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The Determinants of Supply and Demand for Mobile Applications

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Abstract

Since 2008, multiple smartphone platforms have launched versions of "app stores", marketplaces where consumers can purchase and download software applications for their smartphone. This paper provides evidence for both demand and supply of "apps" using data on the size and composition of smartphone user bases and of the apps available for competing platforms. Results from the estimation of a structural model show that the composition of users on a platform is a key determinant of app supply, and counterfactual simulations show that this effect is greater than the effects of within-platform competition and multi-homing costs in explaining the observed market outcome.

JEL classification: L1, L86, L96

Keywords: network effects, telecommunications, software development, platform competition.

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1 Introduction

In July of 2008, Apple launched its "App Store", which allowed consumers that owned an Apple iPhone to purchase and download third-party applications ("apps") to their smartphone. This proved to be a wildly popular new product for consumers, and many firms started developing and marketing apps for Apple's App Store, as well as for competing platforms such as Google's Android Marketplace, Blackberry's App World, and others. This created a classic instance of platform competition where the different smartphones try to attract consumers on one side of the market and application developers on the other. Interestingly, developers continued to prioritize creating apps for Apple's platform well after Google's platform overtook Apple's in installed base,[1] and further, the nature of app competition differed on Apple's platform versus Google's,[2] despite identical terms from the platforms themselves.[3] This paper will examine the forces that led to these outcomes using detailed data on consumer behavior to illuminate the role that consumer heterogeneity plays in the choices made by app developers on the opposite side of the market.

Economists have long been interested in the theory of network effects and their implications.[4] More recently, a number of papers have moved toward estimating network effects, including such notable examples as Rysman (2004) and Ackerberg and Gowrisankaran (2006). The most closely related paper to this project is Gowrisankaran, Park, and Rysman (2011), which looks at indirect network effects in the adoption of DVDs. As in that setting, the smartphone industry is characterized as having an indirect network effect, although via the development of mobile software applications instead of the availability of content. What is unique about the smartphone setting is the availability of detailed consumer-level choice data in the smartphone market, allowing for an empirical investigation of how the characteristics of consumers that join a platform affect choices made on the other side. Furthermore, the demand system in this setting is simpler, as consumers very rarely purchase more than one smartphone (i.e. consumers "single-home").

[1] See Ellison (2011a)

[2] In 2010, 75% of apps on Apple's platform had an upfront price, whereas 57% of apps on Google's platform were available free, and supported by ad revenue (Distimo, 2010).

[3] Both platforms take a 30% share of all sales processed in their stores.

[4] See Farrell and Klemperer (2007) for a survey.

This paper will first examine how the characteristics of the consumers on each platform affect software developers' choices of which platforms to develop for. It is natural to assume that a platform with more users is more attractive to developers, although this paper will examine how the types of users on each platform appeal to developers. Next, this paper will examine how within-platform competition affects developers' choices. It is also natural to assume that developers view a platform that has few other developers on board as more attractive. These first two questions could be seen as related to the classic question of product location choice: should a firm locate far from its competitors (i.e. prioritize a platform with fewer competing apps available), or close to demand (i.e. prioritize a platform with more consumers, or with a more "profitable" type of consumer).[5] Detailed data on consumer characteristics on each platform enables the measurement of these competing forces and the quantification of the value placed on different characteristics by developers.

A final question in this paper is how the tradeoff of multi-homing versus single-homing affected the development of this industry. The cost of developing an app can be quite large; the cost of "porting" it to additional platforms is typically less, although the relative cost of cross-development determines the tradeoff between single-homing (developing for one platform) and multi-homing (developing for multiple platforms).

The approach will be to first provide reduced-form evidence on these three questions. Then, a structural model will be constructed and estimated to capture these features in this setting. This will then allow counterfactual simulations to measure the relative effects of these forces in shaping the observed industry outcome. We will find that the first effect, the composition of the user base, appears to be much more significant than within-platform competition and multi-homing costs in explaining the market outcome.

The contributions of this paper are first, an examination of the interaction of network effects and individual characteristics in a data-rich setting, and second, an analysis of the forces that can lead to different forms of within-platform competition across different platforms. This setting is

[5] In Gentzkow, Shapiro, and Sinkinson (2012), my co-authors and I examine product location choice in the newspaper setting.

ideal for an examination of network effects with individual heterogeneity as consumer demand is simplified by single-homing and rich individual-level data are available.

The paper proceeds as follows: Section 2 describes institutional details and the data used in estimation. Section 3 provides a descriptive analysis of the data. Section 4 discusses a structural model of firm choices. Section 5 presents results of the estimation and counterfactual exercises. Section 6 concludes.

2 Industry and Data Description

2.1 Industry

The market for smartphones has exploded since Apple's introduction of the iPhone in 2007. Significantly, in 2008, Apple introduced it's "App Store", creating a platform through which software developers could create and market applications to consumers. Competing smartphone platforms emerged, with Google's Android Marketplace[6] and Research In Motion's Blackberry App World[7] offering similar capabilities for users of Android and Blackberry smartphones.[8] Consumers have responded enthusiastically to the market for "apps": in 2011, 38.2 billion mobile applications, or "apps", were downloaded to smartphones (Ellison, 2011b). By early 2012, over half of US mobile subscribers owned a smartphone, and in 5 short years, the mobile application industry has grown from nothing to employ nearly 500,000 people in the United States alone (Mandel, 2012).

