This work is distributed as a Discussion Paper by the

STANFORD INSTITUTE FOR ECONOMIC POLICY RESEARCH

SIEPR Discussion Paper No. 13-028

Entrepreneurial Innovation:

Killer Apps in the iPhone Ecosystem

By

Pai-Ling Yin, Jason P. Davis, and Yulia Muzyrya

Stanford Institute for Economic Policy Research
Stanford University
Stanford, CA 94305
(650) 725-1874

Entrepreneurial Innovation:
Killer Apps in the iPhone Ecosystem

By PAI-LING YIN, JASON P. DAVIS, AND YULIA MUZYRYA*

Abstract

The mobile applications (apps) industry has exhibited rapid entry and growth in the midst of a recession. Using unique data from the iPhone application ecosystem, we examine how the development of "killer apps" (apps appearing in the top grossing rank) varies by market and app characteristics. We find that previous app experience and no updating increase the likelihood of becoming a killer game app, while more updates increase the likelihood of becoming a non-game killer app. Development opportunities, level of competition, and demand preferences are possible drivers of the opposing innovation process results in game and non-game markets.

Entrepreneurial Innovation:

Killer Apps in the iPhone Ecosystem

By PAI-LING YIN, JASON P. DAVIS, AND YULIA MUZYRYA*

* Yin: Stanford University, 366 Galvez St, Stanford, CA 94305 (pyin@stanford.edu). Davis: INSEAD, 1 Ayer Rajah Ave, Singapore, 138676 (jason.davis@insead.edu). Muzyrya: University of Michigan, 701 Tappan St, R0440-40, Ann Arbor, MI 48109 (muzyrya@umich.edu). The authors wish to thank Carlos Garay, Jorge Guzman, Jing Li, Abhishek Nagaraj, and Francis Plaza for their indispensable work gathering the data for this project. Jason Davis and Pai-Ling Yin also acknowledge the generous support of the MIT Sloan Karl Chang (1965) Innovation Fund and Edward B. Roberts (1957) Fund for this research.

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, yet there is a lack of empirical research on the processes employed by entrepreneurs to produce innovations.[1] We study innovations 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 and app characteristics. We find that later apps by a developer are more likely to be killer apps if they are games, but there is no significant effect for non-games. More updates help non-game apps, but games with no updates are more likely to be killer apps. The heterogeneity in demand and more intense competition in the games category may explain the difference in successful innovation processes compared to the non-games category, characterized by opportunities for cumulative improvement of apps and homogeneous demand.

I. iPhone Application Ecosystem

Apple CEO Steve Jobs announced in October, 2007 that 3rd party software development would be possible for the iPhone.[2] By March, 2012, Apple reported over 550,000 apps, with 25 billion downloads worldwide for its 315 million devices.[3]

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

[1] 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).

[2] http://en.wikipedia.org/wiki/IOS_SDK#cite_note-4, accessed September 1, 2013.

[3] http://www.apple.com/pr/library/2012/03/05Apples-App-Store-Downloads-Top-25-Billion.html, accessed September 1, 2013.

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 econometrically interpret these process choices as unlikely to suffer from endogeneity. 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. We argue that our analysis is free of the selection bias that typically plague analysis of successful innovations in other data settings.

II. Data and Model

Our measure of successful innovation is whether an app appeared in the top 300 ranking apps by gross sales as determined by iTunes between September 11, 2009 and December 31, 2011 (Killer App).

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 focus on the time and activities before a developer's first app enters into the top grossing rankings. To control as much as possible for unobservable variation across apps, we match developers by their month and year of entry and by the primary category in which they develop apps. We then match the first killer app of each developer to non-killer apps of the control developers by category and cohort (month and year of app release). Finally, we cut off observations on the day an app enters top grossing app rating. Doing this allows us to more strictly compare the innovation processes of a killer app to that of a non-killer app. Since there are many more non-killer apps, this also prevents us from generating standard errors whose precision only results from oversampling non-killer apps. Our resulting sample contains 1,457 killer apps and 34,892 matched control apps.

We utilize the number of user comments (Number of Comments) and the average ratings (Score) based off those reviews as controls for innovation quality. 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 quantity demanded. 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.

We model the probability that an app enters the top grossing rankings as a function of innovation processes and product characteristics. Developers choose the category in which they develop apps, the number of updates, if any, to make to the app (Number of Versions, No Updates) for each app and the timing of those versions (Time between Versions), the size of the app (Size, in megabytes, which affects the storage space consumed on the phone and may reflect the complexity and features of the app), and the price (Price). They 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. The experience of a developer can be captured by controlling for whether this app is the first, second, third, etc. that the developer has released (App Order).

