

Ajit, Tejaswi Channagiri; Jamison, Mark A.

## Conference Paper

# Platform Choices: Impact on Startup Performance

31st European Conference of the International Telecommunications Society (ITS): "Reining in Digital Platforms? Challenging monopolies, promoting competition and developing regulatory regimes", Gothenburg, Sweden, 20th - 21st June 2022

### Provided in Cooperation with:

International Telecommunications Society (ITS)

*Suggested Citation:* Ajit, Tejaswi Channagiri; Jamison, Mark A. (2022) : Platform Choices: Impact on Startup Performance, 31st European Conference of the International Telecommunications Society (ITS): "Reining in Digital Platforms? Challenging monopolies, promoting competition and developing regulatory regimes", Gothenburg, Sweden, 20th - 21st June 2022, International Telecommunications Society (ITS), Calgary

This Version is available at:

<https://hdl.handle.net/10419/265610>

### Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

### Terms of use:

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

# Platform Choices: Impact on Startup Performance

Draft: June 17, 2022

This work is preliminary. Do not quote or cite.

By TEJASWI CHANNAGIRI AJIT AND MARK A. JAMISON <sup>†</sup>

*We study the impact of platform choice (iOS vs Android) for firms that build apps for smart phones. We merge app data from Sensor Tower® with financial performance data from Crunchbase®. We find that apps that begin on Android have greater average downloads per month. However, apps with the greatest average downloads per month are likely to have begun on iOS. On each platform, the categories that attracted most app-based firms had greater skewness and kurtosis in average downloads per month. When endogenizing the choice of platform using propensity-score matching, firms that prefer to launch on iOS first seem likelier than those that launch on Android first to not receive any funding at all. However, they seem to receive greater funding in USD per firm.*

Keywords: platforms; innovation; competition

JEL codes: L13, L15, L51

<sup>†</sup>T. Channagiri, Digital Markets Initiative, Warrington College of Business, University of Florida, 205 Matherly, Gainesville, Florida 32611 (Tejaswi.ChannagiriAjit@warrington.ufl.edu); and M. Jamison (corresponding author), Public Utility Research Center and Digital Markets Initiative, Warrington College of Business, University of Florida, 205 Matherly, Gainesville, Florida 32611 (mark.jamison@warrington.ufl.edu) and Non-Resident Senior Fellow, American Enterprise Institute, 1789 Massachusetts Avenue, NW, Washington, DC 20036.

Digital platforms are a key feature of modern economies (Van Alstyne, Parker, Choudary, 2016). These platforms often bring two or more groups of participants on a common platform to create value through exchange. For example, Apple's iOS and Alphabet's Android bring users of smartphones and app developers together to create value for both. That in turn spawns network effects, leading the platforms on a self-fulfilling growth path. Several companies that have gone public over the last twenty-five years (e.g., Amazon, Google, Uber, and Facebook) have platform rather than traditional pipeline business models that convert raw materials to finished goods.

Since these platforms were launched, much entrepreneurship within the United States and globally has consisted of building complements for the platforms. For example, mobile platforms like iOS and Android have created entrepreneurial opportunities by letting third-party developers build apps that extend the platforms' functionality. Statista® estimates that, as of September 2021, Apple's App Store and Alphabet's Google Play offer over 2 million and 3 million apps respectively. At least 18,000 firms have been launched in the United States alone that build apps iOS or Android or provide other related services (Crunchbase®).

When a firm is founded with the primary objective of building apps for smartphones, a key early-stage decision is which platform to initially launch apps on. This is key for early-stage firms because the cost of software development on a platform is non-trivial for fledgling startups that are typically cash strapped (Kerr, Nanda, & Rhodes-Kropf, 2014). The cost of software development relative to available cash means that multi-homing, i.e., offering the app simultaneously on both platforms, may be prohibitively expensive, requiring these firms to make a choice early on. Yet, we know very little about the consequences of this key early-stage choice for future business success.

In this study, we consider startup firms focused on building apps for mobile platforms. Our goal is to understand whether there are benefits to beginning on

either platform. We consider the competitive funding environment within which these startups exist. Given that most of these startups are situated within a multi-stage financing environment that is based on experimentation (Nanda & Rhodes-Kropf, 2016), the ability to raise a subsequent round of funding is often critical to the success of these startups. Our interest is in understanding whether there are differences in four performance outcomes – (1) average downloads per month, (2) ability to raise early-stage funding (seed and pre-seed), (3) ability to raise mid-stage funding (angel and convertible note), and (4) ability to raise late-stage funding (venture capital). In addition, we seek to understand differences in competition across the platforms.

We leverage a dataset that merges Crunchbase® with Sensor Tower® data. We find that apps that initially launch on Android have greater average downloads per month. However, apps with the greatest average downloads per month are likely to have been initially launched on iOS. On each platform, categories that attracted most app-based firms displayed greater skewness and kurtosis in average downloads per month. When using propensity-score matching to endogenize platform choice, firms that prefer to launch on iOS first seem likelier than those that launch on Android first to not receive any funding at all. However, they appear to receive greater funding in USD per firm.

The rest of the paper is organized as follows. We describe the iOS and Android platforms, focusing especially on the role of app developers and the firms that build apps. We then describe the startup funding environment that is critical to the viability of these firms. That is followed by theory leading to hypotheses. We then present methods, results, and a discussion section. The final section concludes.

## **I. Mobile Platforms**

A key feature of business in recent decades is the shift from industries to ecosystems (Adner, 2021). The value proposition to users is often supplied by firms competing in many industries linked to form an ecosystem. For example, the value from using a smartphone often includes apps which are supplied by third-party developers. A user who hails a ride sharing service via Uber has that app installed on her smartphone supplied, for example, by Samsung, and hosting (Alphabet's) Android platform.