However, app developers face a choice in which platform to develop their applications for. Beyond the cost of developing an app for a single platform, there is a cost to "port" the software to work with another platform.[9] Therefore, the smartphone platforms face the traditional two-sided market conundrum of attracting consumers on one side (who single-home), and app developers on

[6]Launched in October of 2008 and rebranded as "Google Play" in 2012.

[7]Launched in April of 2009.

[8]Additional smartphone platforms exist, such as Symbian, Bada, and Windows Phone. However, the three mentioned are the dominant platforms in terms of the number of applications offered and the market size. See Ellison (2011a)for details.

[9]Discussions with industry sources indicate that porting costs fell dramatically in 2011 with the advent of cross-platform development tools. This could potentially be used to segment the analysis.

the other side (who may single-home, or multi-home at an additional cost). This further creates an indirect network effect in that a consumer's choice to join a platform can increase the value of that platform for all members of it in the next period by attracting more app developers.

While development costs can be large, cross-development costs can be large as well. Towards the end of the time period used in this paper, cross-development tools started to become available. This had the effect of lowering, but not eliminating, cross-development costs.[10] During the time period of this study, cross-development costs were considered to be significant.

2.2 Data Sources

The data to be used in this project comes from both public and proprietary sources. The first data source used in this project is Nielsen's Mobile Insights survey of the US mobile phone market. Nielsen conducts a monthly cross-sectional survey of 25,000 US consumers, gathering data on individual characteristics and product choices (see Sinkinson, 2012 for more details on this dataset). This provides data for both the installed bases of each of the platforms as well as the characteristics of the individuals on each platform, and in particular, the average income levels of the users of each type of smartphone.

The second data source is a hand-collected dataset of the number of apps that are available in the competing app stores.

Both data sources have been compiled for November 2008-July 2011. The following section will provide a descriptive analysis of the data.

3 Descriptive Analysis

This section provides descriptive analysis to establish some basic features of the market for mobile applications. This analysis will take a reduced-form approach, treating many factors as exogenous. Figure 1 provides a sense of trends in both the installed bases of the competing platforms, and

[10] See "The Cross-Platform Conundrum", Accenture Consulting (2012), for details on the situation facing developers who wish to multi-home.

the number of apps available for each platform. Of interest is that Apple continues to maintain a strong lead in the number of apps available well after Android surpasses Apple in installed base. However, as we see in Figure 2, Android had the most success among lower income households[11], only approaching Apple among higher income households[12] towards the end of the data period. A likely cause for this is that Android handsets were often made available at lower initial price points than iPhones.[13]

3.1 Demand for Applications

The first feature of the market to establish is that consumers respond to the availability of apps in their decisions about which smartphones to purchase. Table 1 shows the results from a regression of the share of consumers opting for each of the three smartphone platforms in a given month, on the log of the number of apps available on each platform that month. Controls include platform fixed effects and platform-specific time trends. Of note is that, in general, the Blackberry platform is in decline, while the Android and Apple platforms are growing rapidly (see Figure 1). For that reason, we get that without platform-specific time trends (column 1), the result is only a weak increase in demand from apps. However, when we drop the Blackberry platform (column 2), we gain strong statistical significance and a much larger magnitude. Finally, allowing for platform-specific time trends in purchase shares (column 3), we see that the availability of apps does have a statistically significant impact on demand for smartphones.

3.2 Supply of Applications

Table 2provides some initial evidence that developers respond to the installed base of a platform when deciding which platform to develop for. Here, "installed base" is measured as the share of US adults who own a smartphone that runs a particular operating system, and not a platforms share

[11]Defined as survey respondents reporting annual HH income of up to $50K

[12]Defined as survey respondents reporting annual HH income of over $100K

[13]It wasn't until October of 2011 that Apple had an iPhone model that was free on a 2-year contract (the two-year old iPhone 3GS). In contrast, there had been many Android models available free on contract since June of 2010.

of all current smartphones.[14] This measure is used as the total market for smartphones is growing quickly during this time period. The first four columns show results regressing the change in the number of apps available for a platform on either the raw installed base (columns 1 and 2), or the monthly change in installed base (columns 3 and 4). The results are quite robust in suggesting that developers prefer to release apps for platforms that are larger and that are growing more quickly. The final two columns regress a platform's monthly share of all apps released that month on the change in installed base to show that the result is robust to using shares instead of levels.

Table 3 attempts to determine if the composition of a platform's user base affects that platform's appeal to developers. First, we divide up consumers into four income groups based on household income: (1) Under $50K, (2) $50K-$75K, (3) $75K-$100K, and (4) Over $100K. This table regresses the share of apps released for a platform on its installed base among each of these four income groups. The main result is that increases in installed base among the lower income groups do not lead to a statistically significant increase in a platform's share of apps being released. However, for the higher income groups, the relationship is statistically significant. This provides evidence that developers prefer platforms with higher income users. A likely mechanism is that those consumers present a greater profit potential for application developers. Appendix Tables 6 and 7 provide additional robustness checks for this, first by showing that the result is even stronger if Blackberry is omitted, and second that the result is robust to controlling for the total installed base of each platform.

