The Value of Branding in Two-Sided Platforms

Yutec Sun[*][†]

March 14, 2012

Abstract

This paper explores how the mobile application stores changed the value of branding in the early smartphone market. As the app stores became widely adopted by smartphone operating system providers, the competition of devices has increasingly become a war of building larger two-sided platforms comprised of consumers and third-party developers. I examine whether the value of branding has been adversely affected by the transition to the platform-based market, where attracting more developers tends to lead to market standardization. Based on a model of aggregate smartphone demand and application supply derived from an equilibrium framework, I analyze how much of the brand values are accounted for by the app stores in three smartphone operating system platforms: iPhone, Android, and BlackBerry. The key findings are that the app stores contributed to the brand values of the three platforms, and that the app store's openness to developers was critical for the two-sided platforms in leveraging their brand values effectively.

JEL Classification Codes: L13, L15, L63, M31

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

[*]Ph.D. Candidate. Rotman School of Management, University of Toronto, Toronto, ON M5S 3E6, Canada.

[†]I acknowledge the help of Dr. Craig Froehle of University of Cincinnati and Dr. Dan Ramirez for sharing data. I thank my thesis supervisor, Avi Goldfarb, for his generous support. I also thank my thesis committee members, Victor Aguirregabiria and Ron Borkovsky for their valuable advices.

1 Introduction

This paper explores how the adoption of mobile application stores changed the value of branding in the early smartphone industry. Ever since the app store was introduced to iPhone and Android operating systems (OSs) in 2008, it fundamentally changed the landscape of competition in the smartphone market (Menn, 2009; VisionMobile, 2011). The app store transformed the smartphone devices into a two-sided marketplace platform that allowed third-party developers to price, market, and sell the mobile apps directly to consumers.[1] This app store business model was widely adopted by the existing operating system providers, for without a large enough developers bases, it has become increasingly difficult to remain competitive even for the traditionally strong brands such as Nokia's Symbian, Microsoft's Windows Mobile, and Palm's WebOS.

The new emphasis on the applications raises a question about the importance of branding in the two-sided platforms.[2] In the markets characterized by hardware/software systems, relevant theories suggest that regardless of difference in standalone benefits (e.g., brand and product quality), a platform that attracts more developers can become dominant through a positive feedback effect, where both consumer demand and software supply fuel the growth of each other simultaneously (Chou and Shy, 1990; Church and Gandal, 1992). This positive feedback effect suggests contradicting views about the value of the smartphone OS brands for firms: the value of branding may have been reduced by the transition to the platform-based market, because of greater emphasis on software applications as a driver of market standardization by a single dominant platform. On the contrary, the value of branding may have become greater due to the adoption of the app stores, because brand equity contributes to increased consumer demand directly, and at the same time indirectly through inducing more participation from the developer's side. Despite the ambiguity of the importance of the value of branding in a two-sided platform, there still exists a gap in the literature.

This paper aims to measure the impact of the app store adoptions on the value of the OS brands for smartphone vendors, using product-level data on the U.S. market from January 2007 to December 2009. This period encompasses the launch of the app stores in the five OS platform providers including iPhone, Android, BlackBerry, Windows Mobile, and WebOS. Observing both periods before and after the app store launches allows me to identify what impact these app store adoptions had on the value of each OS platform brands.

The brand value measurement approach follows Goldfarb et al. (2009). They propose an equilibrium framework in which brand value is defined as profit increment generated by brand over and above the quality of search attributes, which are observable to consumers prior to purchase. This measurement approach requires 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. The equilibrium framework of the demand and supply of applications builds on the work of 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 both the apps and the developers.

The analysis of the brand values reveals that the adoption of the app stores strengthened the value of the

[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 is a disagreement among researchers as to whether a market is two-sided, it is often determined by a platform's decision rather than an intrinsic market characteristic as Rysman (2009) notes.

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

three platform brands, iPhone, Android, and BlackBerry. More importantly, iPhone's app store leveraged its brand value the most effectively by virtue of the platform's openness to the developer's participation, even though it had only moderate brand equity overall. In contrast, while BlackBerry owned the most valuable brand among the three, its app store failed to leverage the brand value as effectively as iPhone's, due to the lack of openness to the developers. On the other hand, the lack of brand equity, not the lack of openness, was the limiting factor for Android in leveraging its brand value using the app store.

This paper aims to contribute to the understanding of how the profit contribution of brand equity is impacted by the strategic decision to turn one-sided product into two-sided platform. Taking that decision as given, it studies how the app stores interact with brand equity in generating profits. The smartphone market offers a unique opportunity to explore the implication of the market transition to two-sided platforms, in contrast to other markets studied in the prior literature that were established originally as two-sided markets. This paper finds the empirical evidence that the transition to the platform-based market leveraged the value of the platform brands, and that leveraging the brand value was critically dependent on allowing the developers easy access to the platform.

The outline of the paper is as follows. The next section discusses the relevant theories on the relative importance between brand and indirect network effects in oligopolistic competition, and the associated measurement approaches developed in the literature. Section 3 will describe the details on the data and the characteristics of the smartphone market. Section 4 will present a basic framework for measuring brand values in a two-sided market, followed by the empirical framework for the two sides of the market in Section 5. Estimation results will be presented in Section 6, and Section 7 will discuss the main results on the impact of app stores on brand values. I will discuss some limitations in Section 8, and then will conclude by summarizing the findings in Section 9.

2 Related Literature

This paper builds on the indirect network effects literature and the brand equity measurement literature. Indirect network effects have been generally perceived as a countervailing factor against the effect of product differentiation. While product differentiation leads to oligopoly markets, 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). The market concentration induced by indirect network effects can be observed in many 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 contrary, there exist a few studies that explore indirect network effects as a complement to the value added by a superior brand or product quality. Nair et al. (2004) observe that improvements in product quality not only impact consumer demand directly, but also further enhance the demand by increasing the availability of complementary software through positive feedback effects. Zhu and Iansiti (2012) find that in a market with moderate indirect network effects, as the indirect network effects become stronger, entrant platform with quality advantage wins dominant market share by a larger margin against incumbent platform with installed-base advantage. These findings suggest a possibility that the role of product quality and brand may have become more important ever since the smartphone operating systems became two-sided platforms.

This paper aims to contribute to the literature on two-sided market. Rysman (2009) surveys the literature that has focused on two important subjects: pricing and openness strategies. Many theoretical and empirical studies of pricing strategy have found the cross-group externalities between two participant groups as one of the determinants of unique pricing strategy observed in two-sided market, such as negative prices or prices below marginal costs (Rochet and Tirole, 2003, 2006; Armstrong, 2006; Weyl, 2010; Kaiser and Wright, 2006; Argentesi and Filistrucchi, 2007; Jin and Rysman, 2010). The openness strategy is related to compatibility between platforms and the number of sides of the market (e.g., one-sided or multi-sided). While platform compatibility issue has received significant attention (Chen et al., 2009; Corts and Lederman, 2009; Lee, 2010), the latter issue has remained unexplored to the best of my knowledge.

To empirically measure the cross-group indirect network effects, I adopt the framework developed by Nair et al. (2004). They derive reduced-form models of equilibrium software demand and supply, assuming monopolistically competitive software market and free-entry of application developers. This has an advantage of summarizing the value of applications in a simple index, i.e., the number of applications available for each platform.

Brand-related study is scarce in the literature on two-sided markets and indirect network effects. Similarly, technology products – especially those exhibiting indirect network effects – have been given less attention in the branding research compared to consumer packaged goods in particular. Nevertheless, there is rich literature on the measurement of brand equity.

In traditional differentiated-product markets, researchers have proposed different approaches for measuring brand equity. Keller and Lehmann (2006) categorize them by three distinct perspectives: customer based, financial-market based, and company based. The customer-based perspective aims to evaluate brand based on consumer's perceived values.[3] The financial-market based perspective views brand as a firm's asset that can be traded in financial market, and thus considers brand's long-term future performances as well as contemporaneous financial impact (Mizik, 2009).

The company-based view emphasizes brand's value to firms, and considers contemporaneous product-market 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 modelling approach and consider marginal costs in estimating profit premiums.

This study adopts Goldfarb et al. (2009)'s profit-premium method that views brand value as an additional profit that accrues to a firm due to its brand name, which would not accrue otherwise. Under this perspective, Goldfarb et al. (2009) develop an equilibrium framework to measure brand value to firms based on product-market data. They measure the brand value as the difference of profits between existing branded product and hypothetical unbranded product. The hypothetical product corresponds to the counterfactual scenario that the product manufacturers retain the brand equity equivalent to a reference brand. An equilibrium framework is thus needed to simulate market outcomes under this counterfactual situation.

The source of brand equity in Goldfarb et al. (2009)'s framework encompasses those proposed by cognitive psychology and information economics. Brand's association with user and usage imagery as well as brand personality is identified in cognitive psychology theory (Keller, 1993). Wernerfelt (1988) proposes

[3] Among the examples of this approach are Kamakura and Russell (1993) and Sriram et al. (2007), both of whom estimated a brand equity as an intangible value of a product offering for consumers based on actual purchase data.

an information economics view that brands can be a credible signal of a product's experience quality. Because consumers have uncertainty about the experience quality of a new product, firms may use brands as a market signal to convey information about the unobserved quality with credible commitment. Erdem and Swait (1998) empirically test the psychological underpinnings of this signalling theory based on the theory of imperfect and asymmetric information on the part of consumers.

In the next section, I will describe the analyzed data and the characteristics of the smartphone industry.

3 Data

3.1 Description

The data on 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 handset-carrier-month level. Total 171 product models were observed for the 36-month period, with a total of 3,045 model-carrier-months. 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] Smartphone models older than three years were dropped, because of the extremely small sales of these models. As a result, total 159 handset models were left for the analysis.

Because product launches happened throughout a month, first-month sales were often extraordinarily low compared to other periods. Therefore, only sales from the second month and beyond were considered for estimation. The final dataset for the estimation contained 131 models (2,187 model-carrier-months). In the counterfactual experiments, however, the first-month observations were included.