While the term ecosystem is used to denote “the alignment structure of the multilateral set of partners that need to interact for a focal value proposition to materialize” (Adner, 2017), of specific interest in this study is the notion of a platform ecosystem (Parker & Van Alstyne, 2005). A platform ecosystem is a specific type of ecosystem characterized by a central platform facilitating exchanges between two or more groups of participants and characterized by network effects that lead to self-fulfilling growth (Eisenmann, Parker, & Van Alstyne, 2006).

Two platform ecosystems that have exhibited rapid growth over the last fifteen years are Apple's iOS and Alphabet's Android. In 2007, Apple launched the iPhone. Unlike most cell phones that preceded it, the iPhone offered an AppStore through which users could purchase apps from third-party developers. The following year, Google unveiled its Android operating system that hosted Google Play, a similar store through which Android users could purchase apps from third-party providers. Unlike the iOS, which is only available on the iPhone, the Android operating system is compatible with several smartphones from different manufacturers.

Since the launch of the AppStore and Google Play, millions of developers have attempted to build apps for these two platforms. An interesting feature of apps is

that some apps collectively account for the bulk of downloads through the AppStore and Google Play (Bresnahan, Orsini, & Yin, 2014). The concept of two or multi-sided platforms and network effects applies as much to the apps as it does to the platforms. Most apps supplied on both platforms are hardly ever downloaded and used, but the few that are (e.g., Uber, Lyft, and TikTok) have reached great commercial success.

Given the potential upside associated with building apps for mobile platforms, thousands of firms engaged in this activity have sprung up since the late 2000s. Given the high risk and potentially high reward associated with these firms, they are typically funded by equity rather than debt investors. These investors maintain portfolios so that the many failures are more than compensated for by a few spectacular successes (Nanda, 2015). Given the importance of cash infusion from equity investors to the growth of these startups, securing repeated rounds of funding from these equity investors is often critical to the viability of these firms.

## **II. Startup Funding Environment**

Kerr, Nanda, and Rhodes-Kropf estimate (2014) that 55 percent of startups in the United States that received venture capital funding over a 25-year period beginning 1985 were terminated at a loss, while six percent accounted for 50 per cent of gross returns over that period. In addition, they present evidence suggesting that even experienced investors are unable to predict in advance which startups will succeed. Given the high uncertainty associated with startups aspiring to high growth (including for the startups that build apps in this study), investors prefer to spread their investments out over time, beginning with small investments and investing greater amounts based on milestones achieved by startups.

Nanda (2015) suggests that multi-stage financing is best viewed through the lens of experimentation and abandonment options. Each stage may be viewed as an

experiment that provides information to the same or other investors at subsequent stages. The presence of experiments and abandonment options can make negative NPV investments positive. Ventures that would not be profitable given a certain amount of risk may become profitable when financing is staged and based on experiments (see Nanda, 2015 for an illustration with a decision-tree framework). The less an experiment costs and the more information it yields, the more valuable it is.

In this study, all the firms we consider are firms building apps, aspiring to high-growth, and attempting to raise equity capital in multiple rounds as described above. Consistent with expectations for high-growth startups, a few apps account for most downloads. While most of these firms will never be profitable, the few that are will achieve spectacular financial success. The pattern is often viable only when it is financed within a framework of experimentation and abandonment options.

Most fledgling startup firms require cash for continued viability (Berk & DeMarzo, 2011). An inability to raise a round of funding often implies business termination. Startup firms that build apps for smartphones pass through a series of stages of financing by investors, with firms being eliminated at each stage. In this study, our interest is in understanding how platform choice impacts the possibility of survival at different stages, as well as average downloads per month. We also investigate differences in competition across the platforms.

### **III. Theory**

In building theory predicting how the choice of platform affects important firm outcomes, we focus on key differences between iOS and Android. We begin by noting how the platforms differ and proceed to predict how those differences would influence both who decides to begin on which platform as well as future outcomes.

The differences we consider relate to the user interface for developers, the process each firm uses to screen apps, the devices that use each platform, and the characteristics of those who purchase an iPhone as opposed to an Android phone.

Both iOS and Android offer a software development kit (SDK) for developers. However, there are important differences between them. Apple offers the XCode Integrated Development Environment (IDE) on its Macintosh personal computers. Developers write apps using either Swift or Objective-C, both of which are Apple's proprietary programming languages. Android's SDK houses the Android Studio IDE. The Android Studio is supported on PCs running Windows, Unix/Linux, and MacOS. Developers may use Java, Apache, and XML to write apps.

Apple has a more stringent review process for apps than does Alphabet. Apple's official website states<sup>1</sup> "We review all apps and app updates submitted to the App Store in an effort to determine whether they are reliable, perform as expected, respect user privacy, and are free of objectionable content." Screening is based on technical, content, and design criteria. Although Alphabet too has a basic review process, it is generally recognized as less stringent than Apple's.<sup>2</sup>

A notable difference between iOS and Android is that the former is only available on Apple's iPhone, but the latter is available on devices from many manufacturers including Samsung, Huawei, Xiaomi, Oppo, LG, Lenovo, ZTE, vivo, Sony, RIM, and HTC (Statista, 2021). The much greater variety of devices that host Android implies that developers often need to tailor the app to different devices with different screen sizes, resolutions, and display formats. That should in turn imply greater developments costs on Android when compared to iOS.

Finally, iPhone users differ in important demographic and other attributes from other smartphone users. An important difference appears to be that iPhone users are

<sup>1</sup> <https://developer.apple.com/app-store/review/>

<sup>2</sup> <https://www.nytimes.com/wirecutter/reviews/ios-vs-android/>



loyal to Apple and brand aware (Benenson, Gassman, & Reinfelder, 2013). It is possible the iPhone users are likelier to be first movers and experiment with new apps, given Apple's historic legacy of attracting such customers (Suarez & Lanzolla, 2005).