Finally, Table 4 attempts to examine the effect of app competition on the supply for apps. It is natural to think that app developers would be drawn to a platform on which they would face relatively less competition. Table 4 regresses the a platform's share of apps released in a month on both its installed base, and the number of current "apps per user" on that platform, as a measure of within-platform app competition.[15] The results are strong and statistically significant: while developers seek to develop apps for platforms with larger installed bases of users, they

[14] For example, an installed base for Blackberry of 0.03 would imply 3% of American adults own a blackberry smartphone.

[15] The number of "apps per user" is calculated as the total number of apps divided by: (installed base share among US adults X 220M).

prefer to avoid platforms where they will have to compete with a larger number of applications. Unfortunately, at this point the data cannot distinguish between within-platform competition and a story of developing first for a platform with a larger installed base, and then later releasing the software for other platforms. I am in the process of procuring additional data to shed light on this difference.

4 Structural Analysis

In every time period, there are N firms that consider developing an "app" for one or more platforms. The cost of developing an app is given by C, and the cost of developing it for each additional platform once C has been paid is c. Firms choose to develop for any combination of the following three platforms: Apple, Android, and Blackberry. Firms may also choose the outside option of not developing an app in this period. If a firm decides to develop an app, it becomes available in the following time period. For now we will ignore time subscripts as the following applies to each time period.

Firms choose a "bundle" of platforms to develop for. There are 8 possible bundles: three singletons, three pairs, all platforms, and no platforms. A firm's profit from a bundle B is

$$\pi(B) = \sum_{p \in B} R(p) - C - c(|B| - 1) + \varepsilon_B$$

where p is a platform in bundle B and ε_B is a bundle-specific firm shock distributed i.i.d. type I extreme value. We normalize the profit from the outside option to 0. The function $R(p)$ denotes the revenue earned from releasing an app on platform p. To capture the dynamics identified in the previous section, the function $R(p)$ will be parameterized as

$$R_t(p) = \alpha_p + \beta_1 Z_{p,low} + \beta_2 Z_{p,high} + \gamma \frac{X_p}{Z_{p,total}}$$

The components of this revenue function are α, a constant; $Z_{p,low}$, the platform's penetration

among low-income users; $Z_{p,high}$, the platform's penetration among high-income users; and $\frac{X_p}{Z_{p,total}}$, the number of apps available on platform p divided by the total installed base of the platform. The idea is to capture the appeal of a platform as a function of the user base characteristics, but also capture the effect of competition.

This model contains the following parameters: $\alpha_p, \beta_1, \beta_2, \gamma, C$, and c. Denote the parameter vector by θ. Given this setup and a parameter vector, we can compute the share of firms that choose each bundle in each time period, $s_{tB}(\theta)$. Then, the number of apps on a platform in a time period t, X_{pt} is equal to

$$X_{pt}(\theta) = X_{p(t-1)}(\theta) + \sum_{p \in B} s_{B(t-1)}(\theta)$$

That is, we are able to compute the evolution of X_{pt} given a parameter vector. This allows us to estimate the parameter vector θ using a minimum distance estimator to fit the observed data on X_{pt} to the values predicted by the model.

We will treat the characteristics of a platform's users, the size of its installed base, and the number of potential entrants as exogenous, although this will be relaxed in future work.

4.1 Identification

In the above model, the values of the platform fixed effects, α_p, relative to the development costs would not be identified from the available data. Therefore, we will fix C to a constant value and estimate other parameters relative to C. The α_p terms will be identified by the share of the outside option. However, these are not the parameters of most interest. Instead, it will be the components of the revenue function, β_1,β_2, and γ, which will be identified by the relative shares for each platform in each time period. Additionally, the cross-development cost c will be identified relative to C by the correlation between app growth across platforms that cannot be explained by the components of the revenue function. As there is no data on actual revenues or costs, the actual estimates are of little interest. Instead, counterfactual simulations will be used to investigate the impact of various

features of this industry on the growth of apps.

5 Results

Results for the baseline model are given in Table 5. The value of C is fixed at 20 and N is fifty thousand. All estimated parameters have the expected sign and are significant (the competition parameter γ is weakly significant). Of note is that the cross-development cost, c, is estimated to be 12% of the fixed development cost $(C = 20)$. Figure 4 shows the fit of the model at the estimated parameter vector.

Once estimated, the model can be used to analyze the importance of the composition of the installed base, the effect of competition, and the effect of cross-development costs. Each will be analyzed separately in counterfactual simulations below.

5.1 Composition of the Installed Base

This counterfactual simulation will hold the parameter vector fixed, but change the composition of the installed bases of the Android and Blackberry platforms. For example, as shown in Figure 2, Apple captured more high-income users than Android. For this counterfactual, total installed base will remain the same for Android and Blackberry, but the mix of high and low income users will be set to Apple's mix.

As seen in Figure 5, when Android has Apple's mix of high-income users, it does indeed surpass Apple in number of apps. Blackberry benefits as well, although not nearly as much. This provides evidence of the fact that if Android had been more successful at the high end of the smartphone market, their app library would have surpassed Apple's shortly after their installed base surpassed that of Apple. As will be seen below, no other counterfactual has Android surpassing Apple's true app library size, indicating that this effect is very strong.

