INNOVATION IN ENTREPRENEURIAL FIRMS:

KILLER APPS IN THE IPHONE ECOSYSTEM

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Abstract

The mobile applications (apps) industry has exhibited rapid entry and growth in the midst of a recession. Since Schumpeter (1943), entrepreneurs have been identified as a source of innovations. We study new ventures in the iPhone application ecosystem, examining how the development of "killer apps" (whether a software application appears in the top grossing rank on iTunes) varies by market, firm, and app characteristics. We find that opposing innovation processes are successful in different markets. We propose supply and demand-side sources to explain the heterogeneity in successful mechanisms.

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Since Schumpeter (1943), entrepreneurs have been identified as a source of innovations, yet there is a lack of empirical research on the processes employed by entrepreneurs to produce innovations.[2] In principal, opposing processes for entrepreneurial innovation exist: new ventures may simultaneous explore different products to increase the likelihood of successful innovation, or they may focus their resources to sequentially improve one product. Under what conditions are either of these innovation strategies more successful than the other?

This paper explores innovation by entrepreneurial firms building mobile applications (apps) for Apple's iPhone. We find that both innovation processes may be effective, depending on supply and demand characteristics of the market. Simultaneous innovation processes increase the likelihood of producing killer apps in markets with developed supply tools and demand for variety. Focused innovation processes increase the likelihood of producing killer apps in nascent markets with few developed supply tools and unit demand (demand for a single, best product).

iPhone Application Ecosystem

In October, 2007, Apple CEO Steve Jobs announced that 3rd party software development would be possible for the iPhone.[3] By March 2012, Apple reported to offer over 550,000 apps, with 25 billion apps downloaded worldwide for its 315 million devices.[4]

The iPhone application ecosystem is a particularly ideal setting for our project, since we observe the industry during its infancy. Our industry interviews and the typical uncertainty and experimentation surrounding the early stages of an industry suggest that most firms are not completely clear as to the profit maximizing strategies in mobile applications. As a result, we

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[2] Prior research has focused on other outcomes like resource acquisition (Hallen, 2008; Katila et al., 2008; Sorenson & Stuart, 2001), going public (Gulati & Higgins, 2003; Stuart & Sorenson, 2003), or commercialization (Gans et al., 2001; Hsu, 2006).

[3] http://en.wikipedia.org/wiki/IOS_SDK#cite_note-4, accessed 9/1/13.

[4] http://www.apple.com/pr/library/2012/03/05Apples-App-Store-Downloads-Top-25-Billion.html, accessed 9/1/13.

econometrically interpret these process choices as unlikely to suffer from selection bias. A big advantage of our dataset is that we observe the full risk set of successes and failures, since any app that is ever released for the iPhone can, for the most part, only be distributed through the iTunes store. As a result, we feel comfortable with modeling the developer's choice of strategy as free of the selection bias and endogeneity of strategic choices that typically plague econometric analysis of successful strategies in more developed industries.

Data

Our measure of innovation performance is whether a firm releases a product that becomes a killer app or not (Killer_App_Firm). A top grossing "killer app" is any application that has appeared in the top 300 ranking apps by gross sales in any day between September 11, 2009 and December 31, 2011 as determined by iTunes. We control for firms with apps in "top free" and "top paid" rankings (KA_free, KA_paid) to account for possible visibility and reputational effects.

Our data covers 328,428 apps observed every 2 days (on average) on iTunes between September 6, 2010 and August 31, 2011. The data contains 18 application categories. Games is the largest category, although it only accounts for 18% of all apps in the sample. We identify 3,431 killer apps. Games are the most frequent killer app category, comprising 49% of all killer apps in our sample.

We identify 82,435 firms and divide them into game developers (17%) and non-game developers based on the most frequent category of their apps. There are 1,945 firms with a top grossing killer app, and 35% of them are primarily game developers. This means that only 5% and 2% of game and non-game developers, respectively, create top grossing killer apps.

We focus on the time and activities before a firms' entry into the top grossing app rankings. We match non-killer app firms to killer app firms by focal category and cohort (month and year of release of first app for a firm). We then cut off the observation period of the (multiple) matched firms to equal that of the killer app firms. Doing this allows us to more strictly compare the activity of a killer app firm to the activity of a non-killer app firm, since we only compare actions that both could have made in the same amount of time. Since there are many more non-killer app firms, this also prevents us from generating standard errors whose precision only results from oversampling from the non-killer app population. Our resulting sample contains 1,908 killer app firms and 50,617 matched control firms.

