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Experimentation Strategies and Entrepreneurial Innovation: Inherited Market Differences in the iPhone Ecosystem

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Abstract

Although experimentation is critical to the innovation process in startups, little research has explored the link between different experimentation strategies and entrepreneurial innovation. We use unique data on experimentation strategies and innovation outcomes of firms producing iPhone applications to show that the appropriateness of different strategies depends on market characteristics. Simultaneous experimentation strategies are better suited to markets characterized by strong market inheritance, where innovative know-how, development technologies, and heterogeneous preferences from established markets can be leveraged by entrepreneurs. In markets with fewer skills, fewer developmental technologies, and less understood demand expectations, innovations are more likely to result from sequential product improvements based on customer feedback, allowing the entrepreneur to develop skills and clarify what may be singular customer preferences.

Keywords: Entrepreneur; Innovation; Technology; Strategy; Mobile Apps.

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An important rationale for studying entrepreneurship is that new ventures (i.e., start-ups) are a useful organizational form for the development of innovations. Analysts have suggested that start-up innovations are responsible for "gales of creative destruction" that change industries and disrupt established firms (Schumpeter, 1943). Although some research has linked industry structure, intellectual property policy, and financing conditions to rates of entrepreneurship (Gans, Hsu, and Stern, 2001; Gompers and Lerner, 1999; Teece, 1996), little prior research has investigated why some ventures are more innovative than others in a given industry context, including the role of different strategies used by entrepreneurs to produce innovations. Instead, most prior research about entrepreneurial strategies has focused on outcomes like resource acquisition (Hallen, 2008; Katila, Rosenberger, and Eisenhardt, 2008; Sorenson and Stuart, 2001), going public (Gulati and Higgins, 2003; Stuart and Sorenson, 2003), or bringing existing innovations to market (Gans *et al.*, 2001; Hsu, 2006). In fact, most prior research about producing innovations has taken place in the context of large, established firms (Ahuja, 2000; Ahuja and Katila, 2001; Henderson and Clark, 1990; Katila, 2002; Powell, Koput, and Smith-Doerr, 1996; Rothaermel and Hess, 2007; Stuart, 2000; Tushman and O'Reilly, 1997), perhaps because their centralized R&D labs or product-focused divisions are a better context in which to observe multiple, comparable attempts at innovation and construct large databases of innovation proxy measures like patents and new product introductions.

Although existing literature on established firm innovation is instructive, several outstanding issues remain. First, the performance measures associated with established firms may not be a good fit for entrepreneurial innovation. Generally, innovation refers to new *and* useful products (Schumpeter, 1943), a definition that distinguishes innovations from mere inventions that are new but lack commercial value. While invention-focused measures like patents and product introductions may be a good innovation proxy for established firms (Henderson and Cockburn, 1994; Katila, 2002; Katila and Ahuja, 2002), these outcomes are not tightly linked to entrepreneurial innovation, and may even be misleading. Compared to established firms, new ventures tend to have weaker commercialization capabilities and less capacity to survive commercialization failures (Gans *et al.*, 2001; Teece, 1986), suggesting that product introduction alone is an ineffective measure for startups. In fact, many startups release new products, but only a few are the commercial hits that are in the foreground of entrepreneurial interest (Chatterji, 2009; Mollick, 2013). Outside of biotechnology, few startups develop extensive patent portfolios from which commercial success with innovation might be inferred (Levin *et al.*, 1987; Nelson, 2009; Pahnke, 2010).

Second, and perhaps more significant, the innovation strategies of entrepreneurial firms are not altogether clear. There is a general view that startups are laboratories for experimentation, a form of exploratory search based on gaining market feedback from releasing new products (Lee *et al.*, 2004; March, 1991; Thompke, 2003). Although there is little detailed empirical research on entrepreneurial experimentation, some inferences can be made by considering prior research about established firm innovation in light of the challenges that new ventures face. This suggests two contrasting perspectives. The first emphasizes simultaneous experimentation as a key driver of entrepreneurial innovation (Brown and Eisenhardt, 1997; Thompke, 2003). The central argument is that although new ventures may lack resources or deep expertise in product-markets, they are also free of the commitments that constrain established firms (Ahuja and Lampert, 2001; Henderson and Clark, 1990). Therefore, compared to established firms, they are free to engage in risky behavior with as many highly varied experimental attempts as soon as possible (Lee *et al.*, 2004; Tushman and Anderson, 1986), including simultaneous releases of different products. In this view, entrepreneurship is a broad search for distant innovations amongst many alternatives that are discovered through multiple experiments (Fleming, 2001; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001).

An alternative perspective focuses on sequential experimentation in the development of innovations. Sequential experimentation refers to an ongoing process of invention, product release, and reinvention in a series of product versions (Dosi, 1982; Katila and Chen, 2009). Ideally, each new version improves upon prior versions by incorporating customer feedback and market performance. Although sequential strategies are typically associated with the large resource endowments of established firms, startups may employ them if they can iterate quickly enough before resources run out. Because new ventures lack resources and expertise they should focus on learning through market-feedback, building basic competencies, and iterating on existing products until they are sufficiently innovative (Hellmann and Puri, 2002; Henderson and Cockburn, 1994; Sorensen and Stuart, 2000). In this view, entrepreneurship is a local search for nearby innovations that are reachable through an incremental, hill-climbing approach along well-defined technological trajectories (Dosi, 1982; Fleming, 2001; Katila and Ahuja, 2002).

Taken together, prior research suggests two opposing experimental strategies for entrepreneurial innovation, one emphasizing the capacity of new ventures to undertake highly variable, simultaneous experiments to increase the likelihood of distant innovation, and the other emphasizing their need to sequentially improve technologies through iterative feedback and search for nearby innovations. This state of understanding about entrepreneurial innovation may appear perplexing if not troubling. The aim of this paper is to explore innovation strategies by entrepreneurial firms in a context where both simultaneous and sequential experimentation are possible, and thus take some first steps in resolving this puzzle.

Our central argument is that both experimental strategies may be effective, depending on the markets targeted by entrepreneurs. Although entrepreneurs often pursue opportunities in broad, nascent sectors like clean-tech, cloud computing, or mobile applications, different markets in these broad sectors can differ substantially. In particular, some new markets resemble established markets sufficiently that entrepreneurs can benefit from market inheritance, defined as the degree to which entrepreneurs can utilize diffused knowledge related to experimental capabilities, development technologies and tools, and fine-grained understanding of customer preferences. We build upon these ideas in research on inheritance (e.g., Agarwal *et al.*, 2004; Chatterji, 2009; Klepper, 2001; Klepper and Simons, 2000) to explain market differences that shape entrepreneurial experimentation in the mobile applications ecosystem, and resolve the puzzle about simultaneous versus sequential strategies. We find that simultaneous experimental strategies are better suited to new markets with strong inheritance where entrepreneurs benefit from existing experimentation capabilities, development technologies and tools, and knowledge of customer preferences are inherited from established markets. By contrast, sequential experimental strategies are better suited to new markets with weak inheritance where few skills, few developmental technologies, and little understanding of preferences are inherited from established markets. In our setting, experimentation skills, development technologies, and heterogeneous preferences inherited from established markets seem to enable broad exploration with widely varying, simultaneous innovation experiments, whereas in markets with fewer skills, fewer developmental technologies, and less understood demand expectations, innovations are more likely to result from sequential product improvements based on customer feedback to develop skills and clarify what may be singular customer preferences.