Table 1 contains descriptive statistics for our sample broken out by whether the app is killer or not and a game or not. Average values are used where variation occurs over the observed time of the app. None of the differences are statistically significant due to wide variation in app innovation processes.

[Insert Table 1 Here]

We estimate separate probit models of being a Killer App for game and non-game apps on the set of regressors summarized in Table 1 and cohort and category fixed effects. The errors are robust and clustered on cohort.

III. 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.

[Insert Table 2 Here]

The likelihood of a game app being the first killer app for a developer is significantly and positively affected if that app is a later app produced by the developer (App Order). This is consistent with the typical expectation that more experience improves performance. However, for non-game apps, there is no significant effect from experience with previous apps. This surprisingly contradicts intuition about experience. The next two regression results may provide some insight into why we observe this opposing product-level innovation processes.

The number of updates to an app (Number of Versions) significantly and positively affects the probability that a non-game app will enter the top grossing killer app rankings. More precisely, this result indicates that non-game apps enter the rankings after several updates (recall that we cut off our observation period for each app when it enters the rankings). Although this is possibly the developer's first app, the developer has worked on this app and made several rounds of improvements before it became a killer non-game app. This may be one reason why we found that the first non-game app for a developer has no higher probability of being a killer app than subsequent apps. For game developers, the number of updates has no significant effect on that probability. Instead, game developers positively affect the probability of having a killer app if they do not update (No Update). This last result suggests that while experience is valuable in developing game apps, trying to fix a game app through updates may not be the right way to capitalize on that experience in games. The rest of the regressors have the expected signs and are the same across games and non-games with the exception of Time between Versions. More time between update has a negative and significant effect on the probability of becoming a killer non-game app but an insignificant effect for game apps, since Number of Versions is also insignificant.

The average marginal effects are not that large: being one app later in App Order increases the probability of being a killer game app by at 0.133%. However, given that the baseline probability of becoming a killer app in games in this sample is 7% (535 killer game apps/(7148+535 game apps)), this translates into a 2% increase relative to the baseline. The average marginal effect is 0.116% per extra update for non-games. Relative to the killer non-game baseline rate of 3% (922 killer non-game apps/(27744+922 non-game apps), this translates into a 4% increase in the baseline probability of becoming a killer non-game app. For game apps, the change in probabilities of having a killer app by switching from updating the app to having No Updates is 1.84%, or a 26% increase relative to the baseline.

IV. Discussion

What may be the drivers of the opposing innovation process results we observe in game and non-game markets? One possibility may be the development opportunities and the level of competition in these markets. Many developer tools and libraries with standard gaming algorithms are available for game developers, making entry much easier in this market. 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. The innovative barrier to entry is higher. Our interviews with industry participants 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, camera, communications). If a game app is the first for a developer, it may be disadvantaged by the sophistication of the competition it encounters; subsequent game apps may reflect valuable experience on how to compete in the game market. Furthermore, the intensity of competition may also lead consumers to be less patient for an update to "fix" a game: the developer may be better off incorporating that experience into launching a new game. In contrast, the first app for a developer in any particular non-game category may succeed relative to any subsequent apps by that developer because the developer can improve the app through updates without competitors stealing away consumers as quickly.

Another driver of the opposing product-level innovation results may be related to demand preferences. In markets with heterogeneous preferences, tastes will differ across consumer segments. In markets with homogenous demand, consumers prefer to have a single, best product. We consider the games category to exhibit heterogeneous demand, whereas the non-games category is more characterized by homogeneous demand. Different genres of games exist suggesting different customer segments served. Consider a non-game app like a pdf reader: consumers are more likely to congregate on 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 for which the consumer only wants the best of each type.

Under homogeneous 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 to respond to that feedback in the next version. Under heterogeneous preferences, the feedback may be conflicting for a product, reflecting potentially misaligned preferences, so responding to feedback through updating may not lead to a product that satisfies any of the multiple demand segments. A developer facing homogenous preferences might learn from observing product performance and incorporate that learning into a cumulative innovation process.

This paper analyzes the linkage between product-level innovation processes and market characteristics. Using unique data from the iPhone application ecosystem, we find that previous app experience and no updating increase the likelihood of becoming a killer game app, while more updates increase the likelihood of becoming a non-game killer app. The cumulative improvement innovation process at the product level is consistent with the homogeneous demand, development opportunities, and less competitive environment in non-game categories. We suspect that the opposing app experience effect in the games and non-games market is indicative of firm-level tradeoffs in innovation processes. We intend to explore these firm-level aspects in future work.