Platform	Handset-Months	Avg Share (Platform)	Avg Share (Handset)	Avg Price	Avg Apps	Total No. of Handsets
iPhone	87	0.0383	0.0136	276.84	25,372	7
Android	46	0.0184	0.0064	175.28	13,156	9
BlackBerry	1,049	0.0643	0.0022	140.64	671	35
Windows Mobile	1,107	0.0369	0.0012	153.61	30	69
Symbian	208	0.0034	0.0006	205.00	0	28
Palm	329	0.0134	0.0014	179.73	10	11
Total	2,826					159

Table 1: Descriptive Statistics of Handset-Level Data

The statistics on the third-party applications were found in the reports from various online media. Specifically, these reports provided the monthly number of applications available for iPhone, Android, BlackBerry, Windows Mobile, and Palm.[5] This resulted in total 52 platform-month observations. Although the count of total applications ignores the variation in the quality of the applications, it is assumed to be a reasonable proxy for the aggregate quality of the applications, given the lack of information on the individual applications or developers.

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,

[4]Nokia's Maemo and other Linux-based platforms were dropped due to the small number of observations.

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

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

3.2 Smartphone Industry

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.[6]

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.

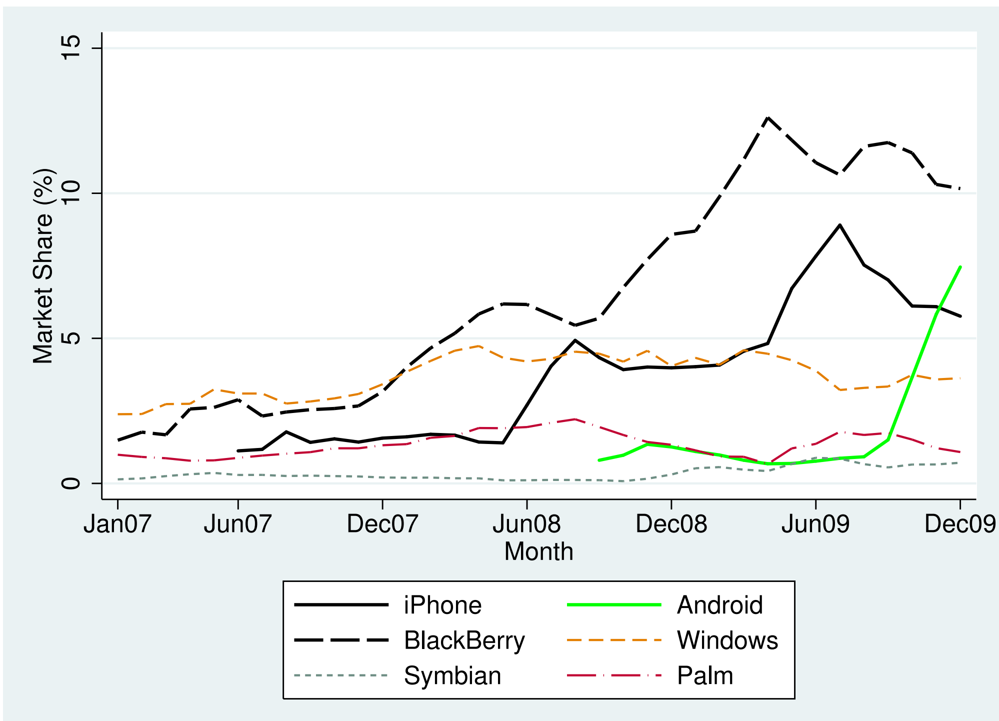

Figure 1: Three-Month Moving Average Unit Sales of Platforms As a Share of All Mobile Phone Sales

The overall sales growth pattern in Figure 1 coincides with the releases of flagship products. iPhone 3G and iPhone 3GS boosted the platform share in July 2008 and July 2009. The rise of the Android shares in October 2009 was driven by the first Android 2.0 handset jointly developed by Google and Motorola. The popular BlackBerry Bold series were released in November 2008.

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

Symbian had the smallest unit sales throughout the entire period, even though Nokia was the largest smartphone vendor in the global market.[7]

Application Market The mobile application stores started to launch from the second half of the observation period. Figure 2 provides the cumulative number of applications supplied for each platform in a 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.

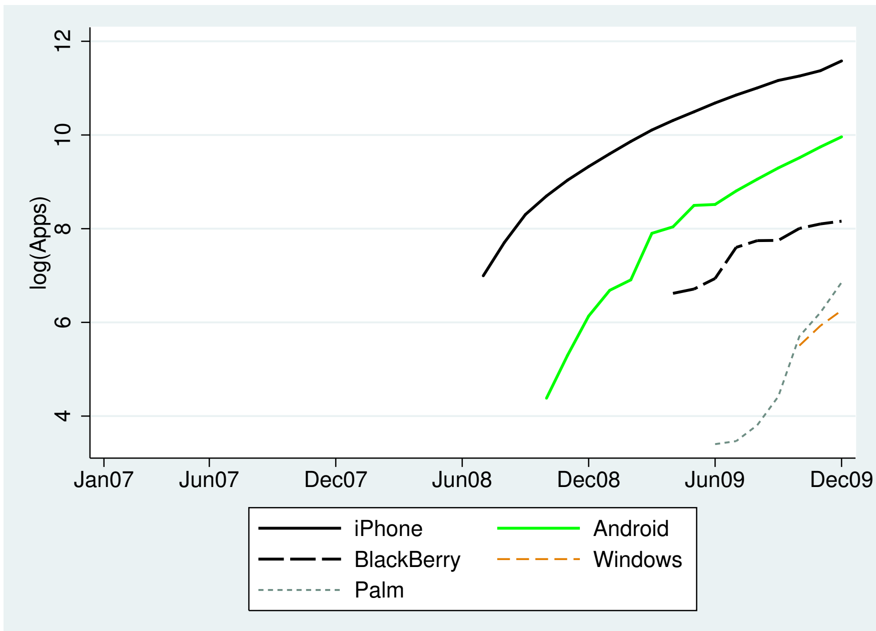

Figure 2: Log of Number of Applications for Each Platform

The app stores drastically lowered the cost of mobile software development. Prior to 2008, the primary distribution channels for the applications were mobile carrier's portals and on-device preloading through the deals with handset makers or mobile network operators. These channels were unavailable for small-scale software firms, for the entry barrier was too high. The app stores not only reduced the financial cost dramatically,[8] but also shortened the time-to-shelf from 68 days through the traditional channels to 22 days via app stores, and the time-to-payment from 82 days to 36 days (VisionMobile, 2010, pp.19-20). The lowered cost barrier attracted a large number of developers; According to an online report by 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 55,00 developers, the multihoming developers were about 3.2% of iOS[9] developers, and 13.8% of Android developers in July 2010. Hence, the number of multihoming developers is believed to have been negligible for the period observed in this study.

[7] According to Gartner, Nokia still had about 47% of the smartphone unit sales in 2009 (Pettey and Tudor, 2010).

[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.

Another important feature of the application stores is the consumer's preference for variety. AppStoreHQ learned from randomly sampled 5,000 Android owners that about 20,000 unique applications were actively used out of estimated total 100,000 available applications (AppStoreHQ, 2011). Moreover, top five genres by the number of actively traded apps were games, books, entertainment, education, and lifestyle in August 2011, which occupied about 56% of total applications. Considering that these genres are horizontally differentiated and usually have short shelf-life, application variety is likely to be an important factor in the value of overall software market.

4 Measuring Brand Value of Two-Sided Platform

This section outlines a basic framework for measuring the brand value of two-sided platforms in handset maker's perspective. In each period, equilibrium prices and applications are determined in a Stackelberg game between handset makers and application developers. First, the handset makers engage in Bertrand competition; they set prices that maximize profits, given the hardware attributes (and software applications, if available) of all players and the prices of competing products. Given the handset products and prices, the level of application supply is determined in a competitive equilibrium.

I assume that the handset makers have perfect information on all the factors affecting the application supply. Hence, the handset makers internalize the response of application developers in their pricing decision, and the handset prices are in equilibrium relationship with the application supply.

To specify handset maker's profit function, suppose a firm has a product indexed by j among J alternatives. Let p_j denote the price of handset j, n_g the 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 platform g built into product j. $\boldsymbol{\beta}$ and $\boldsymbol{n}$ are G-dimensional vectors of brand equities and applications, respectively, and $\boldsymbol{p}$ is J-dimensional price vector. Let $D_j(\boldsymbol{\beta}, \boldsymbol{p}, \boldsymbol{n})$ be demand for product j as a function of brand equities, prices, and applications.[10] Then the producer of handset j chooses price p_j to maximize a per-period profit specified as

$$\Pi_j(\boldsymbol{\beta}, p_j, \boldsymbol{p}_{-j}, n_g, \boldsymbol{n}_{-g}) = (p_j - c_j) D_j(\boldsymbol{\beta}, p_j, \boldsymbol{p}_{-j}, n_g, \boldsymbol{n}_{-g}), \tag{1}$$

given the brand equities $\boldsymbol{\beta}$, the prices of competing handsets $\boldsymbol{p}_{-j}$, and the applications of rival platforms $\boldsymbol{n}_{-g}$.

The current two-sided market framework requires that the application supply is in an equilibrium with the handset demand. Hence, the equilibrium price–application pair $(\boldsymbol{p}^*, \boldsymbol{n}^*)$ satisfies not only that $\boldsymbol{p}^*$ simultaneously maximizes Equation 1 for each j, but also that $\boldsymbol{n}^*$ is the best response to $\boldsymbol{p}^*$.

Suppose product j is a sole product in platform g, then the brand value can be defined 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 $\tilde{\boldsymbol{p}}^*$ and $\tilde{\boldsymbol{n}}^*$ are new equilibrium prices and applications under counterfactual scenario where platform g's brand equity is lost ($\beta_g = 0$). The loss of brand equity in two-sided market causes not only the firms to adjust the equilibrium prices, but also the developers to respond accordingly, resulting in a new equilibrium pair $(\tilde{\boldsymbol{p}}^*, \tilde{\boldsymbol{n}}^*)$. The brand value therefore represents the profit premium for handset maker j in equilibrium

[10] Other product characteristics are omitted deliberately to simplify the notation.

that can be attributed to platform g's brand equity alone.

The reaction of the application developers is the feature that distinguishes the platform-centric smartphone market with the the traditional devices-centric market. I measure the impact of this market transition on the brand values via the following difference:

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

The first bracketed term corresponds to the brand value in the two-sided market as defined above, and the second bracket is the brand value with the equilibrium applications constrained to be zero, representing the brand value in a counterfactual one-sided market where none of the app stores exists. Hence this measurement approach aims to evaluate how the brand values would have been different had it not been for the app stores.