To better understand the experimental development of innovative products by entrepreneurial firms, we analyzed entrepreneurial innovation by new ventures building mobile applications ("apps") for Apple's iPhone. This dataset and context has a number of advantages for our research question. First, because all ventures must register with Apple to sell apps, a full population of firms and a risk set of potential innovations can be constructed. This panel data includes rich, time-varying measures about all the firms, their products, and outcomes. Compared to prior work that mainly uses invention-focused measures of innovation such as patents or new product introductions, this data includes a unique innovation performance measure of innovation that also reflects commercial success – that is, producing a "killer app." Consistent with common usage in the Apple ecosystem, we define a "killer app" as any application that appears on the Top Grossing list of the top 300 applications with the most revenue on Apple's highly visible App Store. Because of the additional usage that derives from this publicity, attaining killer-app status is a highly sought-after achievement that reflects the popularity and commercial success of these innovative products. A second major advantage of this study is that innovation in the iPhone ecosystem is ongoing, which enabled us to interview many entrepreneurs about their activities and intentions. We use this field data to illustrate the experimental strategies and market differences.

The primary contribution of this paper is to outline how market conditions shape experimental strategies for innovation in entrepreneurial ecosystems. Although prior research generally assumes that entrepreneurial firms focus on experimentation, little prior research had explored different experimentation strategies and their link to entrepreneurial innovation, including whether simultaneous or sequential experimentation strategies were most appropriate for new ventures. Using unique panel data on experimentation strategies and innovation outcomes across market categories of iPhone applications, this paper may be unique in analyzing entrepreneurial experimentation strategies, finding that the effectiveness of different strategies depend on inherited market differences. This study also contributes to the literature on industry ecosystems by complementing that literature's focus on the actions of platform owners as determinative of ecosystem innovation: we find that the different strategic approaches of entrepreneurs in different ecosystem markets can also shape innovative production.

BACKGROUND

How do startups innovate? Innovation is often thought of as an evolutionary process in which firms search for superior combinations of knowledge, technologies, and other resources that provide added value for customers. Because of their limited size, scope, and age, entrepreneurial firms are thought to be especially limited in knowledge, technologies, and resource inputs to innovation, and so must rely on exploration strategies. In particular, entrepreneurial firms are thought to rely on experimentation, defined as a form of exploratory search based on gaining market feedback from releasing new products.[1] Although there is general agreement in the literature about this basic view, different experimentation strategies can actually vary substantially with respect to how they direct evolutionary search for innovative combinations.

Simultaneous and sequential experimentation strategies

Simultaneous experimentation strategies direct search towards broad exploration with many varied innovation attempts that are tested in the market at approximately the same time. These two aspects of simultaneous experimentation can be analyzed (and measured) separately: for instance, developing many different products is a common approach in product development.

[1] This definition discriminates experimentation from other forms of exploration described by March (1991) – for instance, vicarious learning – that do not involve gaining direct market feedback from product releases by the focal firm.

Often conceptualized as a portfolio of low cost probing products that are used to test options in the market (Brown and Eisenhardt, 1997; Thompke, 2003), entrepreneurs can choose amongst these alternatives for further investments once customers provide feedback (Chatterji and Fabrizio, 2011; Rothwell *et al.*, 1974). The mobile application company Rovio Entertainment is a good example. Although well known for their 2009 Angry Birds game, many are unaware that Rovio produced over 20 games for the iPhone and other mobile platforms, yet it was their Angry Birds game that found a large market response (Fried, 2012).

The other measurable aspect of simultaneous experimentation is to release these many different products in a batch at approximately the same time (Clark and Fujimoto, 1991). Batching is used to achieve production efficiencies by synchronizing qualitatively similar product development activities (e.g., design, testing, etc.) that are duplicated across products, and receive market feedback at approximately the same time (Eisenhardt and Tabrizi, 1995; Schoonhoven, Eisenhardt, and Lyman, 1990). Similar to experimentation logics in the sciences, producers may wish to eliminate any exogenous differences due to the time of release in order to receive roughly comparable feedback. One entrepreneur described the batching of multiple products:

> "I came from a company where experimental A-B testing was exceedingly important, and one thing we discovered was that the customer response, at least initially, has a lot to do with when you release the product. So when we put out a group of apps, we try to do so at about the same time, typically over a weekend. Then our customers can use them all and tell us which one works, which one doesn't, and why. …then we have some tough decisions to make about which one to support."

In contrast, sequential experimentation strategies direct search towards local exploitative hill-climbing efforts to incrementally improve innovations and their value for customers (Fleming, 2001; Katila, 2002). One aspect of sequential experimentation is to release multiple versions of the same product over time (Brown and Eisenhardt, 1995). Different product versions enable entrepreneurs to incorporate ongoing market feedback into discrete changes in products (Dougherty, 1990; Sutton and Hargadon, 1996). Ideally, these different versions preserve the valuable core features of innovations but provide incremental greater value to customers over time (Gawer and Henderson, 2007; Kim and Kogut, 1996). The mobile photo application Instagram is good example. The two founders added multiple improvements in successive versions that provided value for customers – these included hashtags, filters, tilt shift, high resolution photographs, optional borders, one click rotation, and an updated icon (Facebook, 2011). These version updates produced a highly innovative application – Facebook acquired Instagram in April 2012 for approximately $1 billion.

Another aspect of sequential experimentation is to provide sufficient time between versions for customers to react to old versions and the firm to incorporate product changes based on that feedback. Providing sufficient time for reaction and response increases the likelihood that the value of each new version surpasses the prior version (Schoonhoven *et al.*, 1990; Womack, Jones, and Roos, 1990). Another entrepreneur described his rationale for waiting:

"It can be tempting to continually update since the platform makes it so easy, but we really worry that we'd just waste our effort or, worse, break something. Instead, we try to wait until users have a chance to use it before versioning. And if we don't have any changes that will really improve the experience, we just leave it alone."

Ultimately, simultaneous and sequential experimental strategies are two ends of a continuum, with specific innovation strategies categorized mainly as a matter of convenience.

Inheritance from similar markets

The markets where entrepreneurs compete can vary on a number of dimensions that shape the effectiveness of their innovation strategies. Fundamental to our arguments is the idea that different product-markets in an entrepreneurial ecosystem can vary in their inheritance from similar, previously established markets (Klepper, 2001; Klepper and Simons, 2000).

