ENTREPRENEURIAL DIVERSIFICATION AND THE SCOPE OF NEW FIRMS: MULTIPRODUCT INNOVATION IN IPHONE APPS

JASON P. DAVIS
INSEAD
1 Ayer Rajah Avenue
Singapore 138676
jason.davis@insead.edu

YULIA CHHABRA
Stephen M. Ross School of Business
University of Michigan
701 Tappan Street
Ann Arbor, MI 48109
muzyrya@umich.edu

PAI-LING YIN
Stanford Institute for Economic Policy Research
Stanford University
366 Galvez Street
Stanford, CA 94305
pyin@stanford.edu

Working Paper
January 11, 2016

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, and a grant from the National Science Foundation (NFS IOC Award# 1431275) to fund this research.

Entrepreneurial Diversification and the Scope of New Firms: Multiproduct Innovation in iPhone Apps.

ABSTRACT

In this paper, we explore why entrepreneurial firms undertake within-industry diversification of products. Prior research on diversification reached a consensus that firms should diversify into related markets. Yet the assumptions and empirical base for this theory is drawn from large, established firms with extensive resource portfolios that can take advantage of significant scale and scope advantages. In this paper, we suggest a different perspective in which entrepreneurial diversification is explained by an experimentation rationale in which resource constrained firms use product-entry into new markets to search for the best markets that fit their current capabilities. Because the outcomes of experimentation are inherently uncertain, entrepreneurs use whatever credible signals are possible to constrain the experimentation process. We identify one such source of information, the attention that product-experiments receive through customer feedback. We argue that the salience (amount of feedback) and valence (good or bad feedback) of attention given to products by customers shape whether entrepreneurs will focus or diversify away from prior market categories. We test these ideas using unique data on customer feedback and entrepreneurial diversification decisions available on Apple's iPhone application ecosystem. We find that while new organizations with no feedback may be inclined to continue experimentation through diversification, those who receive significant positive feedback escalate commitment to the focal category with new products. A surprising result is that the presence of bad feedback does not inspire diversification, perhaps because it offers a credible signal that the market is paying attention and may appreciate new product development efforts in the focal category. This study contributes to studies of entrepreneurial strategy with new insights about how escalation of commitment and diversification are linked to dimensions of market attention.

Keywords: Entrepreneurship, Diversification, Innovation

Research on diversification and its link to performance is one of the largest streams of literature in the field of strategy (Fligstein, 1991; Helfat & Eisenhardt, 2001; Hill, Hitt, & Hoskisson, 1992; Markides & Williamson, 1996; Stern & Henderson, 2004). Corporate diversification is an important means by which large, established firms achieve profitability and growth. The scholarly consensus is that large, established firms benefit from related diversification that leverages existing resources into multiple markets that share enough similarities so that resources can be shared across businesses (Hill et al., 1992; Lubatkin, 1987). Sharing resources enables firms to achieve economies of scale sand scope (Helfat & Eisenhardt, 2001; Kogut & Zander, 1992). Unrelated diversification, by contrast, lacks scale and scope benefits because it attempts to use resources that are less applicable in one or both markets, and so tends to destroy value for diversified firms (Chatterjee & Wernerfelt, 1991; Hill et al., 1992; Lane, Cannella, & Lubatkin, 1998). More recent research focuses on the locus of diversification in markets, suggesting that the true benefits of diversification lie less in cross-industry diversification across broad sectors (e.g., pharmaceuticals and medical devices), but within-industry diversification that are driven by product differentiation or technology platforms (Stern & Henderson, 2004; Tanriverdi & Lee, 2008). Within-industry diversification occurs across product categories (e.g., cancer and heart drugs) where resources (e.g., chemistry, manufacturing) and customers (e.g., doctors, hospital administrators, insurance companies) are likely to be more related (Li & Greenwood, 2004).

Yet while this theoretical consensus is well recognized, it is striking how dependent these arguments are on the context of large established firms. What explains the diversification of new firms? The related diversification logic relies on an assumption of a significantly broad resource portfolio and organizational slack with which to enter new markets to capture synergies from related markets (Helfat & Eisenhardt, 2001; Markides & Williamson, 1996). But many entrepreneurial firms diversify early in their lifespan, even before a first product is successful or before scale or scope advantages could be said to exist. Yet diversification is arguably as important for startups as for established firms since the expansion of firm scope to include address a new market is likely to represent a more fundamental strategic and organizational change for a small firm than a large firm. Consider the examples of Google and Yahoo. In its first years after incorporation, Google focused on search-based advertising (Battelle, 2006). Yahoo, by contrast, quickly diversified into the related businesses of web-based-advertising, web-portals, content creation, and platform development for media and entertainment companies (Rindova & Kotha, 2001). Although Google would diversify later as well, many have suggested that Yahoo's early diversification led to its distinction as a media-focused search company compared to Google's application-focus. As this example illustrates, an established firm's strategic options may be path dependent on its early market choices. Diversification is a strategic choice that expands new firm scope in ways that constrain future choices and performance.