5 Empirical Strategy for Measuring Brand Values

5.1 Empirical Model of Two-Sided Platform

The brand valuation method discussed in the previous section requires a structural model of equilibrium consumer demand and application supply. The consumer handset demand function subsumes the equilibrium demand for applications. The equilibrium application demand and supply models are based on Nair et al. (2004)'s framework: a CES utility function of software demand, combined with monopolistic competition and free entry on the developer's market. This paper will focus on describing the model and will provide only sketches of the derivation, leaving the details for further reading.[11]

Consumer Demand Consumers are assumed to consider only the present value of hardware and software available in each period. All smartphone purchases are assumed as replacement demand switching from either previous smartphones or traditional mobile phones. All consumers are assumed to "singlehome," i.e., they do not own multiple handsets simultaneously, whether smartphones or traditional mobile phones. The total market is defined as the entire U.S. mobile phone subscribers, including traditional mobile phone users.

Let U_{ijt} denote consumer i's' utility of smartphone product j at time t. Let g_j denote the OS built in the smartphone j. U_{ijt} is specified as

$$U_{ijt} = \beta_{ig_j} + x'_{jt}\theta_x - \alpha p_{jt} + V_j^{SW}(n_{g_j,t}) + \xi_{jt} + \epsilon_{ijt}, \quad \epsilon_{ijt} \sim EV(0,1), \tag{2}$$

where β_{ig_j} is a random coefficient representing platform g_j's brand equity for consumer i, x_{jt} is the vector of product characteristics of handset j at time t, p_{jt} is handset j's price at time t, $n_{g_j,t}$ is the cumulative number of applications supplied to platform g_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. $V_j^{SW}(n_{g_j,t})$ is the consumer's indirect utility of software applications available for handset j in platform g_j. x_{jt} includes time fixed effects to capture the time-varying quality relative to the outside option, which is traditional mobile phones. The utility of the outside option is normalized to $U_{i0t} = \epsilon_{i0t}$.

The random coefficient β_{ig} captures correlated preferences for the alternatives within platform g. It is

[11] See Nair et al. (2004).

distributed as $\beta_{ig} \sim i.i.d.\, N(\bar{\beta}_g, \sigma^2_{\beta_g})$, where $\bar{\beta}_g$ is the mean brand equity of platform g that is invariant over time. β_{ig} is formally equivalent to an error component that induces correlation between handset-months in platform g (Train, 2003). Combining the random coefficients with extreme-value distributed ϵ_{ijt} leads to a random-coefficients logit specification in Equation 2.[12]

The functional form of the indirect utility $V_j^{SW}(n_{g_j,t})$ can be obtained by adopting representative consumer approach, following the previous literature (Chou and Shy, 1990; Church and Gandal, 1992, 1993; Nair et al., 2004). Specifically, the value of software is modeled by a CES utility function as

$$U_{ijt}^{SW} = \left(\sum_{k=1}^{n_{g_j,t}} (x_{kgt})^a \right)^b + z_{it}, \quad a \in (0,1], b \in (0,1) \tag{3}$$

where x_{kg_jt} is the demand for software k on platform g_j at time t, and z_{it} is a numeraire capturing the value of non-software purchase. Then combined with appropriate supply-side assumptions, I can obtain the competitive equilibrium demand $x^*_{kg_jt}$ in a closed form that equates the equilibrium application supply. Plugging this equilibrium demand back into Equation 3 produces indirect utility in the form of power function $V_j^{SW} = n^{\gamma}_{g_j,t}$, where $\gamma \in (0,1)$.

Instead of using this power function, I use a log specification for estimation, because the non-linearity of $n^{\gamma}_{g_j,t}$ creates a difficulty in applying instrumental-variables method to control for potential endogeneity. Hence if handset j has an app store enabled in the device, the software value function is given by

$$V_j^{SW}(n_{g_j,t}) = \gamma \log(n_{g_j,t}), \tag{4}$$

and $V_j^{SW}(n_{g_j,t}) = 0$ otherwise. In order to allow some flexibility in the shape of the log function, I further transform the software value function as

$$V_j^{SW}(n_{g_j,t}) = \frac{\gamma}{\sigma} \log(n_{g_j,t}/\sigma) = \frac{\gamma}{\sigma} \log(n_{g_j,t}) - \frac{\gamma}{\sigma} \log(\sigma),$$

where σ is a scale factor for $n_{g_j,t}$. Therefore, the final form of the demand model can be written as

$$U_{ijt} = \beta_{ig_j} + x'_{jt}\theta_x - \alpha p_{jt} + \left[\frac{\gamma}{\sigma} \log(n_{g_j,t}) - \frac{\gamma}{\sigma} \right] I_{jt} \log(\sigma) + \xi_{jt} + \epsilon_{ijt}, \tag{5}$$

where $I_{jt} = 1$ if an app store is installed in handset j at time t, and zero otherwise.

Application Supply In equilibrium, application developers are assumed to set prices for each software application to maximize the following profit function:

$$\Pi_k^{SW} = \left(p_{kt}^{SW}(1-\rho_g) - c^{SW} \right) B_{gt}\, x^*_{kgt} - F_{gt},$$

where p_{kt}^{SW} is the price of application k at time t, ρ_g is software royalty payment to platform g,[13] c^{SW} is the marginal cost of providing an application, B_{gt} is the installed base of users of platform g at time t, x^*_{kgt} is the equilibrium demand for application k in platform g at time t, and F_{gt} is developer's fixed cost for

[12] The price response coefficient α is assumed to be homogeneous, for the estimation with a random coefficient for α obtained very small and insignificant estimate for its consumer heterogeneity parameter.

[13] All the platforms collected 30% of revenue from the developers for each application sale throughout the observed periods.

providing an application that varies across platform-months. Lacking individual-level data on the developers, the homogeneous marginal cost assumption allows the researcher to derive a model of application demand and supply that can be estimated using aggregate data. The simplifying assumption can be a reasonable approximation, because the marginal cost related to reproducing and distributing an additional software product is likely to be close to zero in the mobile app stores.

Combined with market-clearing assumption, the equilibrium application supply can be derived as

$$\log n_{gt} = \kappa + \phi \log B_{gt} - \log F_{gt}.$$

In estimation, the fixed cost parameter F_{gt} is decomposed as

$$\log n_{gt} = \kappa + \phi \log B_{gt} - \log F_g - \zeta_t - \eta_{gt} \tag{6}$$

where F_g is platform-specific fixed software development cost that is time-invariant, ζ_t and η_{gt} are common and platform-specific time-varying costs, respectively.

This supply model implies that the effect of the installed bases on the equilibrium application supply is homogeneous across the platforms. Hence, the persistent difference of applications between the platforms are captured by F_g, and the temporal variation in the application supply is accounted for by B_{gt} and ζ_t.

Installed Base To complete the specification of the application supply model, the installed bases in Equation 6 need to be defined, for the user installed bases are unobserved to the researcher. Let M_t be the size of total mobile subscribers. To account for the replacement handset demand, I assume that the consumers of mobile phones and smartphones have the same replacement cycles of $T = 24$ months.[14] Then the timing of a smartphone replacement can be assumed to follow 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 the platform g's installed base at time t is

$$B_{gt} = (1 - r)B_{gt-1} + rM_t s_{gt} \tag{7}$$

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

5.2 Identification

Indirect Network Effects There are two main challenges for identifying the indirect network effects (γ in Equation 5 and ϕ in Equation 6). First, identifying the causal relationship can be difficult due to the simultaneity between the handset demand and the application supply, which is likely to cause the well-known endogeneity bias. The control for the endogeneity, I use average product characteristics in a given platform as instruments for n_{gt} in the demand equation (Equation 5). These instruments are likely to be correlated with application supply through handset sales, while they are assumed to be uncorrelated with the unobserved quality and brand equity, ξ_{jt} and $\bar{\beta}_g$, which is typically assumed in the empirical industrial organization literature (Berry, 1994; Berry et al., 1995). For the instruments of B_{gt} in the supply equation (Equation 6), I use each platform's average product characteristics that are likely to be correlated with user installed bases and are unlikely to be correlated with the application development cost. To satisfy the exclusion restriction

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

for the supply-side instruments, I consider only the attributes relevant to the demand for the smartphones that can operate mobile applications.[15]

The second identification issue arises from the potential correlation between handset demand and application supply that is driven by the factors unobserved to the researcher. Without correctly accounting for this, the model may spuriously find causal relationship between the handset demand and the app supply, even though it is non-existent (Gowrisankaran et al., 2010). The potential drivers of this spurious causality include first, the improvement of brand equity ($\bar{\beta}_g$) and unobserved product quality (ξ_{jt}) in the demand model (Equation 5), and second, the declining unobserved time-varying costs (ζ_t and η_{gt}) in the supply model (Equation 6). The first factors are unlikely to cause an identification problem, because the indirect network effects are identified by multiple app stores, while the quality change is limited to a single platform. Likewise, the platform-specific cost changes are unlikely to cause problem for identification.

Nevertheless, the estimation strategy still has a risk of the spurious correlation, if there is a shift common to all platforms in the unobserved product quality and the application development cost. To address this concern, I include a time trend in the demand and the month fixed effects in the supply model.

Endogenous Price The price coefficient in the demand model is likely to be biased, if potential price endogeneity is ignored. I use the instruments proposed by Berry et al. (1995), i.e., the sum and the mean of the product characteristics of own and rival products, as well as an exogenous variable excluded from the demand model.[16]

Brand Equity The mean brand equity $\bar{\beta}_g$ is identified by the variation of average handset sales across platforms, after the search attributes, the prices, and the applications are controlled for. To account for the possibility that brand equities may change over time, I include fixed effects for major OS revisions as a proxy for OS quality improvements.

Unobserved Consumer Heterogeneity The standard deviation of the random coefficient, $\sigma_{\beta_{g_j}}$ is identified by the within-platform correlation of the unobserved utility components, $(\beta_{ig_j} - \bar{\beta}_{g_j}) + \xi_{jt} + \epsilon_{ijt}$, of the handset-months. This correlation pattern is distinguished from the autocorrelation structure assumed for ξ_{jt} in the estimation procedure. The correlation of ξ_{jt}'s is decreasing with time lag, while the correlation due to the random coefficients persists over time.