Innovative know-how and development tools

In platform based-ecosystems like those for mobile applications, platform-owners are typically responsible for developing the main platform (e.g., the smartphone itself, the store) and related complementary assets like marketing, advertising, and manufacturing, leaving the ecosystem members to develop complementary products (e.g., mobile applications) in various pre-defined categories (Boudreau, 2010; Gawer and Cusumano, 2002). Despite sharing a common platform, the specialized innovative capabilities of producers focusing in these different market-categories may develop at different rates and materials and tools may be more or less available (Adner and Kapoor, 2009; West and Wood, 2013). For example, different market segments in the automotive, clean-technology, and telephony industries may be said to be more or less established, depending on their rate of development or date of emergence. Minivans and sedans, solar panels and biofuels, and mobile and landline categories are generally recognized as differing in maturity along these dimensions. Sometimes, market categories are relatively more established because they resemble markets in other industries – producers in these adjacent market-categories benefit from the similar industry by borrowing and incorporating some technological knowledge or development tools from the old industry into the new one (Agarwal *et al.*, 2004; Chatterji, 2009; Klepper, 2001).

Since this study ultimately uses mobile applications as its empirical context, it is useful to use this setting to illustrate these market inheritance ideas in our context. Apple divides mobile applications for its iPhone and iPad into multiple categories including Finance, Games, Productivity, Sports, and Travel. While producers could make applications in any category, firms tend to focus their innovation efforts on applications in one or a few categories. For example, in our dataset 67% of producers produce applications in one category, 85% produce applications in two or fewer categories, and 93% produce applications in three or fewer categories.

What is most striking to us and other industry analysts is how much more the Games category inherits from the similar, non-app game market relative to other, non-game categories along the market dimensions described above. In our interviews, we discovered that the state of development of innovative capabilities, knowledge of customer preferences, and development tools for Games was significantly higher than in other categories. Why?

Compared to apps in a Non-Games category, the development of apps in the Games category shared strong similarities to the development of mobile game products that preceded the release of the iPhone in 2007. This includes games on other handsets and devices built by prominent mobile phone and device firms like Nokia, Palm, and Motorola, as well as specialized handheld mobile gaming platforms like Nintendo's GameBoy and DS and Sony's PSP (Mollick, 2012; Ozcan and Eisenhardt, 2008). By 2007, an extensive ecosystem of mobile game developers was already well developed, including specialized mobile gaming firms and gaming console developers like Electronic Arts, Capcom, and Activision that developed mobile games as well. Below, we describe how mobile gaming app developers, relative to non-game developers, inherit innovative capabilities and development tools from the game developer industry.

The knowledge and practices related to producing mobile games appear to be significantly more developed than those in non-game markets like mobile productivity applications. By 2009, multiple web forums had emerged to discuss developing games for the iPhone and at least two mobile gaming conferences had emerged to allow participants to interact. In the online forums one can find multiple conversations about similarities between iPhone games and those developed for Nintendo's GameBoy and Sony's PSP. These similarities included the need for brighter graphics, larger characters, and simple finger-movements on mobile platforms compared to larger consoles. The conferences featured multiple tracks on developing iPhone games. By contrast, we could find no conferences focused on mobile productivity applications, to take a prominent example. While it is true that some mobile productivity applications did exist before the iPhone, notably on Windows Mobile and Palm's operating system, these tended to be either simple portings of Microsoft's Office products (Word, Excel, etc.) that many users found frustrating, or simple text-based Calendar or Contacts applications. At a deeper level, it became clear from our interviews that development capabilities that had diffused to entrepreneurs in mobile gaming were more extensive than in other categories like productivity. Game developers tended to use more elaborate product development processes with many structured steps that were specific to the mobile gaming experience. By contrast, many productivity application developers focused their efforts on simply shrinking their existing PC applications to fit the iPhone screen. For example, one iPhone game developer told us:

> "Well, we're a small team, but we are cross-functional, and take a number of discrete steps to make every game: character sketch, finger-sweep design, GUI, earbud music matching, single- and double-hand gameplay test, etc. We use a clear set of standards for each. No one here is a former mobile developer by experience….but like a lot of people making iPhone games, we're all mobile game players and talk a lot about what makes for a good mobile gaming experience. There's a nostalgia we all share. We're all lucky that this industry existed before the iPhone."

The developer tools and materials for building mobile games were more extensive than those for non-game mobile applications. Before the iPhone, the J2ME and Brew programming languages had simplified mobile gaming dramatically. Various emulators and devices to test mobile games also existed, including robots to cycle through various permutations of finger and thumb positions. With the emergence of iPhone games, various intermediary companies like GameSalad, Corona Labs, and Cocos2D emerged to offer iPhone-specific development tools.

While many of these tools could be used for applications in many categories, they tended to focus on resolving technical issues related to graphical user interface and user responsiveness, two factors that were particularly important for games. One games developer summarized:

> "The tools in the gaming area are advanced. I bought cartoon images from a clearinghouse, used GameSalad to lay them out in animation, and used another testing environment to work up gameplay scenarios. I see no contradiction between using these standard tools to free up my creative efforts to make the most innovative game possible."

Taken together, the mobile games application market seemed to benefit from some development knowledge and advanced tools that were inherited from the mobile games industry before the iPhone was released. However, one should not infer that this knowledge is only available to those entrepreneurs with prior work experience in the pre-iPhone mobile game industry. Only one iPhone game developer we interviewed had worked for a gaming company (Electronic Arts). In fact, many entrepreneurs we interviewed were aware of the standard innovative practices, customer preferences, and tools available for iPhone game development. Yet, as we show below, availability of innovative know-how and development tools do not guarantee innovation – indeed, there is wide variation in innovation performance of apps in both Games and Non-Games categories. Instead, our argument is that the relative differences in the inheritance from similar markets shape which strategies are appropriate for innovation.

Demand structure

There is one other distinct difference between markets that seems may be heritable. Although less attention has been paid to demand effects on innovation strategies (exceptions include Adner and Levinthal (2001) and Bohlmann, Golder, and Mitra (2002)), there is reason to believe that nascent markets could inherit the demand structure of established markets if the consumers preferences were similar. Of particular importance to our case is one dimension of demand:

whether consumers have a demand for a variety of products in a market or unit demand for a single (or few) products in the market.