REFERENCES

Gans, Joshua S., David Hsu and Scott Stern. 2001. "When Does Start-Up Innovation Spur the Gale of Creative Destruction?" In RAND Journal of Economics. 571-586.

Gulati, Ranjay and Monica Higgins. 2003. "Which Ties Matter When? The Contingent Effects of Interorganizational Partnerships on IPO Success" In Strategic Management Journal. 127-144.

Hallen, Benjamin. 2008. "The Causes and Consequences of the Initial Network Positions of New Organizations: From Whom do Entrepreneurs Receive Investments" In Administrative Science Quarterly. 685-718.

Hsu, David. 2006. "Venture Capitalists and Cooperative Start-up Commercialization Strategy" In Management Science. 204-219.

Katila, Riitaa, Jeff D. Rosenberger and Kathleen M. Eisenhardt. 2008. "Swimming with Sharks: Technology Ventures, Defense Mechanisms, and Corporate Relationships" In Administrative Science Quarterly. 295-332.

Schumpeter, Joseph. 1943. Capitalism, Socialism and Democracy. New York: Harper.

Sorenson, Olav and Toby E. Stuart. 2001. "Syndication Networks and the Spatial Distribution of Venture Capital Investments" In American Journal of Sociology. 1546-1588.

Stuart, Toby E. and Olav Sorenson. 2003. "Liquidity Events and the Geographic Distribution of Entrepreneurial Activity" In Administrative Science Quarterly. 175-201.

TABLE 1— DESCRIPTIVE STATISTICS FOR KILLER & NON-KILLER, GAME & NON-GAME APPS

	Games Killer	Games Non-Killer	Non-Games Killer	Non-Games Non-Killer
App Order	4.67	2.30	2.62	4.46
	(8.93)	(6.77)	(7.78)	(20.86)
Number of Versions	2.36	1.45	3.42	1.65
	(2.56)	(1.09)	(3.86)	(1.51)
No Updates	0.58	0.74	0.45	0.69
	(0.49)	(0.44)	(0.50)	(0.46)
Time Between Versions	2.90	3.59	7.24	6.34
	(12.81)	(18.16)	(26.08)	(26.14)
Price	2.13	1.00	15.73	1.97
	(2.54)	(1.34)	(87.73)	(10.29)
Size	34.60	12.10	24.44	13.33
	(54.47)	(23.16)	(76.35)	(55.02)
Number of Comments	330.96	8.56	197.38	6.98
	(1478.84)	(116.60)	(1361.51)	(284.69)
Score	4.16	2.35	3.81	1.90
	(0.82)	(2.17)	(1.23)	(2.14)
Observations	535	7148	922	27744

Notes: Means for each variable over all apps in the category designated in each column. Standard deviations are presented in parentheses.

Source: Author calculations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE 2— REGRESSION RESULTS FOR GAME & NON-GAME APPS

	Games Probit	Games Average Marginal Effects	Non-Games Probit	Non-Games Average Marginal Effects
App Order	0.0219***	0.00133***	0.00119	0.0000613
	(0.00504)	(0.000300)	(0.00105)	(0.0000536)
Number of Versions	0.0126	0.000768	0.0224**	0.00116**
	(0.0295)	(0.00180)	(0.0113)	(0.000588)
No Updates	0.317**	0.0184**	0.108	0.00546
	(0.127)	(0.00854)	(0.0688)	(0.00372)
Time Between Versions	-0.00513	-0.000312	-0.00407***	-0.000210***
	(0.00441)	(0.000265)	(0.00154)	(0.0000809)
Price	0.140***	0.00854***	0.00800***	0.000413***
	(0.0351)	(0.00216)	(0.00279)	(0.000139)
Size	0.00445***	0.000271***	0.00132***	0.0000684***
	(0.00133)	(0.0000771)	(0.000259)	(0.0000132)
Log Number of Comments	0.673***	0.0409***	0.533***	0.0275***
	(0.0315)	(0.00129)	(0.0179)	(0.00106)
Score	0.103***	0.00629***	0.0683***	0.00353***
	(0.0340)	(0.00199)	(0.0134)	(0.000690)
Constant	-3.610***		-3.179***	
	(0.196)		(0.167)	
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Category Fixed Effects	No	No	Yes	Yes
Observations	7683	7683	28666	28666
Pseudo R-squared	0.4953	0.4953	0.3512	0.3512

Notes: Standard deviations are presented in parentheses.

Source: Author calculations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.