Why do new firms diversify? Some might argue that new firm diversification is random – that is, entrepreneurs target multiple different customers as a matter of fact, without an intentional diversification logic. This is consistent with a broader view of entrepreneurship as an experimentation process (Thompke, 2003), with all new firm-level choices being unconstrained by the strategic commitments and capabilities of large, established firms. Yet an emerging stream of research is questioning this view in entrepreneurial strategic decisions as multi-varied as product innovation (Chatterji, 2009; Yin, Davis, & Muzyrya, 2014), developing business models in new markets (Katila, Chen, & Piezunka, 2011; McDonald & Eisenhardt, 2014), and accessing financial resources (Hallen, 2008; Pahnke, McDonald, Wang, & Hallen, 2014). In this view, entrepreneurial strategy is less than random in its antecedents and consequences, and is often driven by competition or market conditions (Beckman, Eisenhardt, Meyer, & Rajagopalan, 2012).

We join this emerging view on entrepreneurial strategy by exploring why new organizations might diversify their target markets within an industry. We accept the characterization of new ventures as an organizational forms suited for experimentation, but suggest that entrepreneurial managers redirect experimental diversification based on their evolving understanding of market conditions, yet for reasons that are fundamentally different than the related diversification rationale that applies to established firms. Entrepreneurs enlist diversification as way to identify the best product-markets, and the best fit of their current capabilities to those markets. Within-industry market choice may begin somewhat randomly, but ventures are highly adaptive in their strategies when they release subsequent products. Features of these market-environments and outcomes such as prior product performance, market growth, and industry lifecycle that are well known also effect diversification choices as expected. But given the high degree of uncertainty that entrepreneurs face, we suggest that a less well explored set of factors are used as signals to determine diversification as well. We focus on the degree of attention that products receive in the market through customer feedback. We argue that the salience (amount of feedback) and valence (good or bad feedback) of attention given to products by customers shape whether entrepreneurs will focus or diversify away from prior market categories. We test these ideas using unique data on customer feedback and entrepreneurial diversification decisions available on Apple's iPhone application ecosystem. We find that while new organizations with no feedback may be inclined to continue experimentation through diversification, those who receive significant positive feedback escalate commitment to the focal category with new products (Staw, 1981). A surprising result is that the presence of bad feedback does not inspire diversification, perhaps because it offers a credible signal that the market is paying attention and may appreciate new product development efforts in the focal category that are improvements.

To study this question, we examine diversification by ventures developing mobile applications for Apple's iPhone. This is a particularly appropriate context in which to study entrepreneurial diversification. First, since all firms must register with Apple to sell apps, and data about these apps and firms are available on iTunes, we can construct a full population of firms and risk set of possibly diversified products. The result is a rich population-level panel dataset with many time-varying measures about the products. Second, firms in this context can choose to register apps in 1 of 20 pre-labeled market-categories (e.g., Games, Productivity, News, Social, etc.). Although Games is the most popular category, each category has thousands of apps. Finally, there is significant diversification by firms into multiple categories, although many firms do focus. We calculate that 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. A final major advantage of this study is that innovation in the iPhone ecosystem is ongoing, which enabled us to interview many entrepreneurs about their activities, which informed our theory. Taken together, this is an ideal setting in which to study entrepreneurial diversification.

Method

Analytical Strategy

To study diversification, we need a setting with multiple category-markets where firms could produce multiple sequential products that could range across categories. We require a setting where we can observe entrepreneurial firms within those markets that exhibit variation in strategies employed. To ensure that we are not confounding the relationship between market feedback and diversification 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 wish 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 diversification strategy. Therefore, firms will choose amongst many heterogeneous and uncertain strategies in hopes of discovering a successful choice The fact that experimentation in app markets are driven by uncertainty also helps to avoid the endogeneity problem of more high quality firms choosing one strategy and less talented firms choosing another. However, we argue that both more and less quality firms are pursuing all strategies (i.e., quality is independent of strategic choice), then we can argue that our estimates of the effect of strategic choices on the innovative outcome are unbiased.