A consideration of these four dimensions along which iOS differs from Android lets us begin building theory predicting the development of the iOS and Android ecosystems as well as consequences for firms that choose a specific platform. In addition, our theory points to differences in competition on the platforms. Startup firms that build apps are typically cash strapped. Development on Android implies relatively high costs given the need to tailor to different devices and the lack of a proprietary user-friendly language for app developers. In addition, iOS users are expected to display a greater propensity to experiment with new apps. All these considerations collectively mean that, among firms that build apps for smartphones, iOS should emerge as a more popular choice than Android to launch apps first. We note that our reasoning refers to apps that emerge from firms and not apps in general (Android hosts more apps overall than iOS). Also, we refer to initial launch. Many firms begin on one platform and eventually launch on the other if the app/s succeed/s. It may be effective for a firm to launch on iOS first and then on Android if the initial launch is successful. The success of the initial launch would enable the firm to send positive signals to the same or subsequent investors. That would in turn enable it to raise equity capital to reach new markets by launching on a new platform with greater development costs.

*Hypothesis 1: Startup firms are likely to prefer to begin on iOS as opposed to Android.*

As already noted, the cost of an early experiment on the iOS platform is likely to be lower than on the Android platform. Nanda (2015) notes that falling costs of initial experiments lead to a high failure rate. The low cost of the initial experiment

is likely to entice many firms to startup. Given that there is only space for a few apps to succeed, many of those firms are likely to fail. The lower costs of development on iOS when compared to Android should lead to a larger failure rate for firms that begin on iOS when compared to firms that begin on Android.

*Hypothesis 2: Firms that begin on iOS are likely to fail at a greater rate than firms that begin on Android.*

An integral feature of app ecosystems is that a few apps are likely to account for most downloads. That also implies that, when considering an outcome such as average downloads per month, the distribution is likely to display greater skewness and kurtosis than a Gaussian. Skewness is a measure of asymmetry in the distribution while kurtosis is a measure of the extent to which the distribution is heavy tailed. We posit that this feature is especially stronger for apps that launch first on iOS first as opposed to Android. Given the larger numbers of apps that begin on iOS first, it is likelier that there are “home runs” among those apps. At the same time, those apps are likely to display higher rates of failure. These patterns are collectively consistent with greater skewness and kurtosis in average downloads per month for apps that begin on iOS as opposed to Android.

*Hypothesis 3a: Apps that launch on iOS first are likely to display greater skewness in average downloads per month than those that launch on Android first.*

*Hypothesis 3b: Apps that launch on iOS first are likely to display greater kurtosis in average downloads per month than those that launch on Android first.*

Apps on each of iOS and Android are likely to belong to one of many categories. Each platform has a different classification of app by type, e.g., gaming, social media, tourism, and so on. When considering categories on each platform, the categories that attract a greater number of apps are likely to display greater skewness and kurtosis. A successful app in any category is likely to attract entry

into that category. Most of those entrants are likely to fail. The presence of “superstar” apps and several apps with little or no downloads leads the categories that attract a greater number of apps to display greater skewness and kurtosis in average downloads per month for those apps than categories that attract fewer apps.

*Hypothesis 4a: The greater the number of apps in a category, the greater the skewness in average downloads per month for apps across that category.*

*Hypothesis 4b: The greater the number of apps in a category, the greater the kurtosis in average downloads per month for apps across that category.*

Regarding platform choice, neither iOS nor Android is likely to confer an absolute advantage across any measure of performance. The presence of a clear advantage with one platform would have resulted in the market tipping toward that platform. Arbitrage opportunities are quickly eroded as market participants discover them (Berk and DeMarzo, 2011). The specific four outcomes of interest to us are (1) average downloads per month, (2) early-stage funding (seed and pre-seed), (3) mid-stage funding (angel and convertible note), and (4) late-stage funding (venture capital). We should not expect to see a consistent advantage with either platform on any of these outcomes, given the continued existence of both platforms in the market.

*Hypothesis 5a: Apps that launch on iOS first do not differ in average downloads per month from those that launch on Android first.*

*Hypothesis 5b: Firms that launch apps on iOS first do not differ in early-stage funding raised from those that launch on Android first.*

*Hypothesis 5c: Firms that launch apps on iOS first do not differ in mid-stage funding raised from those that launch on Android first.*

*Hypothesis 5d: Firms that launch apps on iOS first do not differ in late-stage funding raised from those that launch on Android first.*

## IV. Results

We pulled data from Crunchbase for all U.S. based companies based on mobile platforms founded between 2007 and 2020. The specific keywords we searched for were “Mobile,” “Apps,” “Mobile Apps,” “iOS,” and “Android.” That resulted in 18,884 companies. We provided the names of these companies to Sensor Tower.

Sensor Tower provided data on apps from publishers with exact name matches in our Crunchbase pull described above and over five years – from 2016 through 2021. App download data from Sensor Tower includes the U.S. and the rest of the world. They have also provided data on exactly when the specific app was launched on the App Store and Google Play. While it appears that the file contains 1,044,028 records it in fact contains 861,129 app month pairs. The 1,044,028 records are because the App Store and Google Play data are in separate records even though it’s the same app and month. We transformed it into a file with 861,129 app month pairs and with the App Store and Google Play data within the same app month record.