We utilize the number of reviews (Ln_Firm_Rev) and the ratings (Firm_Rating) based off those reviews as our measure of app demand and quality, respectively, and so control for those innovation quality measures. Apple iTunes does not provide a precise measure of the number of downloads; however, in order to submit a review, a user must have downloaded the app, so the reviews can be considered a lower bound on downloads. We use the ratings based on these as a measure of preferences for the app as a measure of quality – customers can give from 1 to 5 "stars" when they rate the apps.

Table 1 contains descriptive statistics for our sample broken out by killer app game versus non-killer app game firms and killer app non-game versus non-killer app non-game firms. None of the differences are statistically significant due to the wide variation across firms.

[INSERT TABLE 1 HERE]

Model

We model the probability that a firm develops a top grossing killer app as a function of innovation processes and product characteristics. Firms choose the number of apps to develop and the timing between those apps, the category in which they develop apps, the number of versions (updates) for each app and the timing of those versions, the size of the app (which influences the storage space consumed by the app on the phone and may reflect the complexity and features of the app), and the price. Firms also choose the app characteristics to maximize demand for the app. The demand for these characteristics is reflected in both the quantity of the app demanded and user assessments of the quality of the app through star ratings.

We estimate the following probit model separately for games and non-games, where *i* indexes the firm, *y* indexes the year, *m* indexes the month, *c* indexes the focal category, and β, Ψ, T, and Λ are estimated parameters.

$$\text{Killer\_App}_i = \Phi(g) = \Phi(\beta_0 + \beta_1\text{Count\_App}_i + \beta_2\text{Av\_Versions}_i + \beta_3\text{Av\_Time\_btw\_Versions}_i + \beta_4\text{Batch}_i + \Psi\text{Controls}_i + \text{T}\text{Cohort}_{ym} + \Lambda\text{Focal\_Cat}_c + \varepsilon_{ymc})$$

The errors are robust and clustered on cohort and focal category to account for autocorrelation across firms in different focal categories but within the same cohort.

RESULTS

Table 2 presents the results of our regressions. The first two columns present the regression results for game firms, and the last two columns present the regression results for non-game firms. Probit results are presented in the first and third columns, while average marginal effects are presented in the second and fourth columns.

The likelihood of producing a killer app is significantly and positively affected by producing multiple apps (Count_App). However, for non-game developers, multiple apps have a negative and significant effect on that probability. The average marginal effects are not that large, at 0.026% and -0.013% per extra app. However, given that the baseline probability of becoming a killer app in games and non-games is 5.6% and 3.1%, this translates into a 0.37% increase and 0.46% decrease relative to the baseline, respectively. Recall from Table 1 that the average difference in apps between killer and non-killer apps for both games and non-games is 4 apps, so the increase (decrease) in apps from the average non-killer to killer levels implies an almost 2% increase in the probability of becoming a killer app relative to the baseline.

The average number of versions per app for a firm (Av_Versions) significantly and positively affects the probability that a non-game developer will enter the top grossing killer app rankings. However, for game developers, updating an app has a negative though not significant effect on that probability. Game developers should simply try a different app, rather than try to update that app. Again, the average marginal effect is not that large at 0.095% per extra version for non-games. Relative to the killer non-game baseline rate of 3.1%, this translate into a 3% increase in the baseline probability of becoming a killer-app firm.

More time between versions (average per app for a firm, Av_Time_btw_Versions) has a positive and significant effect on the probability of having a killer app for non-game developers, but a negative (although insignificant) effect for game developers. The difference between the mean time between versions for a killer versus non-killer firm for non-games is about 17 days, so the increase in probability for becoming a killer app firm by investing that extra time is 17 days x 0.0103%=0.175%. With our non-game killer firm base rate of 3.1%, this increase would represent 5.6% increase in the probability of becoming a non-game killer app firm relative to the baseline.

Finally, simultaneous release of apps (Batch) has a positive and significant effect on the probability of becoming a killer app firm, whereas batching has an insignificant effect for non-games. Switching from a firm who does not batch to one who does batch increases the probability of being a killer app firm by 0.758%. Given our game killer firm base rate of 5.6%, this translates into a 13.5% increase relative to the baseline of being a killer game firm.