Setting: iPhone Application Ecosystem

In October, 2007, Apple enabled third-party application software development for the iPhone. A beta software development kit was released on March 6, 2008. Apple launched the App Store within iTunes on July 10, 2008, the day before the release of the iPhone 3G. Application development accelerated dramatically, with over 550,000 apps for the 315 million iPhones sold by March 2012, involving 25 billion app downloads. Developers can sell applications for the iPhone, iPod, and iPad that are released on the App Store (on iTunes) after approval from Apple. Apples takes 30% of any revenue earned through sales of the apps themselves or in-app purchases, which are sales of other products made within the app. Apps can only be distributed through the App Store. The App Store lists apps by category (e.g., Games, Health & Fitness, Education), which are clearly labeled. Firms choose a category label for each app. Since 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) customers can scan and search for successful apps by category, which facilitates different sub-markets that are interested in different types of apps. Also, any consumer who downloads an app may 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. These ratings and comments are publicly available, and are closely followed by many developers. As a result, this will enable us to make measures of customer feedback, as we describe below.

Data

The data comes from Apple iTunes. The first dataset contains the star ratings accompanying all the comments to all iTunes apps from the time iTunes was launched (July 2008). This dataset also contains the version of the app which was commented and the date of the comment. We do not use any data on the contents of the comments, only the star rating that goes with it. The second dataset provides a more detailed information about each app. It combines the information from the webpages of all publicly listed apps scraped approximately every three days from September 6, 2010 to December 31, 2011. Additionally, we use historical data on daily app rankings on iTunes (top 300 apps in free, paid, and grossing sales categories seaparately) from Appannie.com.

We observe all 328,428 apps by 82,435 developers which were available on iTunes from its launch in July 2008 through August 31, 2011. Our measure of diversification is a dummy variable for whether a developer releases a second app in a different category than the first app. We therefore want to analyze the experiences of the developer with the first app to determine the factors that affect the choice of category for the second app. We cut off the observation period for the developer's first app when the second app is released. We measure this period in days, denoted by the variable TIMETODECISION. If the developer did not release a second app during our sample period, we drop that developer from our sample. Our resulting sample contains 35,431 developers.

The variables available in the raw data are in Table 1.

iTunes offers apps in 20 different categories during the 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 the Books and News categories of apps from the sample because these apps typically are simply digital versions of print content. We also exclude all the developers with only one app because they are not diversified by default. Because we are interested in the diversification decision, the depend variable, *diversification*, is an indicator taking the value of one if the second app by this developer is in a different category than the first one. All explanatory and control variables for the first app released by the developer are measured *before* the release of the second app.

- *Commitment*

  We measure commitment using three variables: *the number of versions, the size of an app, and the time to decision (release of the second app).* The first two variables refer to behavioral "sunk cost" effects. The entrepreneur feels locked in a particular category due to the time and resources used to add/change his code. We are undercounting the number of versions because we can only see the versions which received comments. Deriving total number of versions is not straightforward. The most popular way to number versions, x.x.x, or x.x.xx. This format does not have a one-to-one transformation to the total number of versions. The *time to decision*, days between the release of the first and second apps, measures the marginal costs of creating second app. If the entrepreneur needs new skills to create an app in a different category, then the marginal cost of the second app should be higher for the developers who chose to diversify. The time of the developer is the main cost borne by these small firms.

- *Feedback*

  We use several measures of user feedback: *no feedback* is an indicator taking the value of one if users provided no feedback at all, *good feedback* is an indicator taking the value of one if the first app by firm has received a 5-star rating accompanying the comment, *bad feedback* is an indicator taking the value of one if the first app by firm has received a 1-star rating accompanying the comment. We also count the number of 5-star comments (*num5star*) and the number of 1-star comments (*num1star*). We also sum up the number of 1- and 2-star comments (*num12star*) and the number of 4- and 5-star comments (*num45star*). The variable *score*, the average rating, combines all feedback received by the developer. Finally, we calculate the variance of rating received by the developer. High-variance feedback can be less informative than consistent feedback.

We use additional data from AppAnnie.com with historical rankings of apps on iTunes in three categories: free apps, paid apps, and highest grossing sales apps. Getting into Top 300 in any category can be interpreted as a good feedback.

- *Control Variables*

  We control for the trends in diversification across app developers in different categories and cohorts (month of the first app) using *cohortXcategory* fixed effects. We also control for the demand using *the number of comments*, which serves as a lower bound for the number of downloads (user can only rate an app after downloading). Finally, I control for the *price* of an app.