In the mobile applications setting, entrepreneurs developing mobile app games were able to inherit some knowledge of customer preferences from the non-app gaming market that appeared useful. By the time the iPhone was released, mobile games had already developed into well-developed sub-categories of games (e.g., casual games, first-person shooter) with specific content types (zombies, gardens, pinball machines, etc.) that customers preferred. Preferences across these game and content types reflected both variety and heterogeneity in that a single customer might enjoy single or multiple game-types, and these complex preference sets might different across customers. Fortunately, multiple generations of mobile games had shown developers what customers sometimes liked or, in many cases did *not* like, in each game or content type. Although a flurry of innovations would create new sub-categories (e.g., social games) and content types (e.g., farming) over the next half decade, many basic lessons remained relevant. For instance, customers tended to demand a high degree of responsiveness to finger movements, detailed and colorful graphics, and highly adaptive mobile games that users could start and stop quickly. By contrast, the knowledge and practices associated with developing successful mobile productivity applications were less well known by developers. One productivity application entrepreneur described:

"We really don't know what customers will like. Do they want applications that are as fully featured as PC apps? Or simple content in a newsfeed? Or direct you back to a website to use on the browser? Also, who are the users for our app? People at work? Consumers at home? No one really knows. Someone is going to figure out how to use mobile to improve productivity – I bet it will involve using some of specific iPhone technologies like gryroscope, voice recognition, the embedded camera, or location services…but we're all just guessing."

Taken together, this suggests that markets can vary in their demand preferences in ways that shape entrepreneurial action. We can define the demand for variety as the presence of non-rival demand for multiple products in the same market by consumers. This non-rival demand could be simultaneous, or it could be structured as changing preferences over time. For example, consumers could tire of a product and demand a new product. A more limited definition could simply be horizontal differentiation across consumers in the market. The important implication of either definition is that firms can profit from multiple products (Adner and Levinthal, 2001; Bohlmann *et al.*, 2002). In contrast, we define unit demand as characterized by vertical differentiation, where consumers in the market prefer to have the best version of the product, holding prices equivalent. In this case, firms profit if they succeed in producing the single best product. These definitions reflect ends on a continuum, rather than clear distinctions in demand.

In the iPhone context, the Games category appears to inherit a demand for variety from the non-app gaming market. Evidence for this is the propensity for app developers to advertise their other games to their current users, indicating that potential cannibalization is either small or less costly than the profitability of cross-advertising. There is likely a range of demand preferences spanning variety through unit demand in the many sub-categories included in Non-Games, and we hope to exploit that later. For now, we consider Non-Games as a whole to represent markets that lie more closely on the unit demand end of preferences, since they include productivity apps, whose similar productivity software markets in the desktop computing world tend to exhibit unit demand (e.g., primarily one dominant office productivity suite).

Hypotheses

We consider how market conditions shape the innovation performance of different entrepreneurial strategies, including simultaneous experimentation involving producing multiple products (H1) and batching product releases (H4) and sequential experimentation involving generating multiple product versions (H2) and allowing extensive time between versions (H3).

In a markets inheriting more innovative know-how and development tools, entrepreneurs are more capable of releasing multiple products, since industry-wide development knowledge and supply of tools to build these products are readily available (Abernathy and Utterback, 1978; Rindova and Kotha, 2001; Tushman and Anderson, 1986). Consequently, they should benefit more from releasing more products, since the return from releasing a different product is higher than the return from improving any current product. Moreover, since technologies can be borrowed from the similar market, it is likely that sequential improvements are harder to achieve since the supply tools are already quite sophisticated for producing high-quality products. There may be higher chance of producing an innovative product by experimenting with something different (Brown and Eisenhardt, 1997; Katila and Ahuja, 2002). In contrast, in a novel market less able to inherit supply tools, the lack of industry knowledge and supply tools make it harder to produce quality innovations, so the firm might make better innovative progress by focusing on one product. Furthermore, the state of the art in terms of products in the market is much lower in novel markets, so the incremental gains from improving the product may be larger than they would be in a market that inherits more supply tools where diminishing marginal returns characterize sequential innovation (Cooper and Kleinschmidt, 1993).

With respect to demand preferences, more varied products can satisfy demand for more end users when there is a demand for variety, so each product has the potential to be profitable (Adner and Levinthal, 2001). However, for unit demand, although multiple products might increase the likelihood of finding the market winner, costly resources are expended to pursue losing products, and an alternative strategy of focusing resources to improve a single product may be more profitable. Taken together, this suggests the following:

H1 (Simultaneous Experimentation: Multiple Products): Entrepreneurial firms with more products are more likely to innovate in markets with strong inheritance of innovative know-how, development tools, and demand for variety relative to markets with weak inheritance of these characteristics.

In novel markets that inherit less innovative know-how and development tools, innovation is more likely to require incremental improvements to existing technologies, since the first version would have been unlikely to achieve the standard of quality demanded by consumers (Fleming, 2001; Katila, 2002). The constraints on this first version would have been both a lack of supply in terms of development resources and a lack of clarity about exactly what consumers would want. The sequential updates in the form of new versions could be incorporating consumer feedback about how to improve. Under unit demand, this feedback will be consistent with moving the product towards the market optimum, since all consumers have the same preferences. 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. Moreover, customer preferences are clearer in markets that inherit the expectations from a similar market. Entrepreneurs in these markets may have more success by simply trying a different product, rather than trying to update that product.

H2 (Sequential Experimentation: Multiple Versions): Entrepreneurial firms with more product versions are more likely to innovate in markets with weak inheritance of innovative know-how, development tools, and demand for variety relative to markets with strong inheritance of these characteristics.

Entrepreneurs in novel markets may spend more time on investing in the next version, because it may be costlier in a novel market with undeveloped industry-wide knowledge and supply tools to generate the next sequential innovation. In these cases, the gains to spending time will be larger if that increment is larger (Schoonhoven *et al.*, 1990; Womack *et al.*, 1990). Extra time allows them to make a product with less mistakes as it resolves communication problems (Dougherty, 1990). These same arguments hold for unit demand. In markets inheriting many supply tools, it should be both faster to create the next version, but more importantly, it is not worth the investment of developer time to create the next version, since the incremental gain will be small. In markets with demand for variety, faster versions are more advantageous to more quickly move the firm on to a different product (Bohlmann *et al.*, 2002).

H3 (Sequential Experimentation: Time between Versions): Entrepreneurial firms with greater time between versions are more likely to innovate in markets with weak inheritance of innovative know-how, development tools, and demand for variety relative to markets with strong inheritance of these characteristics.

In markets that inherit more demand tools, clear expectations, and demand for variety, the strategy is to experiment with different products, so simultaneous release should not cannibalize existing products. There is no benefit to sequential release, since the firm is not trying to learn anything from the current product in order to develop the new product. Instead, firms may wish to accelerate products to market as quickly as possible. The firm is simply trying to figure out which of multiple, well-developed products will work so that simultaneous release is useful (Eisenhardt and Tabrizi, 1995; Schoonhoven *et al.*, 1990). In contrast, a firm in a market that inherits less demand tools, unclear expectations, and unit demand might very well learn from observing product performance and incorporate that learning into sequential innovation. Simultaneous experimentation in that case may spread the firm too thin in its ability to capitalize on what is learned from multiple experiments. This suggests the following final hypothesis:

H4 (Simultaneous Experimentation: Batching Product Releases): Entrepreneurial firms which batch product releases are more likely to innovate in markets with strong inheritance of innovative know-how, development tools, and demand for variety relative to markets with weak inheritance of these characteristics.