5.2 Effect of Competition

This counterfactual examines the degree to which competition from existing apps is a factor in developers' choice of platforms. As shown in Table 5, the estimate of γ is negative, implying that developers are deterred from developing for a platform that already has a large number of apps available. This counterfactual will set that parameter to half of its value to determine the impact of competition on developer choice.

As seen in Figure 6, reducing the effect of competition has a significant impact on the growth of apps over time. Apple in particular benefits significantly as it has the most apps available, and so the effect of competition on developer choice would be strongest for Apple.

5.3 Effect of Cross-Development Costs

This counterfactual examines the effect of changing the cost of developing for additional platforms, c. As might be expected, the platform that is currently the most appealing to developers would want to increase c, while platforms that are less attractive would like to lower c.[16] This counterfactual will examine the impact of halving and doubling the estimate of c obtained in the structural model.

As seen in Figure 7, when cross-development costs are halved, Android benefits significantly. Of additional interest is that in later periods when Android is a more attractive platform, Apple benefits as well from the lower cross-development costs. In contrast, Figure 8 shows that Android suffers considerably when cross-development costs are doubled, and Apple is relatively unaffected.

6 Conclusions

This paper provides strong evidence that the composition of users attracted to a platform on one side of the market is a strong determinant of the attractiveness to the other side of the market. If Android had managed to attract the same mix of users as Apple, they would not have lagged in the

[16] Consistent with its position in the market, Google created many tools to reduce the cost of developing for Android, such as the App Inventor for Android software.

number of apps available. While there is also evidence that competition and cross-development costs were significant factors in the development of this industry, the effect from the composition of users is the strongest.

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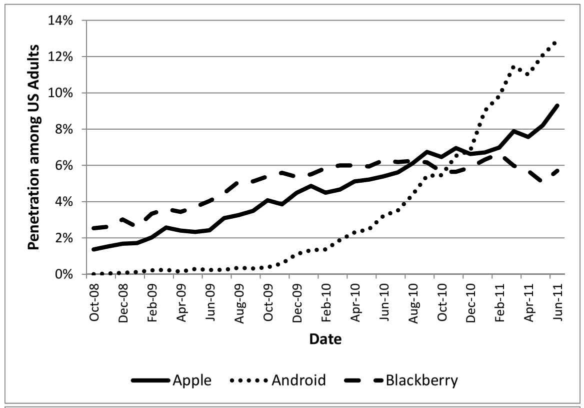
Figures

Figure 1: Platform Installed Base and App Availability, 2008-2011



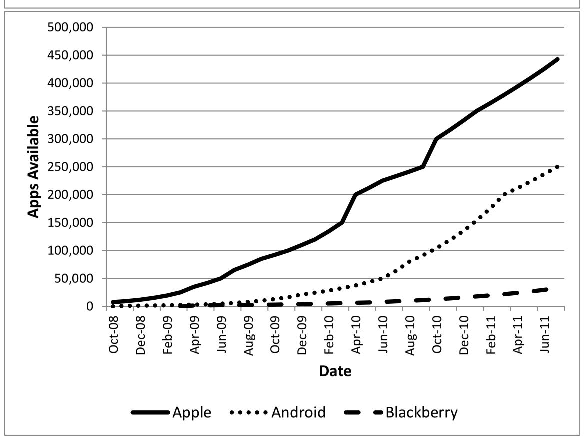
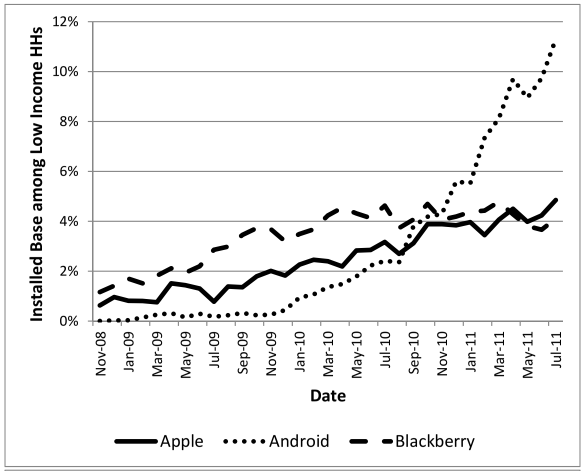