### *A. Patterns in average downloads per month – iOS first versus Android first*

The summary statistics below capture differences in apps that began on iOS (may or may not have launched on Android later) versus those that began on Android (may or may not have launched on iOS later). The variable of interest is average downloads per month. Unit of analysis is the app.

iOS first –

avg_downloads				
	Percentiles	Smallest		
1%	<b>1</b>	<b>0</b>		
5%	<b>1.428571</b>	<b>0</b>		
10%	<b>2</b>	<b>0</b>	Obs	<b>40,563</b>
25%	<b>3.695652</b>	<b>0</b>	Sum of wgt.	<b>40,563</b>
50%	<b>9.5</b>		Mean	<b>8893.466</b>
		Largest	Std. dev.	<b>299649.4</b>
75%	<b>57</b>	<b>1.25e+07</b>		
90%	<b>479.9683</b>	<b>1.52e+07</b>	Variance	<b>8.98e+10</b>
95%	<b>2171.136</b>	<b>2.42e+07</b>	Skewness	<b>98.47513</b>
99%	<b>49071.84</b>	<b>4.37e+07</b>	Kurtosis	<b>12507.78</b>

Android first –

avg_downloads				
	Percentiles	Smallest		
1%	<b>0</b>	<b>0</b>		
5%	<b>1</b>	<b>0</b>		
10%	<b>1.666667</b>	<b>0</b>	Obs	<b>14,870</b>
25%	<b>5</b>	<b>0</b>	Sum of wgt.	<b>14,870</b>
50%	<b>39</b>		Mean	<b>13935.2</b>
		Largest	Std. dev.	<b>185817.7</b>
75%	<b>710.7377</b>	<b>5110921</b>		
90%	<b>6900.279</b>	<b>6061192</b>	Variance	<b>3.45e+10</b>
95%	<b>23294.51</b>	<b>1.15e+07</b>	Skewness	<b>41.62446</b>
99%	<b>218914.9</b>	<b>1.18e+07</b>	Kurtosis	<b>2293.194</b>

Preliminary observations are that apps that began on Android have higher mean average downloads per month than those that began on iOS. However, apps that began on iOS have higher standard deviation of average downloads per month. In addition, apps that began on iOS seem to have higher skewness and kurtosis on average downloads per month. For both Android and iOS, the above suggest that there are some apps with very high average downloads and many with very low average downloads. However, the pattern appears to be even more pronounced for

iOS than for Android, given the greater skewness and kurtosis for the former. Also, the four top apps (in terms of average downloads per month) among apps that launched on iOS first seem to have greater average downloads per month than the four top apps among apps that launched on Android first. This pattern is very consistent when considering average downloads on a year-by-year basis, that is, within each of the years 2016 through 2021.

Of the 40,563 apps that launched on iOS first, 34,640 (85.40%) were eventually dropped. Of the 14,870 apps that launched on Android first, 12,616 were eventually dropped (84.84%).

#### *B. Patterns in average downloads per month – categories within each platform*

We next moved to summary statistics within categories on each of the platforms. For both apps that launched on iOS first and those that launched on Android first, it seems that the categories that attracted most entry within each (iOS first and Android first) were characterized by greater skewness and kurtosis in average downloads per month. In addition, the top four apps (in terms of average downloads per month) among the high-entry categories had much greater average downloads per month than the top four apps among the low-entry categories. For example, one of the most popular categories among apps that began on iOS was “Food & Drink”. One of the least popular categories was “Weather.” Below is the difference in summary statistics.

Food & Drink –

avg_downloads					
	Percentiles	Smallest			
1%	2	0			
5%	3	.5869565			
10%	4	.7272727	Obs	6,330	
25%	5.25	1	Sum of wgt.	6,330	
50%	8		Mean	550.5272	
		Largest	Std. dev.	21251.51	
75%	14.6	243928.8			
90%	39.55926	260249.1	Variance	4.52e+08	
95%	118.3091	646826.4	Skewness	61.49344	
99%	1193.413	1508607	Kurtosis	4148.926	

Weather –

avg_downloads					
	Percentiles	Smallest			
1%	6.25	6.25			
5%	10.41304	8.944445			
10%	21.62	9.678572	Obs	76	
25%	54	10.41304	Sum of wgt.	76	
50%	227.75		Mean	3831.507	
		Largest	Std. dev.	16324.28	
75%	877.5706	23325.13			
90%	6843.937	29535.93	Variance	2.66e+08	
95%	23325.13	29761.27	Skewness	7.173536	
99%	135548	135548	Kurtosis	57.46812	

*C. Patterns in total funding raised – iOS first versus Android first*

When I merged the Sensor Tower data into Crunchbase, I was able to get matches for 4,540 companies that built one or more apps for either or both platforms. The level of analysis here is the publisher or company rather than an app. I counted a publisher as iOS first if the number of apps it launched on iOS first was greater than the number of apps it launched on Android first. I counted a publisher as Android first if the number of apps it launched on Android first was greater than the number of apps it launched on iOS first. I measured average downloads per month as the average across all apps from a publisher in that month.

The tables below show summary statistics indicating how the number of funding rounds and total funding (USD) differed between iOS first and Android first publishers. An assumption is that if a company is missing any funding round information in Crunchbase, then it did not raise funding. Another assumption is that if it is missing total funding (USD) in a funding round, then it raised zero dollars. I believe the first assumption is reasonable as the numbers do agree with my expectations of how often entrepreneurial companies raise external funding. As for the second assumption, I am not sure but perhaps it is a reasonable one for our purposes if the missing USD does not depend on whether the firm began on iOS first or Android first.

#### Number of funding rounds – iOS

num_funding_rounds				
	Percentiles	Smallest		
1%	<b>0</b>	<b>0</b>		
5%	<b>0</b>	<b>0</b>		
10%	<b>0</b>	<b>0</b>	Obs	<b>2,684</b>
25%	<b>0</b>	<b>0</b>	Sum of wgt.	<b>2,684</b>
50%	<b>0</b>		Mean	<b>1.33532</b>
		Largest	Std. dev.	<b>2.044803</b>
75%	<b>2</b>	<b>15</b>		
90%	<b>4</b>	<b>15</b>	Variance	<b>4.181219</b>
95%	<b>5</b>	<b>18</b>	Skewness	<b>2.511285</b>
99%	<b>9</b>	<b>20</b>	Kurtosis	<b>12.59055</b>



Number of funding rounds – Android

num_funding_rounds				
	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	1,751
25%	0	0	Sum of wgt.	1,751
50%	1		Mean	1.556825
		Largest	Std. dev.	2.056918
75%	2	11		
90%	5	13	Variance	4.230912
95%	6	13	Skewness	1.781535
99%	8	14	Kurtosis	6.632343