METHODS

Research strategy

In order to test hypotheses regarding differing entrepreneurial innovation strategies contingent on market conditions, we require a setting with multiple markets representing different inheritances from similar markets on both demand structure and supply tool dimensions. We also need to observe entrepreneurial firms within those markets that exhibit variation in strategies employed. To ensure that we are not confounding the relationship between innovation outcomes, market conditions, and entrepreneurial strategies with other choices and attributes of the firm or the market, we also need a setting that allows us to control for those other choices and attributes. We want to be able to argue that there are no unobservables in our regression that are correlated with our regressors of interest (i.e., measures of strategic choice).

Fortunately, the study of any context containing many entrepreneurial firms naturally lends itself to wide variation in strategies. Since entrepreneurial firms are likely to be more prevalent in new industries, and new industries are characterized by a lot of uncertainty, no firm may be able to identify the best innovation strategy. Therefore, firms will choose amongst many heterogeneous and uncertain strategies in hopes of discovering a successful one.

The fact that experimentation in strategies is driven by uncertainty also helps to avoid the endogeneity problem of more talented firms choosing one strategy and less talented firms choosing another: unless one can control for talent as a regressor, the estimate on the "talented" strategy will be biased upwards, since it reflects both the effect of talent on successful innovation and the chosen strategy. However, if we can argue that both more and less talented firms are pursuing all strategies (i.e., talent is independent of strategic choice), then we can argue that our estimates of the effect of strategic choices on the innovative outcome are unbiased.

An ideal measure of the innovation dependent variable would reflect the utility of the product to the end user net of the utility provided by any existing product to the end user. Since utility is difficult to measure directly, proxies for this would be ratings by the user expressing their preference for the product over existing alternatives and the level of adoption of the product in the market reflected by the quantity of the product that is sold. Note that the quantity sold is a particularly appealing measure since it should reflect consumer choices taking into account prices and competition from alternatives in the market.

Typically, the measure used for innovativeness is patent citations. The drawback to this measure is that it reflects an a priori assessment of the innovative success of a product. Therefore, in new industries which are characterized by a great deal of uncertainty about the as yet mostly undeveloped market demand, the a priori assessments of innovative success are more likely to be wrong. Indeed, Nelson (2009) finds that patents are biased against capturing innovation from younger firms. Yet it is exactly in the context of a new industry that we are likely to observe the largest number of entrepreneurial firms and the most attempts and failures at innovation. The observation of failures is critical to ensuring the robustness of our results: it avoids the selection bias on strategic choices that results from only analyzing firms which are successful enough to be observed in the market. If unsuccessful firms make the exact same choices as successful firms but are never observed, we might mistakenly infer that those strategic choices explain success, when in fact there must be some other factor driving the difference between successful and unsuccessful firms. It is for this reason that our empirical context needs to include a full risk set of potentially innovative products so that we can observe success and failure. Furthermore, since this context is likely to be found in a relatively new industry, we want to use a measure of innovation that reflects end-user market assessment of innovativeness.

Identification of robust results relies on being able to observe a sufficient number of firms choosing each variant in strategic choices. Furthermore, in order to control for time varying market effects which might drive demand for products (as opposed to the firm strategies which create products that are highly demanded due to their innovativeness), we would like to observe a sufficient number of entrepreneurs entering and persisting in each time period so that we can match more innovative and less innovative firms at the cohort and market level.

A longitudinal dataset not only contributes to the goal of being able to control for market unobservables that might bias our estimates, but it is also necessary to test timing hypotheses about sequential (H3) and simultaneous (H4) experimentation. We need to observe entrepreneurial firms over time so that we can create measures of the time between versions (H3) and time between product releases (H4) for each firm.

Finally, to test product development choices regarding sequential (H2) and simultaneous (H1) experimentation, we need to observe enough detail at the product level to identify versioning (H2) and we a setting where entrepreneurial firms actually have the resources to pursue multiple products (or where it is relatively cheap to release multiple products) at the same time so that we observe variation in the number of products (H1).

Using the measure from this setting, we can then model the innovation outcome as a function of simultaneous and sequential experimentation strategies and controls. We can then estimate this model separately for markets with inherited conditions to determine whether simultaneous or sequential experimentation strategies improve innovative outcomes in each market. Note that this research strategy does not impose any restrictions on the outcomes. It allows the data to give us multiple outcomes for each set of market conditions: both simultaneous and sequential experimentation improve innovative outcomes, neither simultaneous nor sequential experimentation improve outcomes, or one or the other improves outcomes. The same or different strategies could improve outcomes for different market conditions.

We only want to analyze firm strategies up until their product actually reveals itself to be an innovation in the market. It is at this point that both the firms and customers recognize the value of the product. After this point, strategies might differ for a firm with a successful innovation. As a result, we will want to compare successfully innovative firms up to the date that their first successfully innovative product achieves success in the market with control firms that started at the same time (same cohort) in the same category until that date. In this way, we compare equivalent timing of strategic choices between successfully innovative firms and firms that fail to successfully innovate during the same span of time in the same category.

Context: iPhone application ecosystem

In October, 2007, Apple CEO Steve Jobs announced the possibility of third-party software development for the iPhone.[2] A beta software development kit was released on March 6, 2008, and Apple launched the App Store within iTunes on July 10, 2008, the day before the release of the iPhone 3G.[3,4] Apple reported to offer more than 550,000 apps for the 315 million iPhones worldwide sold by March 2012, involving 25 billion app downloads.[5]

Developers make applications for the iPhone or iPod (and today, the iPad), and submit the applications for approval to Apple. Once approved, the application is distributed through the App Store. Developers give Apple 30% of any revenue earned through sales of the apps

[2] http://en.wikipedia.org/wiki/IOS_SDK#cite_note-4, accessed 9/1/13.
[3] http://www.apple.com/pr/library/2008/03/06Apple-Announces-iPhone-2-0-Software-Beta.html, accessed 9/1/13.
[4] http://en.wikipedia.org/wiki/IOS_App_Store, accessed 9/1/13.
[5] http://www.apple.com/pr/library/2012/03/05Apples-App-Store-Downloads-Top-25-Billion.html, accessed 9/1/13.

themselves or in-app purchases (IAP), which are sales of other products made within the app. Apple maintains tight control: apps can only be distributed through the App Store.[6]

To help consumers find apps, the App Store lists apps by category (e.g., Games, Health and Fitness, Education). Apple also creates numerous lists to suggest apps that consumers might like, including the top downloaded free and paid apps overall and the top grossing apps (based on sale of the apps and IAP). Numerous apps also exhibit advertising to earn revenue, but these are not counted in the top grossing measure. Since the App Store is the only distribution channel for apps and the number of apps is so large, being featured prominently in the App Store through one of these lists can generate a huge boost to the number of downloads for an app. Furthermore, any consumer who downloads an app is permitted to rate the app from 1-5 stars (with 5 being the best) and include a review to comment on why they gave the app that rating or provide other feedback to other consumers or the developer.