[INSERT TABLE 2 HERE]

DISCUSSION

What may be the drivers of the opposing innovation process results we observe in game and non-game markets? Consumers and developers are familiar with the gaming product on a mobile device due to the popularity of Nintendo's handheld device. Many developer tools and libraries with standard gaming algorithms are available for game developers. Furthermore, game developers are familiar with how to deal with the constraints of a small screen and lack of a keyboard for input. Through interviews with entrepreneurs, we learned that development knowledge and awareness of these tools were relatively well diffused amongst games entrepreneurs. In contrast, most of the non-game categories do not have analogous versions in the mobile world. At best, they can borrow tools from the desktop web browser platform, but they still need to translate the app into something that can deal with the constrained real estate of a mobile device and the constrained input interface on a mobile device. Furthermore, they need to redesign the app to accommodate a user that is not likely to engage with the device for more than a few minutes at a time, in contrast to a few hours at a time at the desktop. Our interviews indicated that the most innovative non-game apps will actually be creating a new and unfamiliar way for the consumer to employ the various powers and features of their mobile device (e.g., GPS, gyroscope, camera, communications, etc.). There may be no existing algorithms at hand, and even consumers may be unsure as to what to expect from the product. In markets like games with established supply tools, incremental improvements are harder to achieve since resources are already available to produce high-quality products. There may be higher chance of producing an innovative product by experimenting with something different. In contrast, the lack of industry knowledge and supply tools in nascent markets like non-games make quality innovations harder, so firms might make better innovative progress by focusing on one product.

We also consider the games category to exhibit demand for variety, whereas the non-games category is more characterized by unit demand. Consumers tend to play multiple games at one time, and app developers tend to cross-advertise their products, suggesting that any potential cannibalization is worth the extra demand. Consider a non-game app like a pdf reader: people do not want multiple pdf readers, they just want the best one. In general, the inclusion of apps that are utilized as tools rather than entertainment in the non-game apps category means that this category will encompass the apps that for which the consumer only wants one of each type.

In markets with demand for variety, multiple products are more likely to capture a larger number of adopters by spanning their heterogeneous tastes. In markets with unit demand, consumers prefer to have a single, best product. Firms compete for the same set of consumers, so innovation processes should focus scarce resources on attaining the global optimum.

Under unit demand, consumer feedback will be informative for attaining the market optimum, since consumers have aligned preferences for the "best" product. The firm benefits from investing time to respond to that feedback in the next version. Under demand for variety, the feedback will be heterogeneous for a product, reflecting the variety of preferences, so responding to feedback through versioning may not lead to a product that satisfies any of the multiple demand segments. A firm with unit demand might learn from observing product performance and incorporate that learning into incremental innovation. Simultaneous processes in that case may spread the firm too thin in its ability to capitalize on what is learned.

This paper analyzes the linkage between entrepreneurial innovation processes and market characteristics. Using unique data from the iPhone application ecosystem, we find robust evidence that simultaneous innovation processes (batch release of multiple products) are beneficial in markets like gaming, where there is demand for variety and established supply tools. Focused innovation processes emphasizing sequential versions produced over substantial time periods are better suited to nascent markets and/or markets with unit demand (non-games).

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Table 1: Descriptive Statistics for Killer & Non-Killer App, Game & Non-Game Firms