Forward-Looking Consumers The assumption of static consumer demand may be violated for two reasons. Consumer's dynamic replacement behaviour may arise from the durable-good nature of the smartphones and rapid technological innovations. Potential smartphone buyers are likely to compare the trade-off between replacing the current holding today against waiting for price drop and/or better technology tomorrow. Hence, anticipating a new generation of technology arriving in the near future, consumers may postpone their purchases as they come closer to major product releases.

To account for this dynamic replacement decision, I adopt a simple reduced-form solution, instead of developing a fully structural model.[17] I use handset's age (number of months elapsed since launch) as

[15]E.g., the total number of touchscreen and Wi-Fi devices.

[16]The list of the instruments is available in the appendix.

[17]Full-structural modelling 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 behaviour.

a proxy to capture the option value of waiting for future products.[18] Approximating the future utility component with a simple reduced form has been proposed in the previous literature,[19] and though not perfect, Lou et al. (2011) found that the reduced-form approximation helped controlling for the dynamics of the consumer demand.

5.3 Estimation Strategy

The models of handset demand and software supply are estimated separately because of the different units of observations. I estimate the handset demand using Berry et al. (1995)'s instrumental-variables method based on the generalized method of moments (GMM). The product attributes in the consumer demand include hardware characteristics, fixed effects for network carriers, handset makers, and months, and the age of handset since launch. The unobserved time-varying quality ξ_{jt} is assumed to be mean independent of these characteristics, so 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 a vector of instruments for handset j at time t, and θ_0 is the vector of true model parameters. The price instruments include 1) an indicator of whether each smartphone is sold via corresponding mobile carrier's distribution channel,[20] 2) the sum of the ages of own firm's handsets, and 3) the total number of app-enabled devices. The instruments for the $\log(n_{gt})$ are the mean of own and rival platform's product attributes such as average number of app-enabled devices, average camera pixels, and average number of Bluetooth-enabled devices.

The standard GMM estimator would be inefficient if the covariance of the above moment condition is either heteroscedastic or autocorrelated. I use a heteroscedasticity and autocorrelation consistent covariance estimator proposed by Newey and West (1987).[21]

The application supply model is estimated by instrumental-variables regression. The user installed bases are instrumented with a logarithm of the age of the latest OS revision and its quadratic term. Time-varying software development cost ζ_t is estimated with a linear time trend.

5.4 Computing Brand Values

Marginal Cost Once the parameters are estimated, the first step is to compute the marginal cost c_j in the profit function (Equation 1) in order to estimate the brand values. Nevo (2001) and Goldfarb et al. (2009) use the first-order condition of profit maximization to back out the marginal cost. I modify this approach to apply to the setting of two-sided platform, by considering the effect of marginal change of price on application supply. The details are discussed in the appendix.

Equilibrium Price and Application Supply Given the knowledge of the demand function $D_j(\cdot)$ and the marginal costs, the next step is to solve for the equilibrium prices and applications under counterfactual

[18] While more accurate proxy for the option value would also involve the ages of all handsets, including them in the proxy measure would be infeasible due to high dimension of state space. Hence, I assume that the own handset's age is a reasonable approximation to the option value of waiting.

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

[20] This is a proxy for mobile network carrier's subsidy, which is unobserved to the researcher.

[21] See appendix for more details.

values of brand equity $\boldsymbol{\beta}$. Because the equilibrium price-application pair can only be expressed as implicit functions, I use a numerical algorithm to solve for the equilibrium prices in the outer loop that nests the solution of the equilibrium applications inside.

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 level of the application supply for all platforms by finding a fixed point of the application supply equation (Equation 6). The following proposition is useful for implementing the fixed point iteration.[22]

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 $T_g(\boldsymbol{N}) = \kappa + \phi \log B_g(\boldsymbol{N}) - \log F$, where $\boldsymbol{N} = (N_1, ..., N_G)$ and $N_g = \log n_g$. 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 demand and the supply sides. 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 such that the change of application demand or supply is multiplied by the response of the other side of the platform.

6 Estimation Results

6.1 Consumer Demand

Table 2 presents the estimation results for the smartphone demand models. Column 1 (Logit) and Column 2 (Logit-IV) estimate the same simple logit model, using ordinary least squares and instrumental-variables regression, respectively. The Logit-IV model uses the instruments proposed in the previous section for price and log(apps), i.e., logarithm of total number of applications.[23] The first panel in the Logit and the Logit-IV models shows that the coefficients for price and log(apps) become smaller, once the potential endogeneity is controlled for. This is consistent with the prediction that pricing and application supply decisions may be positively correlated with unobserved product quality. The negative coefficient of the app store dummy represents the scaling factor for the apps variable (Equation 5).

Column 3–5 (BLP I–III) estimate the full model with random coefficients for touchscreen and app store dummy variables using the same instruments as in the Logit-IV. The BLP I model shows that adding these random coefficients changes the ordering of the brand equity estimates; while iPhone is at the top position in the Logit-IV model, it is positioned at the third in the BLP I model. This implies that the demand for the iPhone platform is generated from the consumers with high valuation of touchscreen and app store more than for the other platforms.

Column 4 (BLP II) adds two fixed effects for OS revisions in order to control for the spurious correlation of application supply and smartphone demand driven by unobserved OS quality improvement. The coefficient

[22] The proof is in the appendix.

[23] The same instruments are used throughout this table. For this reason, the Logit-IV may have failed to pass the test of over-identifying restrictions.

	Logit		Logit-IV		BLP I		BLP II		BLP III	
	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
Price / CPI ($100)	-0.0005	0.0001	-0.0039	0.0005	-1.4441	0.3508	-1.4105	0.3554	-1.3091	0.3258
log(Apps)	0.0016	0.0002	0.0011	0.0003	0.5712	0.2221	0.4472	0.2248	0.3931	0.2472
App Store Enabled	-0.0099	0.0012	-0.0065	0.0019	-6.4193	2.3050	-5.7081	2.2676	-4.9551	2.5094
Brand Equities										
iPhone	0.0018	0.0010	0.0106	0.0019	-6.4259	1.0473	-7.0806	1.0845	-6.9478	1.0662
Android	-0.0102	0.0011	-0.0069	0.0016	-8.8064	0.8023	-8.4591	0.8353	-8.4195	0.8249
BlackBerry	0.0019	0.0005	0.0056	0.0009	-6.0773	0.5016	-6.0114	0.5278	-6.1351	0.4994
Windows	0.0002	0.0005	0.0035	0.0009	-6.6524	0.5333	-6.5931	0.5589	-6.7356	0.5195
Symbian	-0.0009	0.0006	0.0046	0.0012	-6.8822	0.7036	-7.7181	0.6174	-7.7898	0.5562
Palm	0.0004	0.0005	0.0050	0.0010	-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
App Store Enabled					4.3522	1.0446	4.5568	1.0440	4.1204	1.1297
N	2,737		2,737		2,737		2,737		2,737	
R^2	0.5861		0.2527							
F	174.7265		96.9013							
$n\chi^2(d.f.)$			54.906		4.267		4.7798		6.8927	
Overid Test (p-value)			<0.001		0.234		0.188		0.075	

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

Table 2: Estimation of Logit Models of Handset Demand

of log(apps) is reduced from 0.571 to 0.447, while the price coefficient is barely changed. This coincides with the large and significant fixed effect for iPhone OS 3.0, suggesting that the quality improvement of the iPhone OS would be spuriously captured as the value of apps for consumers, leading to the overestimation of the coefficient of log(apps).

More OS version fixed effects are included as a robustness check in Column 5 (BLP III). While the log(apps) coefficient decreases even further and loses significance, all the added fixed effects are insignificant and the model rejects the null of the over-identifying restrictions at 10% significance level ($p = 0.075$). Hence, BLP II is chosen as the basis model for conducting counterfactual experiments in the later section.

The brand equity estimates are similar between BLP II and BLP III. All the brand equities are negative, because the outside good had much larger share than any of the smartphone platforms, and its utility was normalized to zero up to the logit error. Among the top three platforms, BlackBerry has the highest brand equity, Android has the lowest, and iPhone is ranked in between the two. But iPhone's brand equity climbs to the top position later with the update of OS version 3.0, which appears to be consistent with the sales pattern shown in Figure 1.

6.2 Application Supply

Table 3 reports the estimation results for the application supply model, obtained by ordinary least squares (OLS I–II) and instrumental-variables regressions (IV). Instruments for the log(installed bases) are log (age of the latest OS) and its quadratic term. As the OS becomes mature, the age of the OS will be positively correlated with the installed bases, while it is unlikely to be correlated with the time-varying unobserved cost of software development.[24] iPhone's development cost is fixed at zero for normalization.

	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(Application Development Cost)						
Android	0.610	0.726				
BlackBerry	4.464***	0.224	4.343***	0.142	4.505***	0.198
Windows	5.213***	0.236	5.421***	0.154	5.469***	0.172
Palm	2.413**	1.004	3.234***	0.287	3.045***	0.32
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 <0.10, ** p <0.05, *** p <0.01.

iPhone's development cost is normalized to zero.

Table 3: Estimation of Software Supply Model

Across all three specifications, the coefficients for the installed bases are estimated to be positive and significant, confirming the developers's positive valuation of the size of the user installed bases. In OLS I, Android's development cost is small with high standard error. Dropping the Android cost in the OLS II model slightly reduces the coefficient estimate of the installed bases, and its accuracy is improved significantly (from 0.341 to 0.068).

In the IV result, controlling for the potential endogeneity produces a slightly larger coefficient estimate for log(installed base) than in OLS II. This result is counterintuitive, because the potential endogeneity bias would overestimate the coefficient. One possible explanation is that since there is little variation in the application supply left unexplained by the observed variables, the potential omitted-variable bias may not be as significant as in the smartphone demand estimation. Nonetheless, the test of over-identifying restrictions is not rejected at 10% level.

Although there is a small difference in the coefficient of the installed bases, the overall pattern of the development costs remains the same across the three results. The cost estimates indicate that iPhone and Android were the most open to the developers' participation, while BlackBerry and Windows Mobile were the least accessible platforms. Palm was more conducive to the developers' participation, although not as much as the leading two platforms.

Given these estimates, the next section will discuss how the brand equities and the development costs interplayed to produce different outcomes for the brand values of the three platforms.

7 Analysis of the Impact of App Stores on Brand Values

This section examines the changes of the brand values due to the app stores, based on the consumer demand and the application supply estimates obtained in the previous section.

[24]The first-stage regression result is in the appendix.