Figure 2: Smartphone Platform Penetration by Income Group



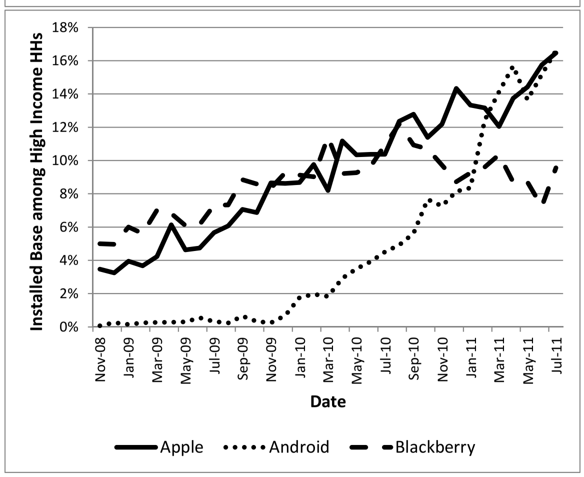


Figure 3: App Availability by Platform, Inception to Sept 2012

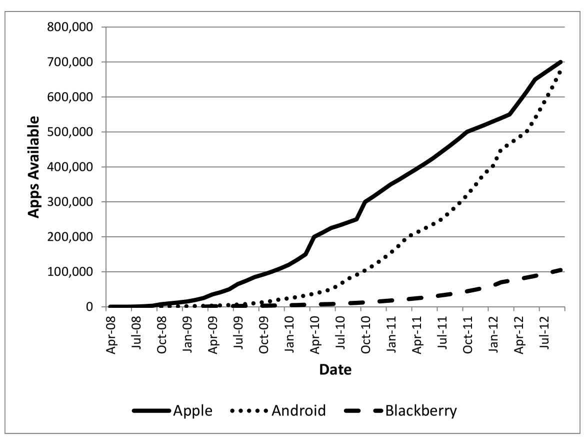


Figure 4: Fit of Structural Model

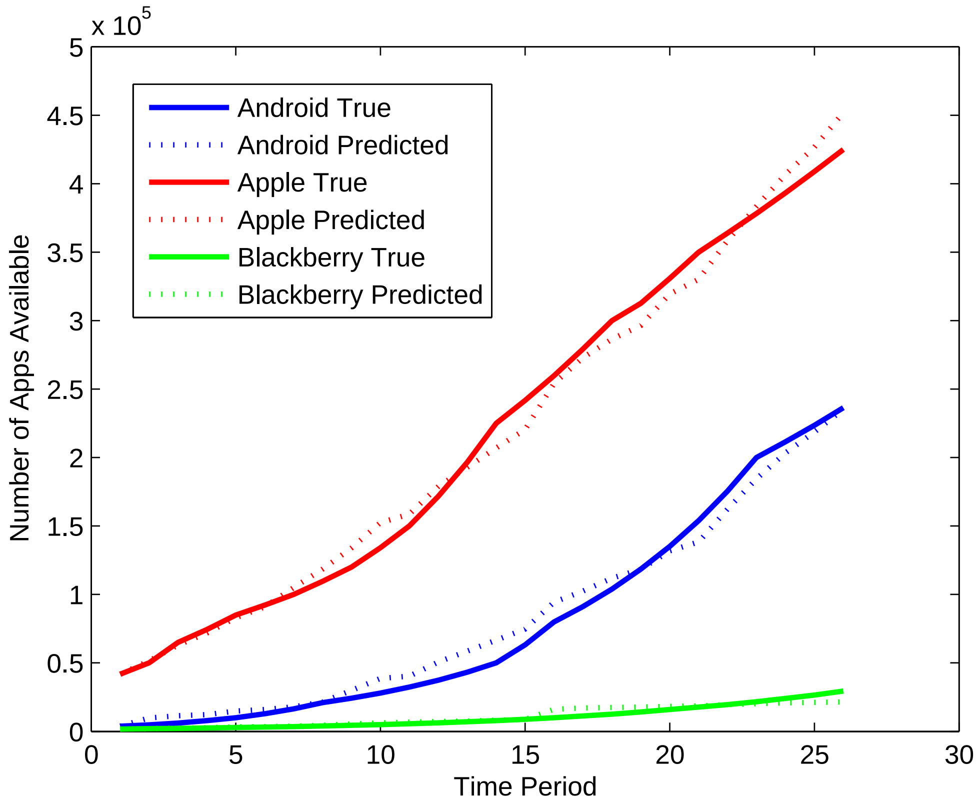


Figure 5: Counterfactual 1: Android and Blackberry have Apple's User Mix

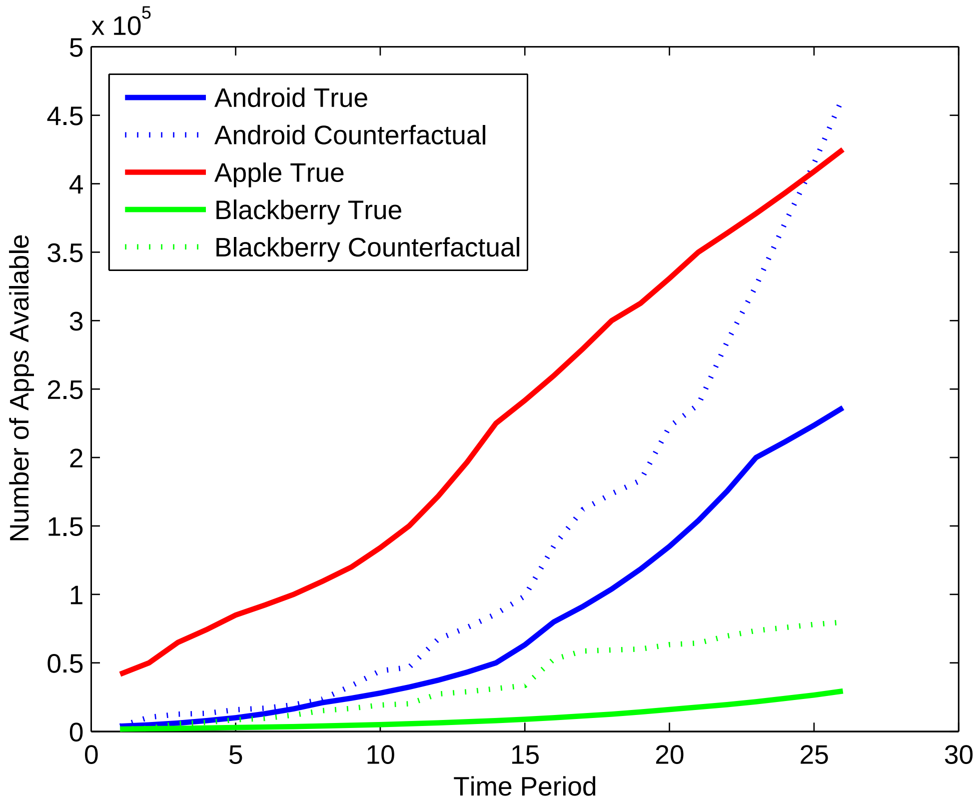


Figure 6: Counterfactual 2: Reduce Effect of Competition on Platform Choice

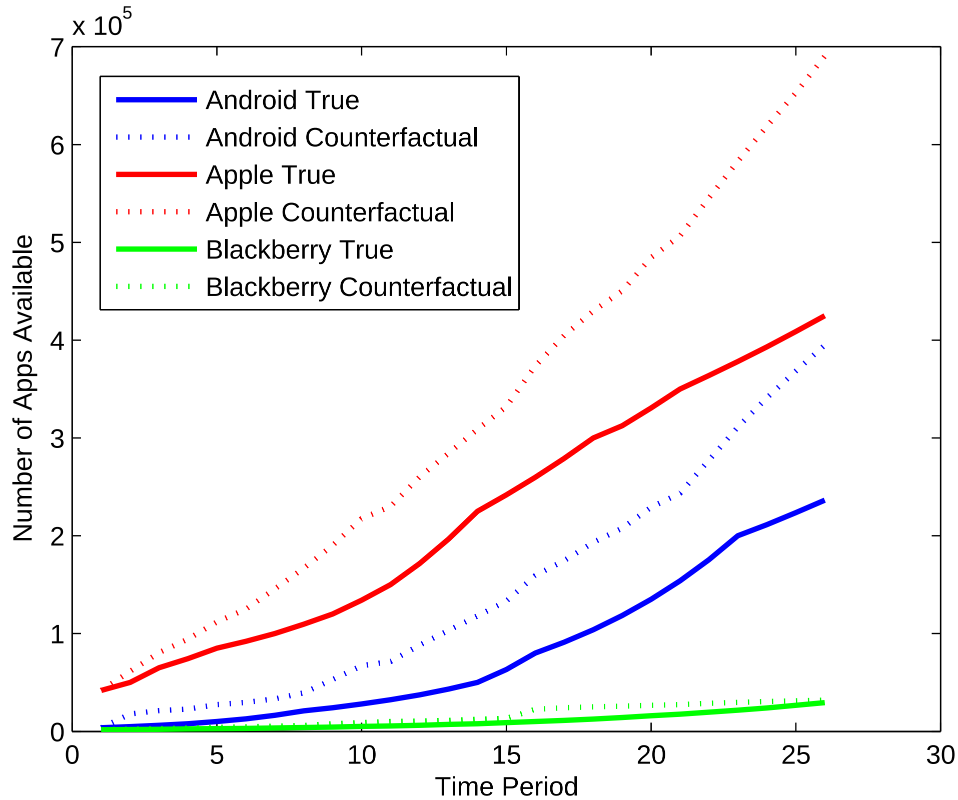


Figure 7: Counterfactual 3a: Cross-Development Costs are Halved

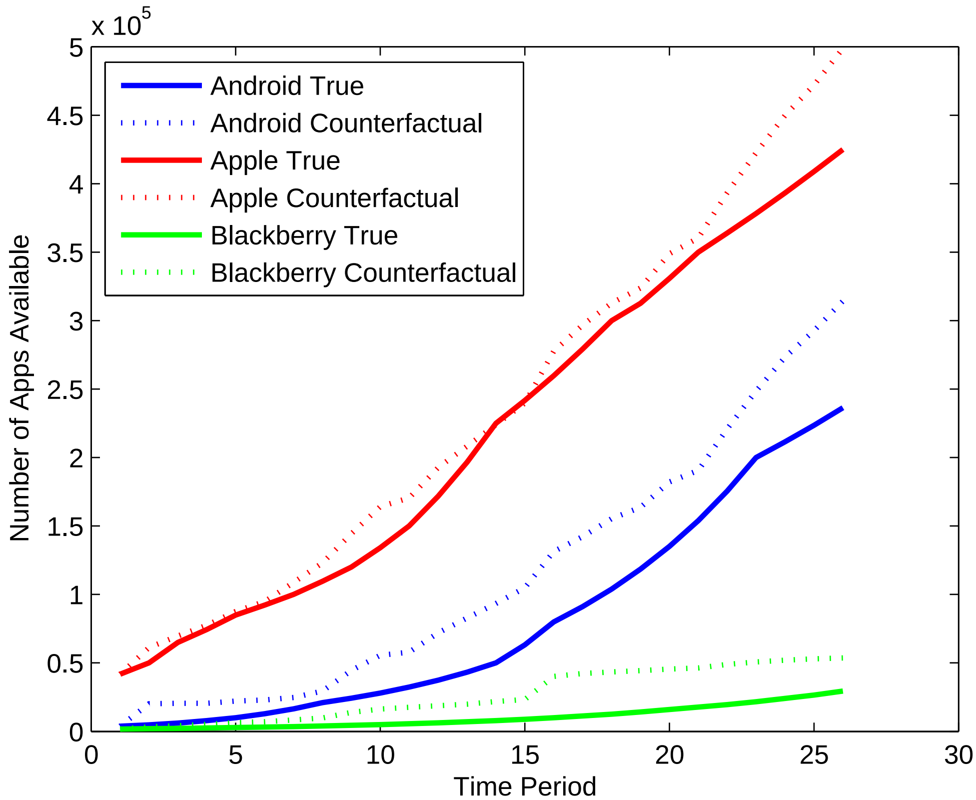
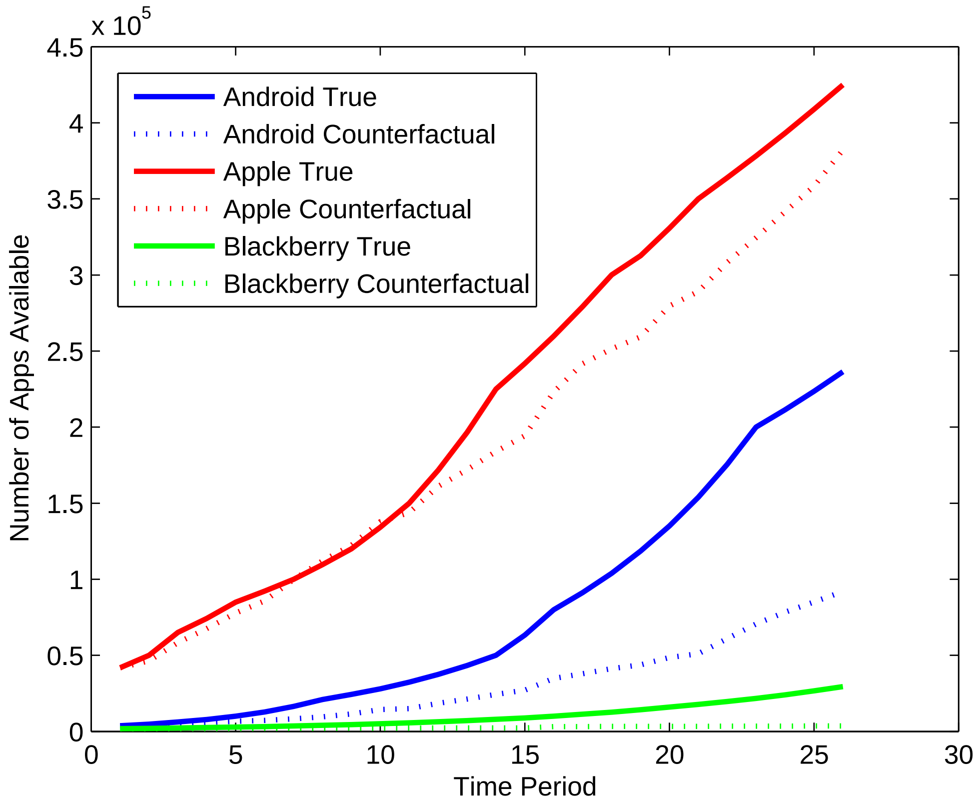


Figure 8: Counterfactual 3b: Cross-Development Costs are Doubled



Tables

In all tables, a dash (-) for a standard error indicates that the parameter was fixed in the given specification. Any parameters listed with a μ or σ are indicating that the estimated parameters are means and standard deviations of random normal variables, respectively.

Table 1: Demand for Mobile Applications

	Dependent Variable: Monthly Share of Purchases by Smartphone Platform		
	(1)	(2)	(3)
Log(apps)	0.001937*	0.02248***	0.004216***
	(0.001084)	(0.003171)	(0.001433)
Platform FEs	X	X	X
Platform Time Trends		X	X
Blackberry Included	X		X
N	117	78	117
R^2	0.1217	0.3646	0.9062

Data reflect observations from 39 months of data. The dependent variable is the monthly share of total smartphone purchases that go to each of the three major platforms: Apple, Android, and Blackberry. The independent variable is the natural logarithm of the number of apps available on that platform in that month. All specifications include platform fixed effects. Specifications (2) and (3) further include platform-month fixed effects. Specification (2) omits the Blackberry platform from the regression. Statistical significance is denoted by *,**, and *** for the 10%, 5%, and 1% levels of significance. All standard errors are clustered at the month level.