Total funding – iOS first

total_funding_usd				
	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	2,684
25%	0	0	Sum of wgt.	2,684
50%	0		Mean	1.21e+07
		Largest	Std. dev.	1.26e+08
75%	1153025	1.39e+09		
90%	1.00e+07	2.17e+09	Variance	1.58e+16
95%	3.20e+07	2.47e+09	Skewness	27.84023
99%	1.76e+08	4.91e+09	Kurtosis	954.9661

## Total funding – Android first

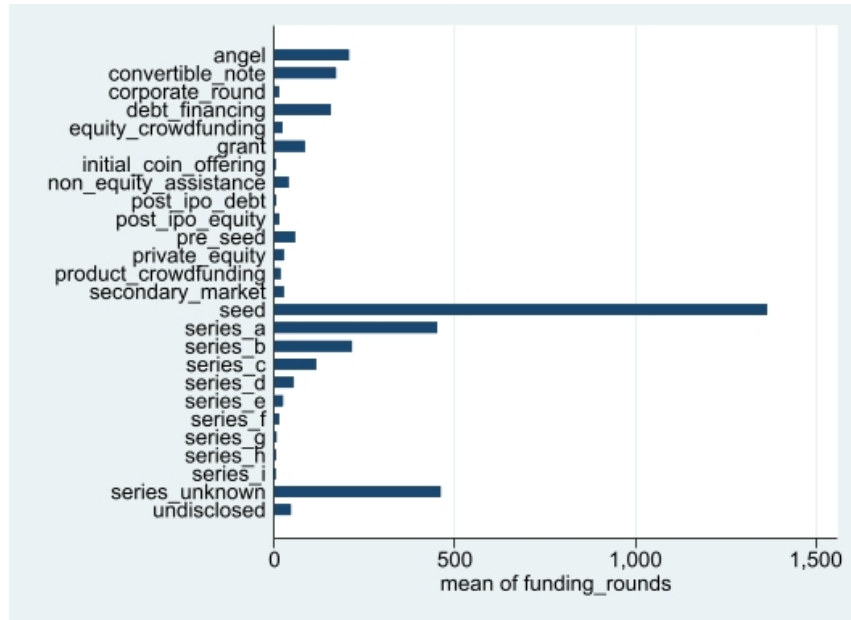
total_funding_usd				
	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	1,751
25%	0	0	Sum of wgt.	1,751
50%	0		Mean	8157750
		Largest	Std. dev.	3.62e+07
75%	2000000	3.69e+08		
90%	1.39e+07	4.31e+08	Variance	1.31e+15
95%	3.30e+07	4.71e+08	Skewness	8.660114
99%	1.74e+08	5.91e+08	Kurtosis	95.96256

742 (42.4%) of the 1,751 Android first firms did not raise any funding while 1,345 (50.1%) of the 2,684 iOS first firms did not raise any funding, which may explain why Android first firms received more funding rounds. iOS first firms exhibit greater skewness and kurtosis than Android first firms and raised more USD on an average. In addition, the top four iOS first firms (by total funding) raised much more USD than the top four Android first firms (by total funding).

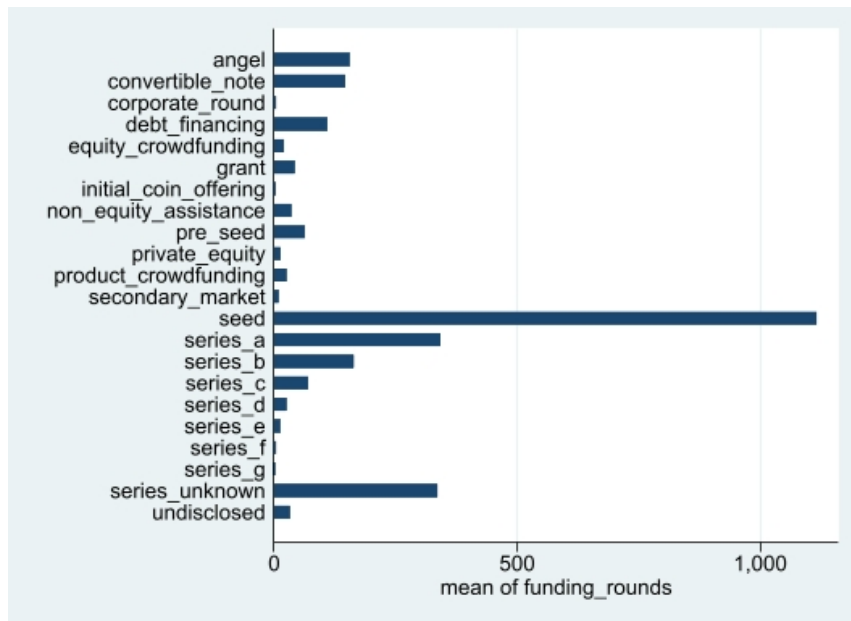
### *D. Breakdown by funding rounds – iOS first and Android first*

The below figures offer a more detailed breakdown of the distribution of funding rounds and funding in USD across specific types of funding rounds and platform (iOS first and Android first).