The ability to observe the iPhone ecosystem during the early days of the industry creates several advantages for our research. Prior research documents a great deal of uncertainty during the infancy of the iPhone ecosystem, and the rapid growth and heterogeneity in firm responses (Bresnahan, Davis, and Yin, 2014; Yin, Davis, and Muzyrya, 2014). Our further industry interviews confirm that developers are experimenting to discover profitable strategies. As a result, we both observe variation in strategies pursued by these firms along several dimensions, and we can econometrically interpret these strategic choices as unlikely to suffer from selection bias. Even if these developers are attempting to choose strategies which are correlated with assets unobservable to the researcher to maximize profits, in this context it is unlikely that they actually know the correct strategies to choose. The fact that we observe many developers and substantial proportions choosing different strategies in all market contexts supports this

[6] There is the possibility of "jailbreaking" the phone to utilize non-approved apps.

assumption. The fact that we also observe a wide variation in the success of apps further supports this assumption (see Table 2 for summary statistics on breakdown of different strategies in our sample). Apps for the iPhone officially must be released and distributed through a single channel, the iTunes store. This allows us to observe the entire population of apps, so we can observe failures. This increases confidence that 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 is an appropriate choice.

We further use extensive controls measuring app quality to control for endogeneity. We benefit immensely from the level of detail that is provided on each app in the App Store. We both observe ratings and rankings by consumers of the apps, providing a demand-based measure of the innovativeness of the apps, and we observe daily rankings of the apps, which reflect the number of downloads for each app. The rankings also reflect some of the market competition among the apps by ordering them in an index relative to each other's performance. Our daily collection of data allows us to create time series information on each app, and both version and product measures are defined by the developers themselves and reported on the App Store as version releases and as distinct product identification numbers.

The platform nature of the iPhone application system creates extremely low entry costs for many entrepreneurs. The typical cost barriers that face an entrepreneur (research and development costs, marketing, and distribution) are provided by Apple in the form of SDK's and the App Store. As a result, we observe many entrepreneurs and wide variation in the number of products produced by these entrepreneurs, since they are able to reallocate resources normally needed to simply launch one product and strategically choose whether to develop that one product further or instead launch multiple products.

The existence of multiple categories provides our variation in market conditions. The division of apps into categories on the App Store creates some natural market boundaries, since the fact that Apple features apps alongside one another within a category generates an initial setting of competition among those apps. Since the many categories of apps in the App Store correspond in different ways to existing non-app markets and products, we will observe variation in the degree of market inheritance to similar markets.

Data and measures

Our measure of innovation performance is whether a firm releases a product that becomes a killer app or not. 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. Gross sales are a combination of revenues from app sales and in-app purchase but do not include advertising revenue. Although other measures of innovation performance are possible (i.e., top free and top paid download-related rankings, customer ratings, reviews), we chose to use top grossing apps as our measure of innovative success, since this is the closest observable measure of innovative commercial success of these applications that is possible in this ecosystem. In comparison to the “top free” and “top paid” downloads rankings, there is much less churn (entry and exit) in gross sales rankings in the “top grossing” list. This ranking thus represents a smaller and potentially stricter standard for innovative success. We control for apps in the other rankings to account for possible visibility and reputational effects.

We examine 328,428 apps observed an average of every 2 days on iTunes between September 6, 2010 and August 31, 2011. (We continue to track these apps until December 31, 2011 to avoid truncation for the latest releases.) There are 18 application categories (only 20 categories total existed during our sample period: Books, Business, Education, Entertainment, Finance, Games, Health and Fitness, Lifestyle, Medical, Music, Navigation, News, Photo and Video, Productivity, Reference, Social Networking, Sports, Travel, Utilities, and Weather). We exclude Books and News because these apps typically are simply digital versions of print content. The largest category is games, reflecting its extensive inheritance from the non-app game market, even though it represents only 18% of all apps in the sample. The second most popular category, and the most popular category for non-game developers, is Entertainment.

Our sample contains 3,431 killer apps. Before entering gross sales ranking, 42% of them already appeared in another top ranked list by the number of downloads (32% in the paid apps list and 12% in the free apps list, including 2% on both). The most frequent killer app category is games, which comprise 49% of the killer apps in our data.

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. In case of ties, we choose the earliest category of the tied categories. 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 developers and non-game developers, respectively, create top grossing killer apps.

We limit our analysis to the actions before a firms' entry into the top grossing app rankings. We believe the comparison of a new developer to a developer who has already entered the gross app rankings is problematic because the use of strategies may overshadowed by the notoriety, reputation, visibility and 'halo' effects arising from the initial success. We stop the observation of firm strategies at that firm's first app's entry to the gross sales ranking.

We match non-killer app firms to killer app firms by cohort, defined as the release year and month for the firm's first app) and focal category and cohort. We then cut off the observation period of the (multiple) matched firms to equal that of the killer app firms. In this way, we can more accurately 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 non-killer app firms outnumber killer app firms, we also avoid creating small standard errors that are simply a reflection of oversampling from the non-killer app population. We drop 37 firms which are active for 0 days (meaning they entered the top gross ranking the day they were released). These firms may have been the result of lags in the processing time of our scrapers, since it took us 2 days to scrape the store, or representative of apps with pre-launch marketing campaigns outside of the iTunes app store. In either case, valid controls are not available. Our resulting sample contains 1,908 killer app firms and 50,617 matched control firms.

Variable definitions are summarized in Table 1. We utilize the number of reviews and the ratings based off those reviews as our measure of app demand and quality, respectively, and so control for those innovation factors. The actual number of downloads is not available from Apple iTunes; however, only those who have downloaded an app can submit reviews for that app, so the reviews can be considered a lower bound on downloads and, thus, are a reasonable proxy measure. Reviews potentially contain feedback for the developer, since the consumer took time to write something about the app. Customers can rate an app with 1 to 5 “stars,” so we use these ratings to measure app quality. We use historical data on comments to recover user ratings for these apps since the launch of iTunes in July 2008.

Table 2 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. There are no statistically significant differences between the groups due to the wide variation in all measures in our sample. Table 3 displays correlations between variables. No variables are highly correlated with each other.