Brand Values Brand values are computed by taking a difference between the profits of the observed equilibrium and the counterfactual equilibrium under the scenario that the brand equity is lost up to a baseline brand. Nokia's Symbian is used as the baseline in the analysis, because it has the lowest brand equity except the three platforms of focus. This involves raising Android's brand equity in the counterfactual experiment instead of lowering it, for Android has in fact lower brand equity than Symbian. Therefore, Android's brand value result must be interpreted as a forgone brand value that would have accrued to Android, if it had Symbian's brand equity.

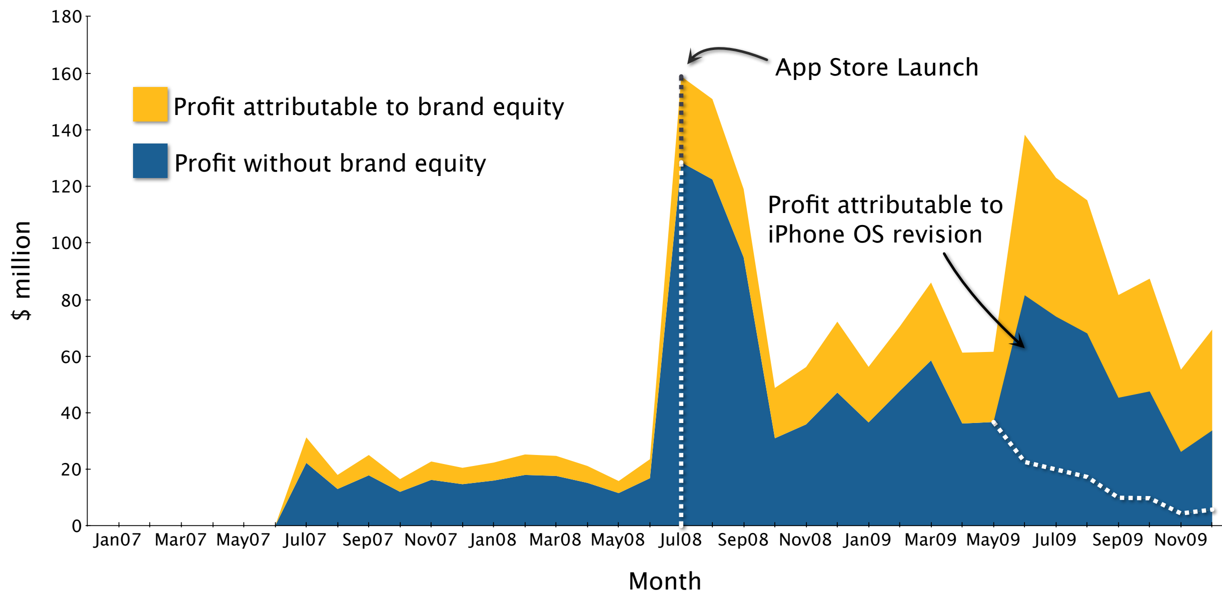

Figure 3: The Value of iPhone Brand

Figure 3 displays the profit curves with and without the change of iPhone's brand equity. The dotted line at July 2008 marks the launch of iPhone's app store. The profit curves show two unusual peaks around July of 2008 and 2009. These coincide with the launch of new product models, i.e., iPhone 3G and iPhone 3GS. The gap between the two curves corresponds to the dollar value of iPhone's brand equity generated over time. In Figure 3, the key difference between the pre- and the post-app-store periods is that iPhone's brand value became larger with the arrival of the app store. However, the brand value does not appear to be gaining significantly greater proportion of the total profits since the launch of the app store, which is contrary to the view that the profit gap may grow over time due to the counter-effect of positive feedback mechanism. It may be because the indirect network effects are not strong enough to reinforce the adverse effect of brand equity loss on the smartphone demand.

The dotted curve that starts at June 2009 denotes the profit trajectory under the scenario that iPhone loses the brand equity improvement achieved through the OS revision, too.[25] Without the huge improvement in the iPhone brand, even more profits would have been lost both in absolute amount and in relative proportion during the last periods.

The same plot is obtained for BlackBerry in Figure 4. First, the overall size of the brand value is larger compared to iPhone's brand value, whether in absolute amount or in relative proportion to the total profits.

[25]This is done by cancelling the fixed effect for iPhone OS 3.0 in the smartphone demand model.

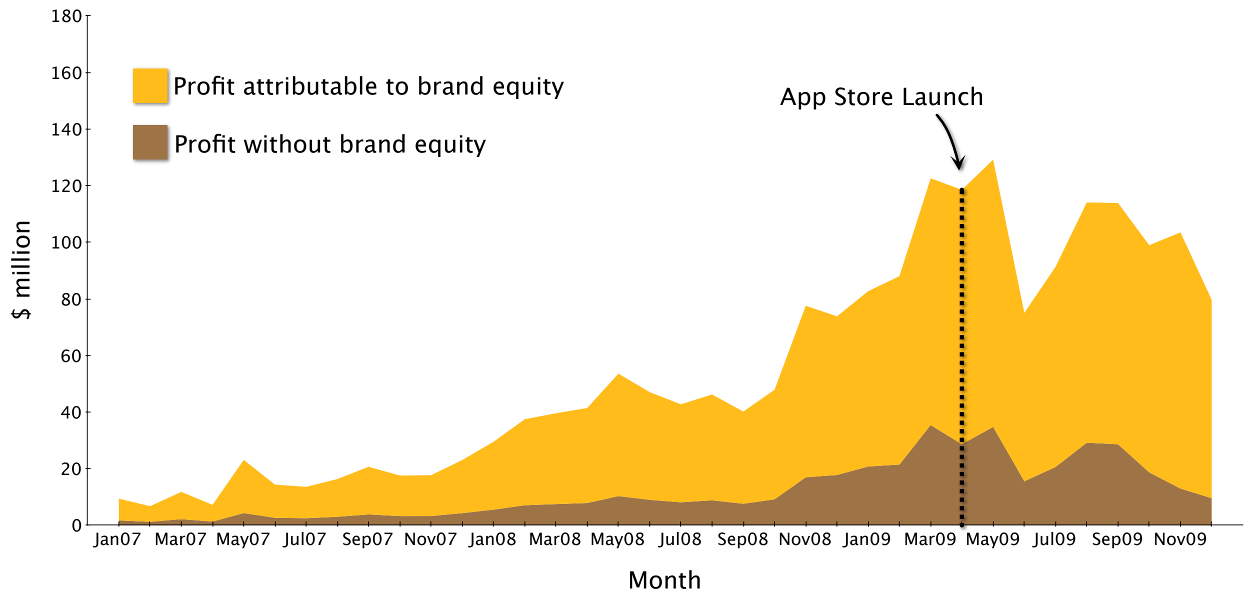

Figure 4: The Value of BlackBerry Brand

This finding is not surprising, given the fact that BlackBerry had the highest brand equity among the three platforms. The second important difference is that BlackBerry's brand value is relatively unaffected by the app store, although there is a marginal growth in the brand value after the launch of the app store. Considering the high development cost of BlackBerry's app store, the app store's contribution to the brand value may have been limited by the lack of accessibility for BlackBerry developers.

Value of Brand	Before July 2008	After July 2008	Both Periods	% Growth
iPhone including OS revision	70	564	357	808%
iPhone excluding OS revision	70	373	245	534%
BlackBerry	233	801	517	344%

Symbian is the benchmark brand for computing brand values.

Table 4: The Growth of Brand Values Since July 2008 (in millions of dollars/year)

Table 4 adds support to the findings obtained in the figures discussed so far. It compares the brand values before and after July 2008, when the first app store was introduced by Apple. The brand value estimates are presented as annual average amounts in the unit of a million dollars. The first row shows the change of iPhone's brand values when the brand value measure includes the new brand equity of iPhone since the version 3.0 upgrade, while the improved brand equity remains unchanged in the second row. As found in the previous figures, the table shows that both iPhone and BlackBerry grew the brand values considerably since July 2008, whether iPhone's brand equity change is considered or not.

Secondly, the table provides a suggestive evidence that the app development cost was the key factor for leveraging the brand values effectively. The growth rate of iPhone's brand value since the app stores is significantly higher than BlackBerry's, regardless of whether the brand equity change is considered or not. Android is omitted in the table, because the platform did not become available until September 2008.

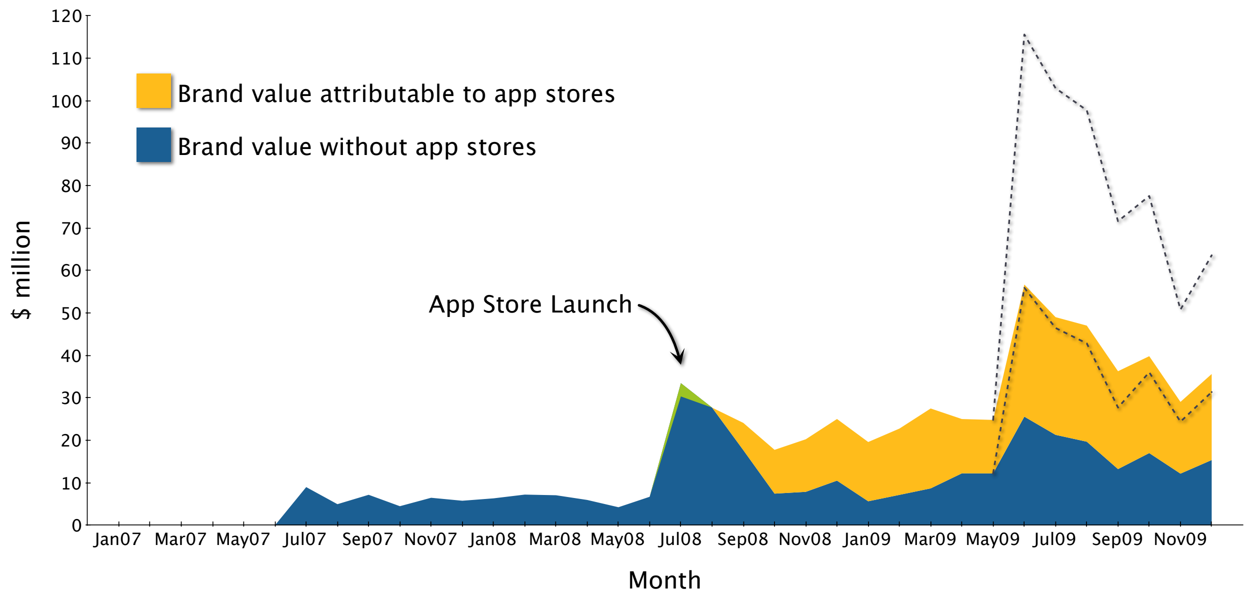

Figure 5: App Stores' Impact on iPhone's Brand Value

Impact of App Stores on Brand Values Figure 5 compares iPhone's brand values between the observed equilibrium and the counterfactual equilibrium under the scenario that none of the platforms had the app stores. The brand value under the counterfactual scenario is identical to the brand value in the observed market equilibrium until July 2008, because no app store was open until then. The brand value figures are obtained following the assumption that the improvement in iPhone's brand equity due to the OS revision remains intact. The two dotted curves correspond to the brand values when these brand equity improvements are included in the measurement of the brand values.