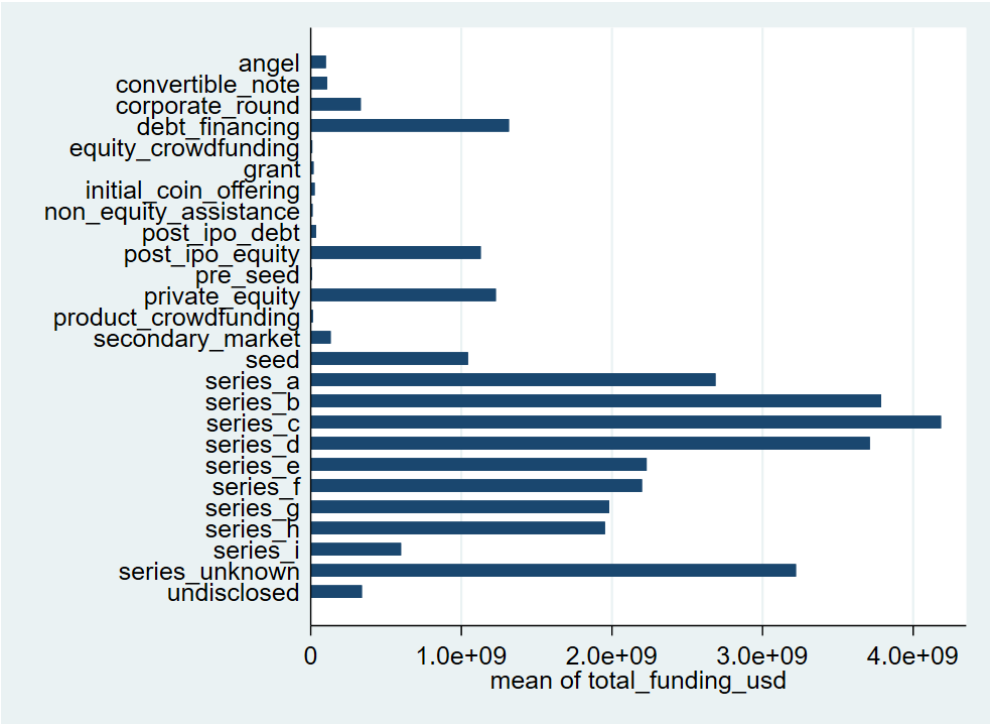
Number of funding rounds – iOS first



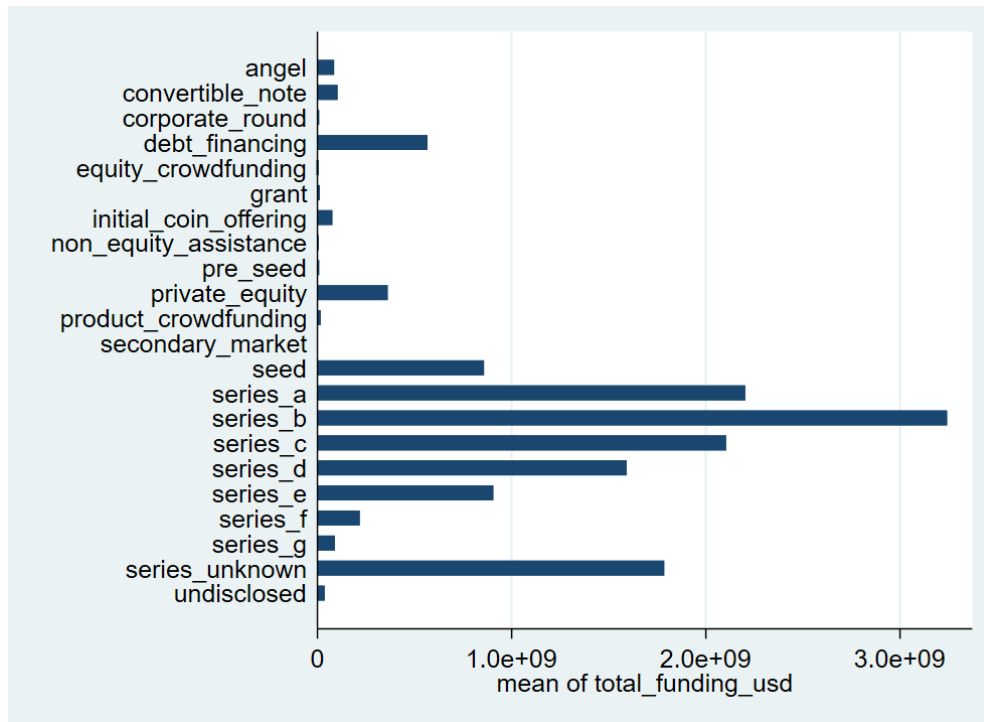
Number of funding rounds – Android first



Total funding (USD) – iOS first



### Total funding (USD) – Android first



### *E. Regression Analysis*

We ran two sets of regression analyses. The first was a straight set regressing the number of funding rounds, total funding (USD), and average monthly downloads against choice of platform (whether the firm began on iOS or Android). We also ran analyses regressing the total funding (USD) in early, middle, and late stages against choice of platform. I defined early stage as seed and pre-seed funding. We defined middle stage as angel and convertible note. We defined late stage as venture capital (all series).

In the second set, we used matching techniques (both propensity score matching and coarsened exact matching) when running regressions for the outcomes listed

above. We matched on the categories the firm belonged to and the year in which it was founded.

Unit of analysis in all analyses below is the publisher/company.

### Number of funding rounds against choice of platform –

```

Negative binomial regression           Number of obs = 4,435
Dispersion: mean                      Wald chi2(1) = 12.60
Log pseudolikelihood = -7227.469     Prob > chi2 = 0.0004
                                       Pseudo R2 = 0.0008

```

num_funding_rounds	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ios_first_publisher _cons	-.153477	.0432451	-3.55	0.000	-.2382359	-.0687181
	.4426483	.0315689	14.02	0.000	.3807744	.5045221
/lnalpha	.3995619	.0381101			.3248675	.4742564
alpha	1.491171	.0568287			1.383847	1.606819

### Total funding (USD) against choice of platform –

```

Linear regression                     Number of obs = 4,435
                                       F(1, 4433) = 2.31
                                       Prob > F = 0.1284
                                       R-squared = 0.0004
                                       Root MSE = 1.0e+08

```

total_funding_usd	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ios_first_publisher _cons	3920196	2577996	1.52	0.128	-1133963	8974354
	8157750	866108.9	9.42	0.000	6459744	9855756