Insert Tables 1, 2, and 3 here

Model

We model the probability that a firm develops a top grossing killer app as a function of firm strategies and product characteristics. Firms choose the number of apps to develop and the timing between those apps, the number of versions (updates) for each app and the timing of those versions, the category in which they develop apps, the size of the app (which determines the memory taken up on the phone by the app and may indicate the 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 consider the game category to be a market that inherited more demand tools, clear expectations, and demand for variety. We consider non-game categories to be more representative of markets that inherit less demand tools, unclear expectations, and unit demand. Both consumers and developers are familiar with the gaming product on a mobile device due to the popularity of Nintendo's handheld device. Many gaming algorithms are available as standardized tools 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. By contrast, non-game categories often do not have similar categories in the non-mobile world. They may be able to utilize tools from the desktop web browser environment, but a significant amount of adjustment needs to be made to convert the app into something effective in the mobile setting, where the screen-space and keyboard space is much more limited. 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. According to our interviews, the most innovative non-game apps will utilize the attributes of the mobile device (e.g., camera, gyroscope, GPS) in novel ways. There may be no existing algorithms at hand, and even consumers may be unsure as to what to expect from the product. Indeed, many new non-game categories have emerged as a result of the evolving markets in non-game categories. 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. For a non-game app like a pdf reader, people just want the best pdf reader, not multiple ones. The non-game apps category will include the app categories in which consumers only want the best one, since it includes apps used as tools or in productivity.

We estimate the following model separately for game and non-game firms using probit regression, where *i* indexes the firm, *y* indexes the year, *m* indexes the month, *c* indexes the focal category, and β, Ψ, Τ, and Λ are parameters to be estimated. The errors are robust and clustered on cohort and focal category. We cluster errors on the cohort to account for autocorrelation across firms in different focal categories but within the same cohort.

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

We estimate the average marginal effects (AME) from the probit model[7] as follows:

$$AME_{Count\_App} = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial\Phi(g)}{\partial Count\_App} =$$

$$= \frac{1}{N}\sum_{i=1}^{N}\frac{\partial\Phi(\beta_0 + \beta_1 Count\_App + X\mathrm{B} + \Gamma Z + \mathrm{T}Cohort + \Lambda FocalCat)}{\partial Count\_App}$$

[7] Detailed discussion of the differences between the average marginal effects (AME) and marginal effects at means (MEM) is in Bartus (2005).

Using the chain rule (g is a notation for a linear model containing our variables of interest and controls):

$$AME_{Count\_App} = \frac{1}{N}\sum_{i=1}^{N}\beta_1\frac{\partial\Phi(g)}{\partial g} = \frac{1}{N}\sum_{i=1}^{N}\beta_1\phi(g)$$

The probability density function is the derivative of a cumulative density function:

$$AME_{Count\_App} = \frac{1}{N}\sum_{i=1}^{N}\beta_1\phi(g)$$

RESULTS

Table 4 presents the results of our regressions. Regression results for game firms are presented in the first two columns, and regression results for non-game firms are in the last two columns. The first and third columns present probit results, while the second and fourth columns present average marginal effects.

Insert Table 4 here

Hypothesis 1 is supported by a positive and significant estimate for the effect of the number of apps on the probability that a game developer will enter the top grossing killer app rankings. 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, respectively. However, given that the baseline probability of becoming a killer app in games and non-games is 5.6% and 3.1%, respectively, this translates into a 0.37% increase and 0.46% decrease relative to the baseline, respectively. Recall from Table 2 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 quantity implies almost 2% increase in the probability of becoming a killer app relative to the baseline.

Hypothesis 2 is supported by a positive and significant estimate for the effect of the number of versions on 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. In the non-game category, sequential improvements are necessary to achieve success, since the first version would have been unlikely to achieve the standard of quality demanded by consumers. The constraints on this first version would have been both a lack of supply in terms of programming tools for the developer, and a lack of clarity in exactly what consumers would want. Indeed, the positive and significant effect of changing categories in non-games is a testament to the uncertainty for the seller about where to find her buyer. The sequential updates in the form of new versions could very well reflect responses by the developer to consumer feedback contained within the reviews. 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 indicates a 3% increase in the baseline probability of being a killer-app firm.

Our results also support Hypothesis 3: more time between 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 represents 5.6% increase in the probability of becoming a non-game killer app firm relative to the baseline.

Finally, our results support Hypothesis 4: batching (simultaneous release of apps) 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 base rate of 5.6%, this indicates a 13.5% increase in the baseline probability of being a killer game firm.

DISCUSSION

In this paper, we consider all firms as entrepreneurs. In fact, there are some app developers that are quite large firms. We consider their entry into mobile apps as an entrepreneurial endeavor, but it will be informative to exploit these developer differences.

This data is limited to what developers do in the United States App Store. We know from our broader industry research and interviews that developers do a great deal of marketing and experimentation in Australia and Canada before releasing their apps in the US. Developers also engage in marketing for their apps through blogs and twitter and encouraging app reviews by industry experts. Some firms will even purchase downloads in the first few days to jumpstart the possibility of appearing on the top lists. These are attempts to improve their rankings on the top lists that we cannot observe, but may be less related to the innovative quality of the app than marketing. We may be able to exploit the residual predictive value from star ratings, which would be more distanced from a marketing influenced valuation of innovative quality, as a control for marketing in future regressions.

Although our measure of top-grossing apps does not include advertising revenue, the industry common knowledge suggests that the majority of revenues for developers actually come from IAP. As a result, this omission may not be that important to measuring the most innovative apps. Furthermore, IAP and price of app are measures which are more closely related to the innovative characteristics of the app, whereas advertising is more distantly related in the sense that apps which have higher advertising revenue likely have more users and are used for longer periods of time by those users.

We hope to exploit more granular category versions in future work to possibly disentangle the effect of inherited demand structure effect from the inherited supply tools effect. An argument can be made, however, that more novel categories which are less able to inherit supply tools and expectations will be highly correlated with unit demand, since customers and developers are in search of a common definition of the "typical" product in that new space.

In conclusion, this paper takes some first steps in understanding the linkage between entrepreneurial strategies and innovation performance. Using unique data from the iPhone application ecosystem, we find robust evidence that simultaneous experimental strategies emphasizing many highly varied products that are released concurrently are better suited to markets that inherit more demand tools, clear expectations, and demand for variety (games). Sequential experimentation strategies emphasizing multiple sequential versions produced over substantial time periods are better suited to novel markets that inherit less demand tools, unclear expectations, and unit demand (non-games). In markets where well-developed innovation capabilities, technological development tools, knowledge of customer preferences, and demand for variety can be inherited from similar markets with simultaneous experimental strategies are more suitable than sequential strategies. If the results presented here are validated in other entrepreneurial ecosystems where markets vary in the market conditions they inherit from similar markets, it may provide a more realistic picture of how entrepreneurs innovate.