Variable	Killer App Firms in Games		Non-Killer App Firms in Games		Killer App Firms in Non-Games		Non-Killer App Firms in Non-Games	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
KA_free	0.355	0.479	0.035	0.183	0.160	0.367	0.015	0.120
KA_paid	0.498	0.500	0.016	0.125	0.362	0.481	0.005	0.070
No_Updates	0.284	0.451	0.534	0.499	0.255	0.436	0.542	0.498
Av_Versions	2.355	1.761	1.679	1.184	2.927	2.668	1.817	1.503
Av_Time_ btw_Versions	33.985	39.229	22.119	43.567	40.808	49.609	23.263	46.739
One_App	0.272	0.445	0.550	0.498	0.352	0.478	0.672	0.469
Count_App	6.510	12.111	2.519	5.148	6.725	16.692	2.665	15.236
Av_Time_ btw_Apps	51.720	82.998	21.803	49.384	51.800	89.912	17.117	50.613
Batch	0.310	0.463	0.131	0.337	0.251	0.434	0.102	0.302
All_Free	0.077	0.266	0.193	0.394	0.052	0.223	0.442	0.497
Av_Price	1.932	8.598	0.995	1.462	9.368	51.436	1.712	9.358
Av_Size	26.415	47.213	10.913	20.177	19.860	55.821	10.245	42.548
Active_Days	234.85	224.91	176.21	192.26	244.99	232.83	161.51	181.30
Ln_Firm_ Rev	4.789	1.935	1.705	1.492	4.080	1.863	1.258	1.361
Firm_Rating	3.794	0.875	2.576	1.879	3.479	1.161	2.107	1.982
Change_Cat	0.060	0.238	0.023	0.150	0.159	0.366	0.037	0.190
Change_Rel_ Date	0.069	0.254	0.015	0.120	0.031	0.174	0.015	0.123
Obs.	665	665	11164	11164	1243	1243	39453	39453

Table 2: Regression Results for Game and Non-Game Firms

Killer_App_Firm	Game Developers		Non-Game Developers	
	Probit	AME	Probit	AME
Count_App	0.00622***	0.000260***	-0.00323***	-0.000129***
	(0.00191)	(0.0000791)	(0.00112)	(0.0000440)
Av_Versions	-0.0200	-0.000837	0.0237**	0.000949**
	(0.0289)	(0.00120)	(0.0109)	(0.000432)
Av_Time_btw_Vers	-0.000525	-0.0000219	0.00258***	0.000103***
	(0.00105)	(0.0000437)	(0.000570)	(0.0000230)
Batch	0.169*	0.00758*	0.106	0.00443
	(0.0873)	(0.00436)	(0.0712)	(0.00315)
KA_free	0.268**	0.0130**	0.0129	0.000518
	(0.106)	(0.00612)	(0.0787)	(0.00320)
KA_paid	1.298***	0.121***	1.515***	0.151***
	(0.0884)	(0.0134)	(0.0727)	(0.0128)
No_Updates	0.277***	0.0118**	0.247***	0.0102***
	(0.101)	(0.00501)	(0.0599)	(0.00284)
One_App	0.0810	0.00338	0.209***	0.00845***
	(0.101)	(0.00443)	(0.0670)	(0.00305)
Av_Time_btw_Apps	0.00441***	0.000184***	0.00299***	0.000120***
	(0.000620)	(0.0000251)	(0.000413)	(0.0000169)
All_Free	-0.124	-0.00500	-1.172***	-0.0331***
	(0.111)	(0.00406)	(0.0670)	(0.000564)
Av_Price	0.0748***	0.00312***	0.00749***	0.000300***
	(0.0149)	(0.000683)	(0.00225)	(0.0000887)
Av_Size	0.00404***	0.000169***	0.00155***	0.0000619***
	(0.00109)	(0.0000443)	(0.000269)	(0.0000108)
Active_Days	-0.00236***	-0.0000985***	-0.00278***	-0.000111***
	(0.000447)	(0.0000184)	(0.000355)	(0.0000138)
Ln_Firm_Rev	0.466***	0.0195***	0.540***	0.0216***
	(0.0292)	(0.00122)	(0.0202)	(0.000607)
Firm_Rating	0.0822***	0.00343***	0.0365**	0.00146**
	(0.0260)	(0.00106)	(0.0182)	(0.000727)
Change_Cat_Control	0.278	0.0136	0.118	0.00505
	(0.169)	(0.00979)	(0.108)	(0.00494)
Change_Rel_Date_Control	0.172	0.00790	0.333***	0.0159***
	(0.112)	(0.00578)	(0.0543)	(0.00305)
Constant	-3.484***		-3.306***	
	(0.155)		(0.098)	
Cohort Effects	Yes	Yes	Yes	Yes
Focal Category Effects	No	Yes	No	Yes
Obs	11829	11829	40696	40696
Pseudo-R-sq	0.5054	0.5054	0.4936	0.4936
LL	-1266.37	-1266.37	-2815.66	-2815.66

Standard errors are in parentheses, * p<0.1, ** p<0.05, *** p<0.01.