranges from 15.9% to 96.0%. This result provides supporting evidence for the positive effect of the app stores for all three brands. Second, iPhone increased its brand value by virtue of the app store substantially more than BlackBerry did, despite having much less brand equity than BlackBerry. iPhone's app store accounts for 96% of the brand value growth ($173 million), which is considerably higher than the 15.9% growth ($110 million) for BlackBerry's brand value. Although BlackBerry possessed the most valuable brand worth $712 million even without the apps, the high development cost for the BlackBerry developers limited the growth of BlackBerry's brand value. Hence platform openness, rather than consumer brand equity, was a more critical factor in leveraging the two-sided network for growing brand value. This finding is further confirmed by the growth rate of Android's brand value, which was only 48.2% but still higher than BlackBerry's. On the other hand, this result also implies that Android would not have lost the opportunity to achieve substantial growth in brand value with its open platform if only it had brand equity at least on par with the reference brand's. Hence, the result demonstrates that leveraging the two-sided network in a platform is likely to be successful only if it has established a certain level of brand equity on the consumer side.

8.3 Do App Stores Always Increase Brand Values?

Through the analysis of the brand values so far, I have reached two main conclusions: 1) the app stores benefited the value of all three platform brands, and 2) platform openness to developers was a critical factor in brand value growth for the platforms adopting the app stores. The second conclusion would be invalid if a demand-side factor, namely the heterogeneity in consumer preference for apps between different platform users, caused the difference in the app stores' contribution to the brand values. For example, if the iPhone users valued smartphone apps more than the BlackBerry users did, I would have still obtained the same results as shown in Table 5. To test this alternative explanation, I estimate various smartphone demand models that allow heterogeneous preference for apps across different platform users. However, the results indicate that the data does not support the heterogeneity across the platform users at least at the aggregate level.[29]

On the other hand, the first conclusion would be trivial if the consumers' positive valuation of the applications simply implies the apps' beneficial effect on the brand values. Hence I conduct another counterfactual experiment to explore whether different implementation of the app stores could have resulted in a different outcome. Specifically I simulate a scenario that iPhone had the same high development cost as BlackBerry by increasing iPhone's fixed cost F_g in Equation 4 up to the level of BlackBerry's. This experiment can also be considered as a robustness test for the second conclusion because if the different brand value growth was driven by the factors other than the development costs in Table 5, the result should remain the same under the counterfactual scenario.

Table 6 shows that iPhone's app store, if without the developer's easy access to the platform, could have been detrimental to its brand value. The model predicts that given the high cost of app supply, iPhone would have attracted only a small number of apps and the poor app collection would have reduced the sales of its smartphones, resulting in the decline of the brand value by 45.3% compared to its brand value without the app stores. At the same time, the consumers would have chosen the two rival platforms instead of iPhone, boosting their brand values even further compared to the original brand values in Table 5; if iPhone lost its openness, Android's brand value would have increased from \$238 million to \$258 million, and BlackBerry's brand value from \$830 million to \$872 million. Hence, without providing the developers easy access, iPhone's app store would have lost attractiveness to the developers, thus losing the brand value as well. On the contrary, it is worth noting that BlackBerry was still able to gain additional brand value even with the same closed app store. Because BlackBerry has already established a large user base, the developers still

[29] The estimation results are available in the appendix.

	Brand Value w/o App Stores	Brand Value w/ App Stores	Change of Brand Value	% Increase of Brand Value
iPhone				
Median	194.6	56.5	-99.4	-45.3%
25%, 75% percentiles	[19.1, 379.8]	[-33.9, 228.5]	[-145.5, -37.4]	[-72.1, -21.2]
10%, 90% percentiles	[-216.5, 561.3]	[-174.8, 438.9]	[-191.0, 53.0]	[-105.3, 1.0]
Android*				
Median	153.8	258.6	69.2	71.0%
25%, 75% percentiles	[28.6, 326.2]	[21.6, 665.4]	[-19.7, 240.0]	[19.1, 121.9]
10%, 90% percentiles	[-49.1, 523.5]	[-101.0, 976.3]	[–72.8, 507.2]	[-23.5, 202.0]
BlackBerry				
Median	717.6	872.6	153.2	21.4%
25%, 75% percentiles	[605.9, 876.5]	[735.8, 1,063.9]	[111.5, 204.5]	[16.0, 27.3]
10%, 90% percentiles	[520.9, 1,050.4]	[626.3, 1,279.3]	[72.1, 264.2]	[10.6, 33.2]

Symbian is the benchmark brand for computing brand values.

*Forgone brand values of Android for HTC, Motorola, and Samsung combined.

Table 6: The contribution of app stores to brand values when iPhone has the same fixed cost as BlackBerry (in millions of dollars/year)

found BlackBerry's software market sufficiently attractive despite its cost disadvantage. However, because iPhone was a relatively new entrant without having such a large installed base, it would have been difficult for the developers to justify the high cost for the iPhone app development.

9 Limitations and Future Research

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 if individual-level data on the developers become available.