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Table 1: Variable descriptions

Variable name	Description
Killer_App_Firm	An indicator for a firm with an app in the iTunes gross sales ranking for at least one day
KA_free	An indicator for a firm with at least one app in the free ranking for at least one day
KA_paid	An indicator for a firm with at least one app in the paid ranking for at least one day
No_Updates	An indicator for a firm with no updates (versions) for any of its apps
Av_Versions	The average number of versions per app by firm
Av_Time_btw_Versions	The average number of days between versions
One_App	An indicator for a firm which released only one app
Count_App	The number of apps per firm.
Av_Time_btw_Apps	The average number of days between apps
Batch	An indicator for a firm which at least once released at least two apps within two days of each other
All_Free	An indicator for a firm which listed all its apps for free
Av_Price	The average price for an app by firm.
Av_Size	The average size of an app by firm in MB
Active_Days	The number of days before a firm (or its match) enters the gross killer app ranking
Ln_Firm_Rev	The number of reviews received by firm (natural logarithm)
Firm_Rating	The average number of stars received by firm based on its reviews
Change_cat	An indicator for firms with at least one app changing its category
Change_rel_date	An indicator for firms with at least one app changing its release date
Cohort Effects	A set of 38 indicators for the year and month of the first app released by a firm
Focal Category Effects	A set of 18 indicators for the focal category of a firm

Table 2: Descriptive statistics for killer and non-killer app game firms, killer and non-killer app 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	Min	Max	Mean	Sd	Min	Max	Mean	Sd	Min	Max	Mean	Sd	Min	Max
KA_free	0.355	0.479	0	1	0.035	0.183	0	1	0.160	0.367	0	1	0.015	0.120	0	1
KA_paid	0.498	0.500	0	1	0.016	0.125	0	1	0.362	0.481	0	1	0.005	0.070	0	1
No_Updates	0.284	0.451	0	1	0.534	0.499	0	1	0.255	0.436	0	1	0.542	0.498	0	1
Av_Versions	2.355	1.761	1	16	1.679	1.184	1	18	2.927	2.668	1	27	1.817	1.503	1	37
Av_Time_ btw_Versions	33.985	39.229	0	275	22.119	43.567	0	588	40.808	49.609	0	499	23.263	46.739	0	1043
One_App	0.272	0.445	0	1	0.550	0.498	0	1	0.352	0.478	0	1	0.672	0.469	0	1
Count_App	6.510	12.111	1	181	2.519	5.148	1	314	6.725	16.692	1	232	2.665	15.236	1	1577
Av_Time_ btw_Apps	51.720	82.998	0	702	21.803	49.384	0	658	51.800	89.912	0	730	17.117	50.613	0	992
Batch	0.310	0.463	0	1	0.131	0.337	0	1	0.251	0.434	0	1	0.102	0.302	0	1
All_Free	0.077	0.266	0	1	0.193	0.394	0	1.00	0.052	0.223	0	1	0.442	0.497	0	1
Av_Price	1.932	8.598	0	218.07	0.995	1.462	0	56.311	9.368	51.436	0	998.95	1.712	9.358	0	999.99
Av_Size	26.415	47.213	0.05	533.74	10.913	20.177	0	737	19.860	55.821	0	716.78	10.245	42.548	0	1009.76
Active_Days	234.85	224.91	1	1127	176.21	192.26	1	1127	244.99	232.83	1	1211	161.51	181.30	1	1197
Ln_Firm_ Rev	4.789	1.935	0	10.082	1.705	1.492	0	9.003	4.080	1.863	0	10.381	1.258	1.361	0	10.744
Firm_Rating	3.794	0.875	0	5	2.576	1.879	0	5	3.479	1.161	0	5	2.107	1.982	0	5
Change_Cat	0.060	0.238	0	1	0.023	0.150	0	1	0.159	0.366	0	1	0.037	0.190	0	1
Change_Rel_ Date	0.069	0.254	0	1	0.015	0.120	0	1	0.031	0.174	0	1	0.015	0.123	0	1
Obs.	665	665	665	665	11164	11164	11164	11164	1243	1243	1243	1243	39453	39453	39453	39453

Table 3: Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	KA firm	1																
2	KA_free	0.2429	1															
3	KA_paid	0.5138	0.2322	1														
4	No_Updates	-0.1029	-0.1293	-0.1078	1													
5	Av_Versions	0.1177	0.1547	0.1114	-0.5824	1												
6	Av_Time_ btw_Versions	0.0625	0.0699	0.0589	-0.5421	0.2914	1											
7	One_App	-0.1248	-0.1107	-0.121	0.3337	-0.1169	-0.2315	1										
8	Count_App	0.0547	0.0653	0.0629	-0.0961	0.0153	0.0842	-0.1701	1									
9	Av_Time_ btw_Apps	0.1197	0.094	0.0916	-0.2598	0.2085	0.2729	-0.4846	0.0194	1								
10	Batch	0.0962	0.0914	0.0928	-0.1525	0.0188	0.0982	-0.4718	0.2419	0.0064	1							
11	All_Free	-0.1261	-0.0111	-0.1122	0.1291	-0.0464	-0.09	0.3561	-0.0815	-0.1579	-0.1969	1						
12	Av_Price	0.0853	-0.0133	-0.0027	0.0004	0.0064	0.0135	-0.017	0.0079	0.0006	0.0294	-0.1179	1					
13	Av_Size	0.0558	0.0115	0.0196	0.0163	-0.0282	-0.0178	-0.0167	0.0159	-0.0103	0.0443	-0.0557	0.0861	1				
14	Active_Days	0.077	0.1237	0.0898	-0.403	0.4033	0.5121	-0.3549	0.1243	0.4583	0.1491	-0.1625	0.0057	-0.0498	1			
15	Ln_Firm _Rev	0.3632	0.3909	0.3317	-0.4158	0.3885	0.3011	-0.3869	0.18	0.3046	0.25	-0.1999	-0.0098	0.0144	0.4902	1		
16	Firm_Rating	0.1315	0.0973	0.1009	-0.1582	0.1717	0.1038	0.029	-0.0337	0.0749	-0.0614	-0.065	-0.0219	0.0007	0.1555	0.5563	1	
17	Change_Cat	0.0436	0.0313	0.0519	-0.004	-0.0206	0.001	-0.0506	0.0695	-0.0008	0.075	-0.0233	0.0022	0.019	-0.0075	0.0395	-0.0229	1
18	Change_Rel _Date	0.0891	0.0638	0.0799	-0.0804	0.0761	0.0334	-0.0926	0.0547	0.0268	0.0845	-0.0581	-0.0031	0.0065	0.0198	0.1029	0.0144	0.0477

Table 4: Regression results for game and non-game firms

Killer_App_Firm	Game Developers		Non-Game Developers	
	Probit	AME	Probit	AME
Count_App (H1)	0.00622**	0.000260**	-0.00323**	-0.000129**
	(0.00191)	(0.0000791)	(0.00112)	(0.0000440)
Av_Versions (H2)	-0.0200	-0.000837	0.0237*	0.000949*
	(0.0289)	(0.00120)	(0.0109)	(0.000432)
Av_Time_btw_Vers (H3)	-0.000525	-0.0000219	0.00258***	0.000103***
	(0.00105)	(0.0000437)	(0.000570)	(0.0000230)
Batch (H4)	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, $^{+}$ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

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