Empirical Model

We model the decision of a developer to diversify or not as a function of his commitment, $c(\cdot)$, user feedback, $f(\cdot)$, cohort and category specific factors (fixed effects) and individual-level term, ε_i, the value of which is known to the developer, unknown to the econometrician and the distribution is known to econometrician. The developer makes decision using function g which takes c, f, and ε as its arguments:

$$D_i^* = g_i(c_i, f_i, \varepsilon_i)$$

The developer will diversify if values of commitment and feedback are relatively low:

$$g_i(c_i, f_i, \varepsilon_i) < \bar{g}$$

We do not observe the value of $g_i(c_i, f_i, \varepsilon_i)$, we only observe the decision to diversify in the second app:

$$D_i = \mathbb{1}[g_i(c_i, f_i, \varepsilon_i) < \bar{g}]$$

$$D_i = \mathbb{1}[D_i^* < \bar{g}]$$

Assume that $g(\cdot)$ is linear and parameters are additively separable:

$$D_i = \mathbb{1}[\beta c_i + \gamma f_i + \varepsilon_i < \bar{g}]$$

$$D_i = \mathbb{1}[\varepsilon_i < \bar{g} - \beta c_i - \gamma f_i]$$

Assume that conditional on data (X), individual-specific term, $\varepsilon_i|X \sim N(0, \sigma^2)$ and $\frac{\varepsilon_i}{\sigma}|X \sim N(0, 1)$:

$$D_i = \mathbb{1}[\frac{\varepsilon_i}{\sigma} < \frac{\bar{g} - \beta c_i - \gamma f_i}{\sigma}|X]$$

If we condition on data (X), then expression $\frac{\bar{g}-\beta c_i-\gamma f_i}{\sigma}|X$ is a number. D_i is distributed Bernoulli with $p = \Phi(\frac{\bar{g}-\beta c_i-\gamma f_i}{\sigma})$

$$\mathbb{E}(D_i|X) = \Phi(\frac{\bar{g} - \beta c_i - \gamma f_i}{\sigma}) = \Phi(\frac{\bar{g}}{\sigma} - \frac{\beta}{\sigma}c_i - \frac{\gamma}{\sigma}f_i)$$

We estimate parameters $\frac{\beta}{\sigma}$ and $\frac{\gamma}{\sigma}$, which represent the shift in the distribution when commitment and feedback factors respectively increase by one unit. Because this interpretation is not very intuitive, we will also estimate average marginal effects (AME) as in Bartus (2005). The average marginal effect for the k^{th} continuous variable (commitment factor) is:

$$AME_k = \beta_k \frac{1}{n} \Sigma_{i=1}^n \phi(\frac{\bar{g} - \beta c_i - \gamma f_i}{\sigma}),$$

where $\phi(\cdot)$ is the first derivative of $\Phi(\cdot)$ and i is the values of variables for the i^{th} developer.

The AME for continuous feedback variables is calculated similarly replacing parameter β with γ. The AME for the k^{th} indicator variable is:

$$AME_k = \frac{1}{n} \Sigma_{i=1}^n [\Phi(\frac{\bar{g} - \beta c_i - \gamma f_i}{\sigma}|x_i^k = 1) - \Phi(\frac{\bar{g} - \beta c_i - \gamma f_i}{\sigma}|x_i^k = 0)].$$

The AMEs are interpreted as OLS estimates. In other words, AME represents the percentage increase in probability of diversification following one unit increase in explanatory variable.

Results

Summary Statistics for two groups of developers (those who chose to diversify and release an app in a different category and those who chose to stay in the same category) are in Table 3. The means of commitment variables (time to decision, app size, and the number of versions) suggest that it takes longer to come up with an app in a different category (marginal cost of the second app in a different category is higher) and "sunk costs" (the number of versions for the first app and app size) are higher for developers who chose to not diversify.

Developers who diversify receive, on average, less feedback. They are 3% less likely to get any feedback at all but, if they do get feedback, it is, on average, 10 comments less than that of developers who stayed in their category for the second app. Developers who do not diversify also receive more good feedback. They are 4% more likely to get positive feedback and when they do it is almost twice the number of good comments than what diversified developers get. They are also twice more likely to be ranked in the Top 300 best free, paid, and highest grossing sales apps on iTunes. Surprisingly, they are as likely as diversified developers to get bad feedback and, if we count the number of comments, developers who stay within their initial category get *more* negative comments than diversified developers. In such a way, I think salience, the amount of feedback, is more important than valence, the type of feedback, for diversification decisions.