I chose to impose a static pricing assumption on the competition between the smartphone vendors due to the lack of data on smartphone marginal costs. Without such information, estimating margins and brand values would be infeasible in a dynamic-pricing game framework because there are no first-order conditions to exploit as in the Bertrand competition.[30] On the other hand, violation of the static-pricing assumption has ambiguous implications on the marginal cost estimates. Consumer heterogeneity provides an incentive for firms to engage in intertemporal price discrimination while network effects create an incentive for penetra-

[30]To account for the dynamic pricing, other researchers used external information sources to fit a marginal cost function separately (Liu, 2010) or included a time trend in the profit function to capture the time-varying marginal cost parsimoniously (Dubé et al., 2010). While Liu (2010) had to collect the marginal cost information for only two products, this study requires tracking over 150 products. Moreover, it would be impossible to identify the time-varying product-specific marginal costs without strong assumption driving the result. Although the difficulty of estimating the marginal cost can be alleviated by assuming constant marginal costs, this assumption would be too restrictive, considering the rapidly declining trend of the costs over time in the smartphone market. Therefore, I chose to use the static framework for modeling the pricing strategy.

tion pricing. However, unless each platform has a different incentive for the two pricing strategies, the main result, which is about the app stores' contribution to the brand values, is likely to remain unchanged.

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 app stores' impact on brand value may have been underestimated for the iPhone platform. This is because the brand equity loss of a market-leading platform may result in losing dominance in the developer side as well due to brand equity's second order effect on brand value via market expectations. However, the implication for other platforms is unclear and warrants future research.

10 Conclusion

This paper examines the impact of app stores on the value of three OS platform brands: iPhone, Android, and Blackberry. The results suggest that the app stores significantly contributed to the growth in brand values of all three platforms, while there exists a substantial variation in the degree of brand value growth. Despite possessing lower consumer brand equity than BlackBerry, iPhone was able to increase the brand value more effectively than BlackBerry by virtue of its openness to developers. Conversely, BlackBerry achieved only limited brand value growth even with the largest consumer brand equity due to the lack of openness. In contrast, because Android had little brand equity established in the consumer side, it had to forgo the opportunity to grow the brand value considerably, which was made available by its open app store. These core findings can be summarized as follows: *providing developers with an open platform is the key to growing brand value by leveraging the two-sided network in a platform, but only if it has built brand equity enough to attract consumers.* Finally, this paper also shows that the beneficial effect of the app stores is not trivial, for iPhone would have lost the brand value by becoming a two-sided platform without the openness of its app store.

By studying the smartphone market, this paper answers how the value of the OS brands was influenced by the market transition from one-sided to two-sided platforms. It provides a balanced view of the importance of the consumer's and the developer's participation for building the value of platform brands. In this sense, my findings are consistent with Shapiro and Varian (1999)'s view that "a superior technology is not enough to win." The lesson from the findings is that open platform strategy is vital to the success of platform branding, especially for those new entrants that do not possess large user bases. Hence this study contributes to the understanding of how a two-sided platform strategy contributed to the rise of the new OS brands in the early smartphone market.

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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 7: Estimation of logit models of smartphone handset demand

B First-Stage Regression Results

Dependent Variable:	Price		log(Apps)	
	Parameter	Std. Error	Parameter	Std. Error
Appstore enabled	-0.4399	0.6420	0.1918	0.1879
iPhone	3.2272	0.2982	0.4429	0.0873
Android	1.3334	0.3336	2.4800	0.0976
BlackBerry	1.1756	0.1816	0.2294	0.0531
Windows	1.3961	0.1569	-0.0578	0.0459
Symbian	1.8957	0.1539	0.0230	0.0450
Palm	1.7923	0.1628	-0.0076	0.0476
Month	-0.0607	0.0042	0.0064	0.0012
CPU	0.1286	0.0280	-0.0097	0.0082
Camera megapixel	0.1733	0.0308	0.0376	0.0090
Screen size*Resolution	0.0739	0.0126	-0.0415	0.0037
Memory 500MB	0.2966	0.1531	0.1156	0.0448
Memory 1GB	0.1329	0.1468	0.0539	0.0429
Handset age	0.0025	0.0029	-0.0012	0.0008
AT&T	-0.1414	0.0647	0.0057	0.0189
Verizon	-0.2648	0.0676	-0.0467	0.0198
T-Mobile	0.0645	0.0745	0.0014	0.0218
Sprint	0.1526	0.0686	1e-4	0.0201
Touchscreen	0.1414	0.2376	0.2305	0.0695
Keyboard	0.2508	0.0395	0.0546	0.0116
3G data	0.2172	0.0559	0.0272	0.0163
Bluetooth 2.0	0.4135	0.0714	-0.1067	0.0209
Excluded Instruments				
Carrier support	-0.5273	0.0819	-0.0264	0.0239
log(own OS Memory)*Month*Appstore	-0.0054	0.0017	0.0273	0.0005
Other OS Appstore	-0.0014	0.0018	-0.0037	0.0005
Other OS Camera	0.3229	0.1825	-0.4110	0.0534
Own firm Appstore	0.0078	0.0058	0.0484	0.0017
Own OS Bluetooth	0.3296	0.5916	2.3724	0.1731
Own firm Handset age	0.0007	0.0003	-0.0003	0.0001
Observations	2,737		2,737	
R^2	0.7575		0.9927	
F	291.64		12741.37	
$F_{6,2710}$ on excluded instruments$^+$	14.09		677.36	

$^+$ Angrist-Pischike multivariate F-test (Angrist and Pischke, 2009, p.217).

Table 8: First-stage regression results for smartphone demand estimation

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 9: 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 $B_{gt} = rM_t \sum_{l \in A_g} s_{lt} + (1-r) B_{gt-1}$, 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 $\beta < 1$. $\square$

C Estimation Results for Alternative Specifications

Table 10 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

	I		II		III		IV	
Observations = 2,737	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	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 10: Estimation of alternative models of smartphone handset demand

include 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 11: Smartphone demand estimation with alternative application demand function