Average downloads per month across apps –

Linear regression	Number of obs	=	<b>4,435</b>
	F(1, 4433)	=	<b>0.00</b>
	Prob > F	=	<b>0.9893</b>
	R-squared	=	<b>0.0000</b>
	Root MSE	=	<b>1.4e+05</b>

avg_downloads_per~s	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ios_first_publisher	<b>54.67917</b>	<b>4082.934</b>	<b>0.01</b>	<b>0.989</b>	<b>-7949.909</b>	<b>8059.267</b>
_cons	<b>13670.69</b>	<b>3014.063</b>	<b>4.54</b>	<b>0.000</b>	<b>7761.621</b>	<b>19579.76</b>

Number of early-stage funding rounds (pre-seed and seed) as a function of platform choice –

Negative binomial regression	Number of obs =	<b>1,653</b>
	Wald chi2(1) =	<b>1.60</b>
Dispersion: <b>mean</b>	Prob > chi2 =	<b>0.2058</b>
Log pseudolikelihood = <b>-2274.2282</b>	Pseudo R2 =	<b>0.0002</b>

early_stage_rounds	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ios_first_publisher	<b>-.0380829</b>	<b>.0300973</b>	<b>-1.27</b>	<b>0.206</b>	<b>-.0970725</b>	<b>.0209068</b>
_cons	<b>.4739129</b>	<b>.0225946</b>	<b>20.97</b>	<b>0.000</b>	<b>.4296282</b>	<b>.5181976</b>
/lnalpha	<b>-25.04037</b>	.	.	.	.	.
alpha	<b>1.33e-11</b>	.	.	.	.	.

Total early-stage funding (pre-seed and seed) in USD as a function of platform choice –

```

Linear regression                               Number of obs   =    1,653
                                                F(1, 1651)     =    0.19
                                                Prob > F       =    0.6660
                                                R-squared     =    0.0001
                                                Root MSE     =    1.7e+06
    
```

early_stage_fundi~d	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ios_first_publisher	<b>-36989.44</b>	<b>85665.54</b>	<b>-0.43</b>	<b>0.666</b>	<b>-205014</b>	<b>131035.1</b>
_cons	<b>1180356</b>	<b>62479.8</b>	<b>18.89</b>	<b>0.000</b>	<b>1057808</b>	<b>1302904</b>

Number of middle-stage funding rounds (angel and convertible note) as a function of platform choice –

```

Negative binomial regression                   Number of obs =    523
                                                Wald chi2(1) =    0.25
Dispersion: mean                               Prob > chi2 =    0.6197
Log pseudolikelihood = -654.74972             Pseudo R2 =    0.0001
    
```

number_middle_stage_rounds	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ios_first_publisher	<b>-.0273825</b>	<b>.0551799</b>	<b>-0.50</b>	<b>0.620</b>	<b>-.1355332</b>	<b>.0807681</b>
_cons	<b>.2993163</b>	<b>.0448097</b>	<b>6.68</b>	<b>0.000</b>	<b>.2114908</b>	<b>.3871417</b>
/lnalpha	<b>-24.86923</b>	.	.	.	.	.
alpha	<b>1.58e-11</b>	.	.	.	.	.



Total middle-stage funding (angel and convertible note) in USD as a function of platform choice –

Linear regression

Number of obs	=	523
F(1, 521)	=	1.04
Prob > F	=	0.3077
R-squared	=	0.0024
Root MSE	=	7.0e+07

total_middle_stage~d	Robust		t	P> t	[95% conf. interval]	
	Coefficient	std. err.				
ios_first_publisher	-6954520	6810451	-1.02	0.308	-2.03e+07	6424799
_cons	7683064	6809953	1.13	0.260	-5695277	2.11e+07

Number of late-stage funding rounds (all venture capital) as a function of platform choice –

Negative binomial regression

Number of obs	=	1,045
Wald chi2(1)	=	0.10
Prob > chi2	=	0.7578
Pseudo R2	=	0.0000

Dispersion: mean  
Log pseudolikelihood = -1883.2924

number_late_stage_rounds	Robust		z	P> z	[95% conf. interval]	
	Coefficient	std. err.				
ios_first_publisher	-.0143142	.046426	-0.31	0.758	-.1053074	.0766791
_cons	.8472979	.0332129	25.51	0.000	.7822017	.912394
/lnalpha	-2.399922	.2274333			-2.845683	-1.954161
alpha	.0907251	.0206339			.0580946	.1416833

Total late-stage funding (all venture capital) in USD as a function of platform choice –

Linear regression

Number of obs	=	1,045
F(1, 1043)	=	0.15
Prob > F	=	0.7027
R-squared	=	0.0002
Root MSE	=	3.7e+08

total_late_stage~d	Robust		t	P> t	[95% conf. interval]	
	Coefficient	std. err.				
ios_first_publisher	-9471589	2.48e+07	-0.38	0.703	-5.82e+07	3.92e+07
_cons	5.50e+07	2.26e+07	2.44	0.015	1.07e+07	9.93e+07

### F. Regression Analyses – Propensity Score Matching

We used propensity score matching, matching on categories and year founded, and reran all the models in the previous section.