Immediately after the launch of iPhone's app store, iPhone's brand value in the absence of the app stores is slightly higher than the brand value when the app stores are present, because of the estimation result that the consumers had negative valuation of the app store that provided few available apps. Except for the first periods since the app store launch, however, the brand values are higher when the app stores are present, supporting the previous finding that the app store was beneficial to the value of the iPhone brand. Moreover, iPhone's brand value appears to grow fast during early periods of the app store. This appears to result from the positive feedback from the developer's side with respect to iPhone's brand equity.

The impact of the app stores on BlackBerry's brand value is shown in Figure 6. Similarly as iPhone, BlackBerry's brand value when the app stores are present exceeds the brand value in the absence of the app stores, except in the first few periods of the app store launch. The overall size of BlackBerry's brand value tends to be larger than iPhone's, which is not surprising considering its much higher brand equity. However, the contribution of the app store as a proportion to the total profit is much smaller in comparison with iPhone, despite the high brand equity. Considering that BlackBerry also had a high development cost, this result suggests that the growth of BlackBerry's brand value since the app store adoption had been limited by the lack of openness to the developers. Another interesting point is that BlackBerry's brand value was growing significantly until the app store was launched. In this period, RIM introduced a number of blockbuster products including BlackBerry Pearl, BlackBerry Bold, and BlackBerry Curve. Hence, BlackBerry appears

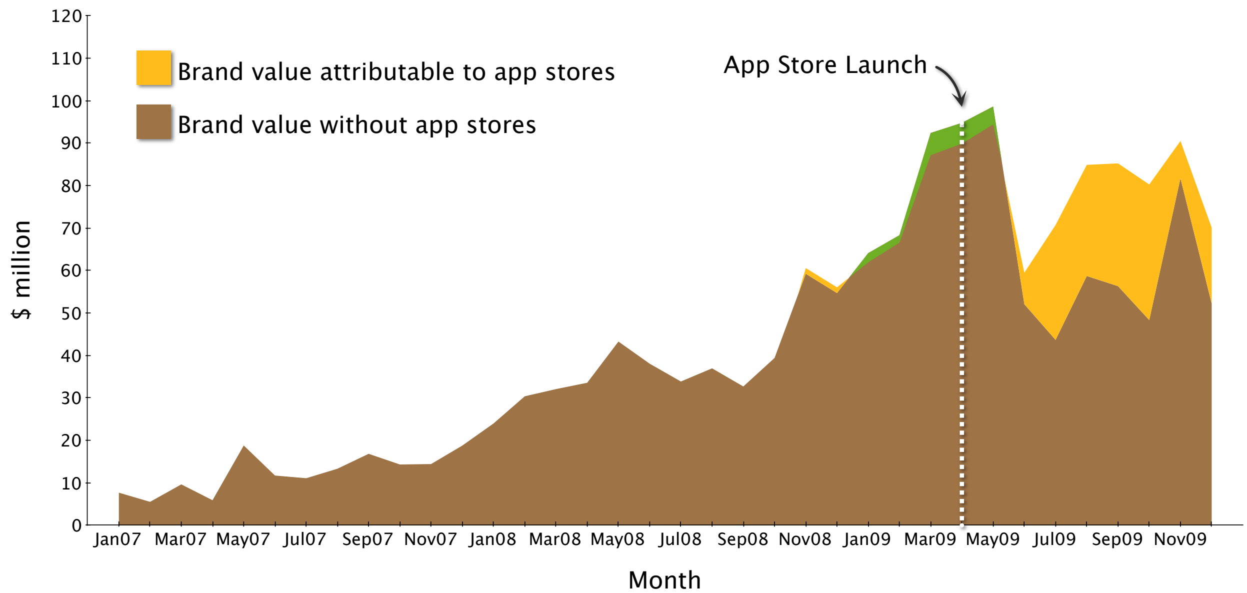

Figure 6: App Stores' Impact on BlackBerry's Brand Value

to have successfully leveraged its brand value by extending its strong brand to child product lines.

The opposite result is obtained for Android. Android's brand value is obtained by combining the profits of Android OEM firms, i.e., HTC, Motorola, and Samsung. As seen in Figure 7, Android's overall (foregone) brand value is modest compared with the other two platforms. This shows that Android's brand value growth had started to gain momentum in the last sample periods. More interestingly, the contribution of Android's app store to the brand value was initially growing in proportion to the total profits, but was later reduced during the last periods. This indicates that while Android's early brand value may have relied on its open app store to a large extent, it reduced the dependence on the app store substantially in later periods. This result coincides with the fact that Android, jointly with Verizon Wireless, spent $100 million on promoting its flagship device, Motorola Droid during the 2009 holiday season. Nonetheless, the relative contribution of the app store on Android's brand value is significantly higher than in the case of BlackBerry's app store.

	Brand Value w/o App Store	Brand Value w/ App Store	Change of Brand Value	% Increase of Brand Value
iPhone including OS revision	277	564	287	103%
iPhone excluding OS revision	183	373	190	103%
Android*	(345)	(536)	(191)	55%
BlackBerry	782	968	186	24%

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)

Table 5 summarizes the app stores' influence on the brand values, only taking into account the periods since 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 side. For comparison, the brand value figures are converted into annual average amounts in the unit of a million dollars. As mentioned earlier, Android's brand values denote the

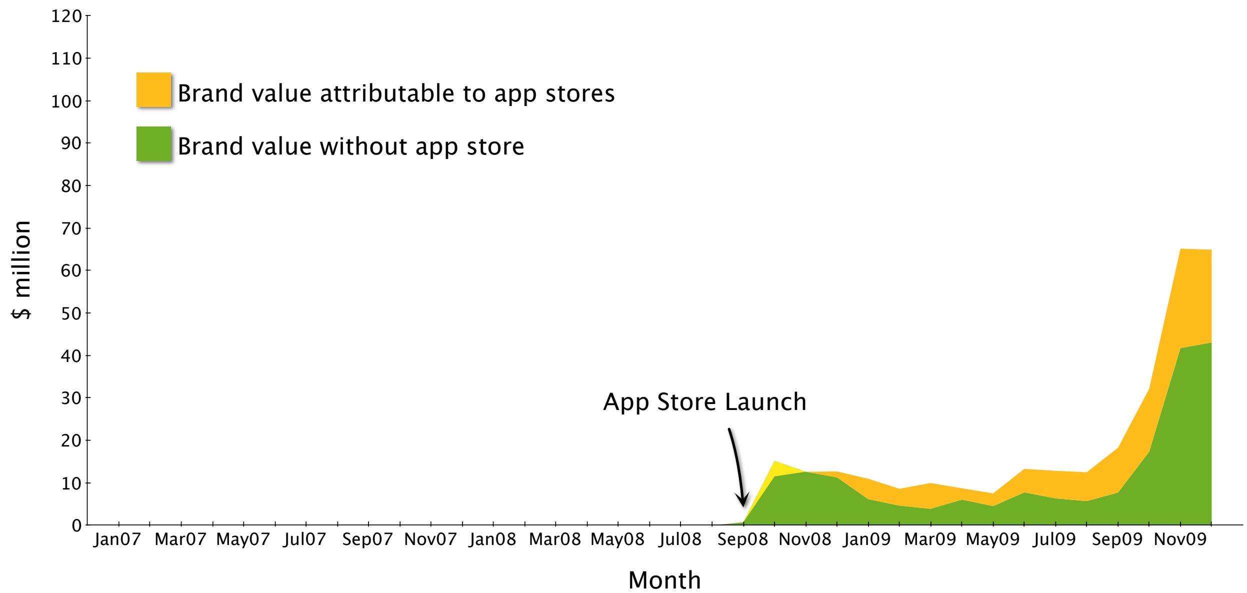

Figure 7: App Stores' Impact on Android's Brand Value

forgone brand values for the three handset vendors.

Table 5 confirms the main results obtained in the previous analysis. First, the app stores helped growing the brand values for all three platforms. The growth rate of the brand values due to the app stores ranges from 24% to 103% of the brand values that are obtained without the developer's side. This result confirms the positive effect of the app stores for the brand values. Secondly, iPhone increased brand value via app store substantially more than BlackBerry, despite having much less brand equity. Conversely, the high development cost limited the growth of BlackBerry's brand value, even though it had the largest brand equity among the three platforms in the consumer's side. Hence, the effectiveness of leveraging brand value via app store relies more on the app store's openness rather than the brand equity resources. Thirdly, the app store's contribution to Android's brand value is moderate, although it is higher than in BlackBerry's. Considering its open app store, Android would have been able to leverage the brand value even more, if it had a higher brand equity. The lack of brand equity, not the lack of open platform strategy, prevented the platform from leveraging the brand value more. Despite the fact that Android's brand value concept is a counterfactual forgone value, the result demonstrates that a strategy to leverage brand value via app store will be effective, only when it is supported by a certain level of brand equity in the consumer's side.

Robustness Check As a robustness check, I conducted another counterfactual experiment by assuming that iPhone's app store had the same app development cost as BlackBerry's. This is done by changing the fixed cost parameter F_g of the iPhone app store in Equation 6. If the different growth rates of iPhone and BlackBerry brand values in table 5 are driven by the factors other than the development costs, the gap between the growth rates of two brand values should remain the same even after the change is made for the fixed cost for iPhone's app store.