Table 2: Supply of Mobile Applications

	Dependent Variable: Monthly Change in Apps Available			
Independent Variable	(1)	(2)	(3)	(4)
Installed Base (%)	$128,874.5^{***}$	$147,898.8^{***}$		
	$(16,267.82)$	$(21,740.25)$		
Change in Installed Base (%)			$449,494.3^{***}$	$346,252.3^{*}$
			$(183,657.7)$	$(178,925.8)$
Platform FEs		X		X
N	99	99	96	96
R^2	0.1828	0.5376	0.0631	0.3517

Dependent Variable:	Monthly Share of New Apps Released	
Independent Variable	(5)	(6)
Installed Base (%)		
Change in Installed Base (%)	11.5210^{**}	7.5186^{***}
	(4.3752)	(2.0386)
Platform FEs		X
N	91	91
R^2	0.0367	0.7406

Data reflect observations from up to 32 months of data. The dependent variable is either the monthly change in the level of apps available on each of the three major platforms, or the share of new apps released that month that are on that platform. The independent variable is either the share of US Adults that own a smartphone of that platform type, or the monthly change in that figure. Statistical significance is denoted by *,**, and *** for the 10%, 5%, and 1% levels of significance. All standard errors are clustered at the month level.

Table 3: Supply of Apps vs Income Groups

	Dependent Variable: Monthly Share of Apps Released for a Platform			
Installed base among:	(1)	(2)	(3)	(4)
HH Income <$50K	-0.3759			
	(0.7251)			
HH Income $50K-$75K		0.4667		
		(0.4338)		
HH Income $75K-$100K			0.8534^{**}	
			(0.3577)	
HH Income >$100K				1.1919^{***}
				(0.3448)
N	78	78	78	78
R^2	0.0009	0.0020	0.0092	0.0320

Data reflect observations from 26 months of data. The dependent variable is a platform's monthly share of apps released that month. The independent variable is the installed base among a certain income group. Statistical significance is denoted by *,**, and *** for the 10%, 5%, and 1% levels of significance. All standard errors are clustered at the month level.

Table 4: The Effect of Within-Platform Competition

	Dependent Variable: Monthly Share of Apps Released for a Platform	
	(1)	(2)
Apps per User	-24.5175^{***}	-24.9705^{***}
	(3.7483)	(3.7800)
Installed Base (%)	2.3829^{***}	2.4629^{***}
	(0.4876)	(0.5138)
Platform FEs	X	X
Blackberry Included?	X	
N	91	64
R^2	0.8292	0.7006

Data reflect observations from up to 32 months of data. The dependent variable is a platform's monthly share of apps released that month. The independent variable is the installed base and the current number of apps divided by the installed base in users. Statistical significance is denoted by *,**, and *** for the 10%, 5%, and 1% levels of significance. All standard errors are clustered at the month level.

Table 5: Estimated of Structural Parameters

Parameter	Estimate
$\alpha_{Android}$	3.664^{**}
	(1.611)
α_{Apple}	17.530^{***}
	(5.833)
$\alpha_{Blackberry}$	-2.905^{**}
	(1.1378)
β_1	-92.85^{***}
	(33.385)
β_2	75.572^{**}
	(30.590)
γ	-172.74^{*}
	(89.623)
c	2.423^{**}
	(0.9941)

Data reflect observations from up to 32 months of data. The dependent variable is a platform's monthly share of apps released that month. The independent variable is the installed base and the current number of apps divided by the installed base in users. Statistical significance is denoted by *,**, and *** for the 10%, 5%, and 1% levels of significance. All standard errors are clustered at the month level.

Appendix

A Robustness Checks

The following tables provide robustness checks for the reduced form analysis:

Table 6: Supply of Apps vs Income Groups

	Dependent Variable: Monthly Share of Apps Released for a Platform, Omitting Blackberry			
Installed base among:	(1)	(2)	(3)	(4)
HH Income <$50K	0.9635*			
	(0.5607)			
HH Income $50K-$75K		1.6512**		
		(0.7031)		
HH Income $75K-$100K			1.6716***	
			(0.5972)	
HH Income >$100K				1.7836***
				(0.4851)
N	52	52	52	52
R^2	0.0118	0.0517	0.0749	0.1515

Data reflect observations from 26 months of data. The dependent variable is a platform's monthly share of apps released that month. The independent variable is the installed base among a certain income group. The Blackberry platform is omitted from the analysis. Statistical significance is denoted by *,**, and *** for the 10%, 5%, and 1% levels of significance. All standard errors are clustered at the month level.

Table 7: Supply of Apps vs Income Groups

	Dependent Variable: Monthly Share of Apps Released for a Platform			
Installed base among:	(1)	(2)	(3)	(4)
HH Income <$50K	-12.0836^{***}			
	(4.3592)			
HH Income $50K-$75K		-8.3300		
		(5.8860)		
HH Income $75K-$100K			5.8540	
			(4.6224)	
HH Income >$100K				5.2275^{***}
				(1.7606)
Total Installed Base	9.7669^{***}	8.6550	-5.8326	-6.6686^{**}
	(3.0629)	(5.6818)	(5.2400)	(2.6681)
N	78	78	78	78
R^2	0.0947	0.0244	0.0228	0.0945

Data reflect observations from 26 months of data. The dependent variable is a platform's monthly share of apps released that month. The independent variable is the installed base among a certain income group. Statistical significance is denoted by *,**, and *** for the 10%, 5%, and 1% levels of significance. All standard errors are clustered at the month level.