#### Number of funding rounds against choice of platform –

Treatment-effects estimation		Number of obs	=	<b>4,435</b>
Estimator : <b>propensity-score matching</b>		Matches: requested	=	<b>1</b>
Outcome model : <b>matching</b>		min	=	<b>1</b>
Treatment model: <b>logit</b>		max	=	<b>65</b>

	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
<b>ATE</b>						
ios_first_publisher (1 vs 0)	<b>-.162892</b>	<b>.0669547</b>	<b>-2.43</b>	<b>0.015</b>	<b>-.2941208</b>	<b>-.0316632</b>

#### Total funding (USD) against choice of platform –

Treatment-effects estimation		Number of obs	=	<b>4,435</b>
Estimator : <b>propensity-score matching</b>		Matches: requested	=	<b>1</b>
Outcome model : <b>matching</b>		min	=	<b>1</b>
Treatment model: <b>logit</b>		max	=	<b>65</b>

	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
<b>ATE</b>						
ios_first_publisher (1 vs 0)	<b>6011720</b>	<b>2786269</b>	<b>2.16</b>	<b>0.031</b>	<b>550732.6</b>	<b>1.15e+07</b>

#### Average downloads per month across all apps against choice of platform –

Treatment-effects estimation		Number of obs	=	<b>4,435</b>
Estimator : <b>propensity-score matching</b>		Matches: requested	=	<b>1</b>
Outcome model : <b>matching</b>		min	=	<b>1</b>
Treatment model: <b>logit</b>		max	=	<b>65</b>

	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
<b>ATE</b>						
ios_first_publisher (1 vs 0)	<b>-1526.711</b>	<b>4379.753</b>	<b>-0.35</b>	<b>0.727</b>	<b>-10110.87</b>	<b>7057.448</b>

Number of early-stage funding rounds (pre-seed and seed) as a function of platform choice<sup>3</sup> –

Treatment-effects estimation		Number of obs	=	<b>1,653</b>
Estimator	: <b>propensity-score matching</b>	Matches: requested	=	<b>1</b>
Outcome model	: <b>matching</b>	min	=	<b>1</b>
Treatment model	: <b>logit</b>	max	=	<b>14</b>

---

early_stage_rounds	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
<b>ATE</b>						
ios_first_publisher (1 vs 0)	<b>-.0396606</b>	<b>.0506115</b>	<b>-0.78</b>	<b>0.433</b>	<b>-.1388574</b>	<b>.0595362</b>

Total early-stage funding (pre-seed and seed) in USD as a function of platform choice<sup>4</sup> –

Treatment-effects estimation		Number of obs	=	<b>1,653</b>
Estimator	: <b>propensity-score matching</b>	Matches: requested	=	<b>1</b>
Outcome model	: <b>matching</b>	min	=	<b>1</b>
Treatment model	: <b>logit</b>	max	=	<b>14</b>

---

early_stage_fundi~d	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
<b>ATE</b>						
ios_first_publisher (1 vs 0)	<b>21644.73</b>	<b>95857.69</b>	<b>0.23</b>	<b>0.821</b>	<b>-166232.9</b>	<b>209522.3</b>

<sup>3</sup> We removed two categories “agriculture and farming” and “natural resources” as they predicted success perfectly.

<sup>4</sup> We removed two categories “agriculture and farming” and “natural resources” as they predicted success perfectly.

Number of middle-stage funding rounds (angel and convertible note) as a function of platform choice<sup>5</sup> –

Treatment-effects estimation	Number of obs	=	523
Estimator : <b>propensity-score matching</b>	Matches: requested	=	1
Outcome model : <b>matching</b>	min	=	1
Treatment model: <b>logit</b>	max	=	5

---

number_middle_stages	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]
<b>ATE</b>					
ios_first_publisher (1 vs 0)	<b>-.0500956</b>	<b>.0814197</b>	<b>-0.62</b>	<b>0.538</b>	<b>-.2096753 .1094841</b>

Total middle-stage funding (angel and convertible note) in USD as a function of platform choice<sup>6</sup> –

Treatment-effects estimation	Number of obs	=	523
Estimator : <b>propensity-score matching</b>	Matches: requested	=	1
Outcome model : <b>matching</b>	min	=	1
Treatment model: <b>logit</b>	max	=	5

---

total_middle_stage_usd	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]
<b>ATE</b>					
ios_first_publisher (1 vs 0)	<b>-6330963</b>	<b>1.14e+07</b>	<b>-0.55</b>	<b>0.579</b>	<b>-2.87e+07 1.60e+07</b>

<sup>5</sup> We removed the categories “energy,” “sustainability,” and “natural resources” as they either predicted success or failure perfectly or caused collinearity.

<sup>6</sup> We removed the categories “energy,” “sustainability,” and “natural resources” as they either predicted success or failure perfectly or caused collinearity.

Number of late-stage funding rounds (venture capital – all series) as a function of platform choice –

Treatment-effects estimation		Number of obs	=	1,045		
Estimator	: propensity-score matching	Matches: requested	=	1		
Outcome model	: matching	min	=	1		
Treatment model	: logit	max	=	11		
number_late_stage~s	AI robust		z	P> z	[95% conf. interval]	
	Coefficient	std. err.				
<b>ATE</b>						
ios_first_publisher (1 vs 0)	<b>-.1309062</b>	<b>.1205007</b>	<b>-1.09</b>	<b>0.277</b>	<b>-.3670833</b>	<b>.1052709</b>

Total late-stage funding (venture capital – all series) in USD as a function of platform choice –

Treatment-effects estimation		Number of obs	=	1,045		
Estimator	: propensity-score matching	Matches: requested	=	1		
Outcome model	: matching	min	=	1		
Treatment model	: logit	max	=	11		
total_late_stage~d	AI robust		z	P> z	[95% conf. interval]	
	Coefficient	std. err.				
<b>ATE</b>						
ios_first_publisher (1 vs 0)	<b>-2.12e+07</b>	<b>2.29e+07</b>	<b>-0.92</b>	<b>0.356</b>	<b>-6.61e+07</b>	<b>2.38e+07</b>

## V. Conclusion

We study the impact of platform choice (iOS vs Android) for firms that build apps for smart phones. We find that apps that begin on Android have greater average downloads per month. However, apps with the greatest average downloads per month are likely to have begun on iOS. On each platform, the categories that attracted most app-based firms had greater skewness and kurtosis in average downloads per month. When endogenizing the choice of platform using propensity-score matching, firms that prefer to launch on iOS first seem likelier than those that

launch on Android first to not receive any funding at all. However, they seem to receive greater funding in USD per firm.