Table 6 shows that the app store, if not supported by developer's easy access to the platform, could have been detrimental to iPhone's brand value. Given the high cost of application supply, the model predicts that iPhone would have very small number of apps for most of the time, and that the poor application availability

	Brand Value w/o App Store	Brand Value w/ App Store	Change of Brand Value	% Increase of Brand Value
iPhone including OS revision	277	129	-148	-53%
iPhone excluding OS revision	183	107	-76	-42%
Android*	(345)	(615)	(270)	105%
BlackBerry	782	1,108	326	42%

Symbian is the benchmark brand for computing brand values.

*Total forgone brand value of Android for HTC, Motorola, and Samsung.

Table 6: The Contribution of the App Stores to Brand Values When iPhone had the Same App Store as BlackBerry (in millions of dollars/year)

would have a negative impact on its smartphone demand. At the same time, the consumers would switch to the two rival platforms, boosting their brand values when the app stores are present. Hence, without having the easy accessibility for the developers, iPhone's app store would lose competitiveness in the developer's side and thus lose the brand value as well. The reason why BlackBerry was able to gain the brand value with such a high-cost app store can be explained by the different user installed bases. Because BlackBerry sold significantly more units than iPhone did, the developers still found BlackBerry's software market to be attractive despite its high cost structure. However, because iPhone was a new entrant without having such a large installed base, it would be difficult to justify the high cost of developing for the iPhone platform for most developers.

8 Limitations

So far this paper has assumed that all the players, consumers, developers, and handset makers are myopic. I discuss the implication of the violation of each assumption for the findings.

First, forward-looking consumers and developers may choose the platform that is expected to attract the largest installed bases in the future. Then the smartphone market will likely be standardized by a single winning platform in the long term, if the indirect network effects are sufficiently high. If this is the case, the app store's impact on brand value will be even greater for iPhone than is predicted by the static model, because its brand equity loss may lead to losing dominance in the developer's side, too. Hence, brand equity is likely to be found more valuable in two-sided market at least for iPhone, due to its additional impact on the market's expectation. However, the prediction for other platforms is unclear, and warrants future research.

Secondly, violation of the static-pricing assumption can lead to biases in the marginal cost estimates. Liu (2010) discusses two main incentives for dynamic pricing behaviour: heterogeneous consumer preference and network effects. Consumer heterogeneity provides incentive for a durable-good firm to engage in intertemporal price discrimination by skimming an enthusiast market first, and then lowering the price for casual consumers later. In this case, the marginal cost obtained under the static pricing assumption will be biased upward in early periods, and biased downward later. Network effects create an incentive for firms in a platform war to subsidize consumers' early adoption by charging lower initial prices (often below marginal costs) in an effort to build the scale of demand first, and then to charge higher prices later once it obtains a dominant market position. If this incentive is strong, my marginal cost estimate will be biased downward in early periods. Depending on the bias in the marginal costs, the brand value estimates will be changed as well.

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 in a simple way (Dubé et al., 2010). While Liu (2010) had to collect the marginal cost information for only two products, this study requires tracking over 100 products, which would be too costly. Moreover, it would be impossible to identify the time-varying product-specific marginal costs without making very strong assumption.[26] Due to this difficulty, I chose to model the pricing decision using a static framework.

9 Conclusion

This paper examines the impact of the app stores on the value of three OS platform brands: iPhone, Android, and Blackberry. The results suggest that the app stores significantly contributed to leveraging the brand values of all three platforms, while there exists a substantial difference in the degree of the leveraging effect. Despite the brand equity lower than BlackBerry's, iPhone was able to leverage the brand value via the app store more effectively than BlackBerry by virtue of its openness to the developers. Conversely, BlackBerry's lack of openness limited its ability to leverage the most valuable brand among the three. In contrast, the growth of Android's (forgone) brand value was constrained by the lack of brand equity, despite the open app store policy. These core findings can be summarized as follows: *offering developers more accessibility to the platform is the key for leveraging brand value in a two-sided platform, provided that it is supported by at least a moderate level of brand equity to generate developer's interest.*

By studying the smartphone market, this paper answers how the value of the OS brands was influenced by the market transformation from one-sided to two-sided platforms. It finds that a two-sided market is likely to favour the platform that offers easier access on the developer's side, given a sufficiently strong brand in the consumer's side. In this sense, the findings are consistent with Shapiro and Varian (1999)'s view that "a superior technology is not enough to win." However, this paper also emphasizes the importance of having at least a certain level of brand equity as well. The lesson from the rise of iPhone and Android platforms in the early smartphone market is that even relatively weak brands can become more valuable as a market moves to two-sided platforms, but only when developers are given easy access to the platforms.

This paper is not without limitations. Smartphone vendor's dynamic pricing is ignored for lack of marginal cost data. In measuring brand values, marketing activity was also ignored due to data limitation. The indirect network effects might have overstated the value of applications, if they spuriously captured direct network effects. For example, data on individual-level smartphone demand within a social network may be able to identify the indirect network effects separately from direct network effects arising from social learning. Finally, the assumption of homogeneous handset replacement demand can be relaxed, if data on ownership transition are available.

Despite these limitations, this paper provides insight into the brand values of two-sided platforms in the rapidly evolving smartphone market.

[26] The difficulty of the marginal cost estimation can be mitigated by assuming time-invariant marginal costs. The constant marginal cost assumption would be too restrictive though, because the smartphones are high-technology products, which typically exhibit rapidly declining marginal costs over time.

References

Ailawadi, K. L., D. R. Lehmann, and S. A. Neslin (2003): "Revenue Premium as an Outcome Measure of Brand Equity," *Journal of Marketing*, 67, 1–17.

Angrist, J. D. and J.-S. Pischke (2009): *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton Univ Press.

AppStoreHQ (2010): "iOS vs Android? Over 1,000 Developers (Including Some Top Names) Are Having It Both Ways," `http://blog.appstorehq.com/post/760323632/ios-vs-android-over-1-000-developers-including-some`.

——— (2011): "It's the Apps, Stupid!" `http://blog.appstorehq.com/post/6590466369/its-the-apps-stupid`.

Argentesi, E. and L. Filistrucchi (2007): "Estimating Market Power in a Two-Sided Market: The Case of Newspapers," *Journal of Applied Econometrics*, 22, 1247–1266.

Armstrong, M. (2006): "Competition in Two-sided Markets," *RAND Journal of Economics*, 37, 668–691.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63, 841–90.

Berry, S. T. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, 25, 242–262.

Carranza, J. E. (2010): "Product Innovation and Adoption in Market Equilibrium: The Case of Digital Cameras," *International Journal of Industrial Organization*, 28, 604–618.

Chen, J., U. Doraszelski, and J. Joseph E. Harrington (2009): "Avoiding Market Dominance: Product Compatibility in Markets with Network Effects," *RAND Journal of Economics*, 40, 455–485.

Ching, A. T., T. Erdem, and M. P. Keane (2011): "Learning Models: An Assessment of Progress, Challenges and New Developments," *Working Paper*.

Chou, C. and O. Shy (1990): "Network Effects Without Network Externalities," *International Journal of Industrial Organization*, 8, 259–270.

Church, J. and N. Gandal (1992): "Network Effects, Software Provision, and Standardization," *The Journal of Industrial Economics*, 40, 85–103.

——— (1993): "Complementary Network Externalities and Technological Adoption," *International Journal of Industrial Organization*, 11, 239–260.

Corts, K. S. and M. Lederman (2009): "Software Exclusivity and the Scope of Indirect Network Effects in the US Home Video Game Market," *International Journal of Industrial Organization*, 27, 121–136.

Dubé, J.-P. H., G. J. Hitsch, and P. K. Chintagunta (2010): "Tipping and Concentration in Markets with Indirect Network Effects," *Marketing Science*, 29, 216–249.

Erdem, T. and J. Swait (1998): "Brand Equity as a Signaling Phenomenon," *Journal of Consumer Psychology*, 7, 131–157.

Geweke, J. F. and M. P. Keane (2000): *Bayesian Inference for Dynamic Discrete Choice Models without the Need for Dynamic Programming*, Cambridge University Press, chap. 4.

Goldfarb, A., Q. Lu, and S. Moorthy (2009): "Measuring Brand Value in an Equilibrium Framework," *Marketing Science*, 28, 69–86.

Gowrisankaran, G., M. Park, and M. Rysman (2010): "Measuring Network Effects in a Dynamic Environment," *Working Paper*.

Jin, G. Z. and M. Rysman (2010): "Platform Pricing at Sportscard Conventions," *Working Paper*.

Kaiser, U. and J. Wright (2006): "Price Structure in Two-Sided Markets: Evidence from the Magazine Industry," *International Journal of Industrial Organization*, 24, 1–28.

Kamakura, W. A. and G. J. Russell (1993): "Measuring Brand Value with Scanner Data," *International Journal of Research in Marketing*, 10, 9–22.

Keller, K. L. (1993): "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *The Journal of Marketing*, 57, 1–22.

Keller, K. L. and D. R. Lehmann (2006): "Brands and Branding: Research Findings and Future Priorities," *Marketing Science*, 25, 740.

Lee, R. S. (2010): "Vertical Integration and Exclusivity in Platform and Two-Sided Markets," *Working Paper*.

——— (2011): "Dynamic Demand Estimation in Platform and Two-Sided Markets: The Welfare Cost of Software Incompatibility," *Working Paper*.

Liu, H. (2010): "Dynamics of Pricing in the Video Game Console Market: Skimming or Penetration?" *Journal of Marketing Research*, 47, 428–443.

Lou, W., D. Prentice, and X. Yin (2011): "What Difference Does Dynamics Make? The Case of Digital Cameras," *International Journal of Industrical Organization*.

Menn, J. (2009): "Store Set to Be Apple of Master's Eye," *Financial Times*, `http://www.ft.com/cms/s/2/8bbd4b80-ed8b-11de-ba12-00144feab49a.html#axzz1RrncWMb7`.

Mizik, N. (2009): "Assessing the Total Financial Performance Impact of Marketing Assets with Limited Time-Series Data: A Method and an Application to Brand Equity Research," *Marketing Science Institute Working Paper*, report No. 09-116.

Nair, H., P. Chintagunta, and J.-P. Dubé (2004): "Empirical Analysis of Indirect Network Effects in the Market for Personal Digital Assistants," *Quantitative Marketing and Economics*, 2, 23–58.

Nevo, A. (2001): "Measuring Market Power in the Ready-To-Eat Cereal Industry," *Econometrica*, 69, 307–342.

Newey, W. K. and K. D. West (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703–708.

Ohashi, H. (2003): "The Role of Network Effects in the US VCR Market, 1978–1986," *Journal of Economics & Management Strategy*, 12, 447–494.

Pettey, C. and B. Tudor (2010): "Gartner Says Worldwide Mobile Phone Sales to End Users Grew 8 Per Cent in Fourth Quarter 2009; Market Remained Flat in 2009," `http://www.gartner.com/it/page.jsp?id=1306513`.

Rochet, J.-C. and J. Tirole (2003): "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association*, 1, 990–1029.

——— (2006): "Two-Sided Markets: A Progress Report," *The RAND Journal of Economics*, 37, 645–667.

Rysman, M. (2009): "The Economics of Two-Sided Markets," *The Journal of Economic Perspectives*, 23, 125–143.

Shapiro, C. and H. R. Varian (1999): *Information Ruels: A Strategic Guide to the Network Economy*, Harvard Business School Press.

Sriram, S., S. Balachander, and M. U. Kalwani (2007): "Monitoring the Dynamics of Brand Equity Using Store-Level Data," *Journal of Marketing*, 71, 61–78.

Sullivan, M. W. (1998): "How Brand Names Affect the Demand for Twin Automobiles," *Journal of Marketing Research*, 35, 154–165.

Sun, M. and E. Tse (2007): "When Does the Winner Take All in Two-Sided Markets?" *Review of Network Economics*, 6, 2.

Train, K. (2003): *Discrete Choice Methods with Simulation*, Cambridge University Press.

VisionMobile (2010): "Mobile Developer Economics 2010 and Beyond," .

——— (2011): "Mobile Developer Economics 2011," .

Wernerfelt, B. (1988): "Umbrella Branding as a Signal of New Product Quality: An Example of Signalling by Posting a Bond," *The Rand Journal of Economics*, 19, 458–466.

Weyl, E. G. (2010): "A Price Theory of Multi-Sided Platforms," *American Economic Review*, 100, 1642–1672.

Zhu, F. and M. Iansiti (2012): "Entry into Platform-Based Markets," *Strategic Management Journal*, 33, 88–106.

A Robust GMM Covariance Estimator

The GMM moment is defined in the paper as

$$G(\theta) = \mathrm{E} Z_{jt}\xi_{jt}$$

where $Z_{jt} \in \mathbf{R}^L$ is a L-dimensional vector of instruments for handset j at time t. Then the sample moment can be obtained as

$$g(\theta) = \frac{1}{JT}\sum_j \sum_t Z_{jt} w_{jt}$$

where $w_{jt} = \beta_{gt} - x'_{jt}\theta_x + \alpha p_{jt} - V_j^{sw}(n_{gt})$. The GMM objective function is defined as

$$\mathrm{E}\Big[\Big(\sum_{j,t} Z_{jt}\xi_{jt}\Big)'\Phi^{-1}\Big(\sum_{j,t} Z_{jt}\xi_{jt}\Big)\Big]$$

where Φ is given as

$$\Phi = \mathrm{E}\Big(\sum_{j,t} Z_{jt}\xi_{j,t}\Big)\Big(\sum_{j,t} Z_{jt}\xi_{jt}\Big)'$$

The first-stage estimator of Φ is $\frac{1}{J}\sum_j \sum_t w_{jt}^2 Z_{jt} Z'_{jt}$. The second-stage uses a robust GMM covariance estimator proposed by Newey and West (1987).

$$\hat{\Phi}^{(2)} = \frac{1}{J}\sum_j \Big[\sum_t w_{jt}^2 Z_{jt} Z'_{jt} + \sum_{l=1}^{L}\big(1 - \frac{l}{L+1}\big)\sum_{t=l+1}^{T} w_{jt} w_{jt-l}(Z_{jt} Z'_{jt-l} + Z_{jt-l} Z'_{jt})\Big]$$

B Computation of Marginal Cost

Let g_j be the OS platform of handset $j \in J$, and $A_{g_j} = \{k \in J : g_k = g_j\}$ be the set of all handsets in the platform of handset j, and $\bar{A}_{g_j} = \{k \in J : g_k = g_j, apps_k > 0\}$ 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:

$$\frac{\partial \pi}{\partial p_j} = s_j + \sum_{k \in F} (p_k - c_k) \frac{ds_k}{dp_j} = 0$$

where

$$\frac{ds_k}{dp_j} = \int \frac{\partial s_{ik}}{\partial p_j} + \sum_g \frac{\partial s_{ik}}{\partial \log N_g} \frac{\partial \log N_g}{\partial p_j} F(d\nu_i). \tag{8}$$

Note that

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

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

Define matrices $dSdN$ and $dNdP$ such that

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

Then the marginal cost is

$$c = p + (\Omega_1 + \Omega_2)'^{-1} s$$

where

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

and $\Omega_2 = dSdN \cdot dNdP$.

C Fixed Point Algorithm for Equilibrium Application Supply

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 $T_g(\boldsymbol{N}) = \kappa + \phi \log B_g(\boldsymbol{N}) - \log F$, where $\boldsymbol{N} = (N_1, ..., N_G)$ and $N_g = \log n_g$. If $\phi\gamma < 1$, then T has a unique fixed point in X and is a contraction mapping of modulus $\beta < 1$.*

Proof. It suffices to show that $\|T_g(\boldsymbol{N}) - T_g(\boldsymbol{N}')\| < \beta \|N_g - N_g'\|$ for $\beta \in (0, 1)$. 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

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

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

Hence,

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

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 $\beta < 1$. □

D Estimation Results

The following table provides the full estimation results of Table 2.

	Logit		Logit-IV		BLP I		BLP II		BLP III	
	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.	Est.	s.e.
Price and Indirect Network Effects										
Price / CPI ($100)	-0.0005	0.0001	-0.0039	0.0005	-1.4441	0.3508	-1.4105	0.3554	-1.3091	0.3258
log(Apps)	0.0016	0.0002	0.0011	0.0003	0.5712	0.2221	0.4472	0.2248	0.3931	0.2472
App Store Enabled	-0.0099	0.0012	-0.0065	0.0019	-6.4193	2.3050	-5.7081	2.2676	-4.9551	2.5094
Brand Equities										
iPhone	0.0018	0.0010	0.0106	0.0019	-6.4259	1.0473	-7.0806	1.0845	-6.9478	1.0662
Android	-0.0102	0.0011	-0.0069	0.0016	-8.8064	0.8023	-8.4591	0.8353	-8.4195	0.8249
BlackBerry	0.0019	0.0005	0.0056	0.0009	-6.0773	0.5016	-6.0114	0.5278	-6.1351	0.4994
Windows	0.0002	0.0005	0.0035	0.0009	-6.6524	0.5333	-6.5931	0.5589	-6.7356	0.5195
Symbian	-0.0009	0.0006	0.0046	0.0012	-6.8822	0.7036	-7.7181	0.6174	-7.7898	0.5562
Palm	0.0004	0.0005	0.0050	0.0010	-5.8483	0.6533	-5.8406	0.6710	-6.0588	0.6251
Product Attributes Searchable to Consumers										
CPU (GHz)	-0.0009	0.0001	-0.0004	0.0002	-0.1214	0.0811	-0.1370	0.0790	-0.1290	0.0792
Camera Megapixel	0.0010	0.0001	0.0018	0.0002	0.6189	0.1140	0.5976	0.1116	0.5747	0.1054
Screen Size * Resolution	0.0002	0.0000	0.0004	0.0001	0.1228	0.0419	0.1268	0.0436	0.1376	0.0442
Memory500MB					0.4278	0.5499	0.4441	0.5410	0.2848	0.5027
Memory1GB					0.5008	0.4108	0.4847	0.4119	0.4755	0.3831
Handset Age	0.0000	0.0000	0.0000	0.0000	-0.0261	0.0066	-0.0251	0.0067	-0.0290	0.0072
AT&T	0.0021	0.0002	0.0010	0.0004	0.8894	0.1942	0.9137	0.1916	0.9658	0.1764
Verizon	0.0019	0.0003	0.0008	0.0004	0.5185	0.2113	0.5442	0.2084	0.5981	0.1960
T-Mobile	0.0018	0.0003	0.0017	0.0004	1.1267	0.1766	1.1220	0.1750	1.1671	0.1647
Sprint	0.0012	0.0003	0.0013	0.0003	0.9797	0.1608	0.9952	0.1594	0.9910	0.1485
Touchscreen	0.0124	0.0007	0.0127	0.0010	-0.2680	0.8464	-0.7352	0.8900	-0.8827	0.9073
Keyboard	0.0009	0.0001	0.0018	0.0002	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	0.0007	0.0004	0.5175	0.2347	0.4619	0.2276	0.3987	0.2157
Month	0.0000	0.0000	-0.0002	0.0000	-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										
SD Touchscreen					3.3643	0.8504	4.0574	0.8855	3.8063	0.8836
SD App Store Enabled					4.3522	1.0446	4.5568	1.044	4.1204	1.1297
N	2,737		2,737		2,737		2,737		2,737	
R^2	0.5861		0.2527							
F	174.7265		96.9013							
$n\chi^2(d.f.)$			54.906		4.267		4.7798		6.8927	
Overid Test (p-value)			$<$0.001		0.234		0.188		0.075	

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

Table 7: Estimation of Logit Models of Handset Demand

E First-Stage Regression: Smartphone Demand Estimation

The results for the first-stage regression of the smartphone demand estimation are reported for the price and log(apps). The F-test on the excluded instruments is based on Angrist and Pischke (2009) to account for the multiple endogenous variables.

Dependent Variable:	Price		log(Apps)	
	Parameter	Std. Error	Parameter	Std. Error
App Store 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	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
H&set 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*App Store	-0.0054	0.0017	0.0273	0.0005
Other OS Anyapp	-0.0014	0.0018	-0.0037	0.0005
Other OS Camera	0.3229	0.1825	-0.4110	0.0534
Own firm Anyapp	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
N	2737		2737	
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

F First-Stage Regression: Application Supply Estimation

The first-stage regression result for the application supply estimation is displayed in the following table. The instruments of the installed bases, the OS age and its quadratic term have the expected signs and significance.

Dependent variable: log(Installed Base)

	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
N	52			
R^2	0.76			
F	276.91			

iPhone's development cost is normalized to zero.
Robust estimate of the standard error is used.
The p-value of Hansen's test($\chi^2(1)$) is 0.5741.

Table 9: First-Stage Regression Result