Probit regressions are in Tables 4-6. They largely confirm the patterns observed in unconditional means. Commitment variables are statistically significant implying that developers are to some extent "locked in" their first category and take into consideration "sunk costs". The coefficient estimates on feedback variables are also consistent with the patterns in unconditional means, however, not all of them are statistically significant. Entering Top Ranking before the release of the second app is a strong predictor of staying in the same category. The availability of feedback seems to be more important for diversification decision than the contents. Bad feedback contains information. While it can discourage some developers, it also can prove useful to others, thus, prompting them to stay in the same category.

Discussion

We began by noting that prior research on diversification reached a consensus that firms should diversify into related markets. Yet the assumptions and empirical base for this theory is drawn from large, established firms with extensive resource portfolios that can take advantage of significant scale and scope advantages. In this paper, we suggest a different perspective in which entrepreneurial diversification is explained by an experimentation rationale in which resource constrained firms use product-entry into new markets to search for the best markets that fit their current capabilities. Because the outcomes of experimentation are inherently uncertain, entrepreneurs use whatever credible signals are possible to constrain the experimentation process. We identify one such source of information, the attention that product-experiments receive through customer feedback. We argue that the salience (amount of feedback) and valence (good or bad feedback) of attention given to products by customers shape whether entrepreneurs will focus or diversify away from prior market categories. We test these ideas using unique data on customer feedback and entrepreneurial diversification decisions available on Apple's iPhone application ecosystem. We find that while new organizations with no feedback may be inclined to continue experimentation through diversification, those who receive significant positive feedback escalate commitment to the focal category with new products. A surprising result is that the presence of bad feedback does not inspire diversification, perhaps because it offers a credible signal that the market is paying attention and may appreciate new product development efforts in the focal category. This study contributes to studies of entrepreneurial strategy with new insights about how escalation of commitment and diversification are linked to dimensions of market attention.

References

Battelle, J. 2006. ***The Search: How Google and Its Rivals Rewrote the Rules of Business and Transformed Our Culture: Portfolio Trade***. Boston, MA, London: Nicholas Brearley Publishing.

Beckman, C. M., Eisenhardt, K., Meyer, A., & Rajagopalan, N. 2012. Technology Entrepreneurship. ***Strategic Entrepreneurship Journal***, 6(2): 89-93.

Chatterjee, S., & Wernerfelt, B. 1991. The Link Between Resources and Type of Diversification. ***Strategic Management Journal***, 12(1): 33-48.

Chatterji, A. 2009. Spawned with a Silver Spoon? Entrepreneurial Performance and Innovation in the Medical Device Industry. ***Strategic Management Journal***, 30: 185-206.

Fligstein, N. 1991. The structural transformation of american industry: An institutional account ofthe causes of diversification in the largest firms, 1919-1979. In W. W. Powell, & P. J. DiMaggio (Eds.), ***The New Institutionalism in Organizational Analysis***: 311-335. Chicago: Chicago University Press.

Hallen, B. 2008. The Causes and Consequences of the Initial Network Positions of New Organizations: From Whom do Entrepreneurs Receive Investments. ***Administrative Science Quarterly***, 53(4): 685-718.

Helfat, C. E., & Eisenhardt, K. M. 2004. Intertemporal Economies of Scope, Organizational Modularity, and the Dynamics of Diversification. ***Strategic Management Journal***, 25: 1217–1232.

Hill, C. W. L., Hitt, M. A., & Hoskisson, R. E. 1992. Cooperative versus competitive structures in related and unrelated diversified firms. ***Organization Science***, 3(4): 501-521.

Katila, R., Chen, E. L., & Piezunka, H. 2011. All the right moves: how entrepreneurs compete effectively in new and old markets. ***Strategic Entrepreneurship Journal***, 6: 116-132.

Kogut, B., & Zander, U. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. ***Organization Science***, 3(3): 383-397.

Lane, P. J., Cannella, A. A., & Lubatkin, M. H. 1998. Agency problems as antecendents to unrelated mergers and diversification: Amihud and Lev reconsidered. ***Strategic Management Journal***, 19: 555-578.

Li, S. X., & Greenwood, R. 2004. The effect of within-industry diversification on firm performance: synergy creation, multi-market contact and market structuration. ***Strategic Management Journal***, 25(12): 1131-1153.

Lubatkin, M. H. 1987. Merger Strategies and Stockholder Value. ***Strategic Management Journal***, 8: 39-53.

Markides, C. C., & Williamson, P. J. 1996. Corporate diversification and organizational structure: A resource-based view. ***Academy of Management Journal***, 39(2): 340-367.

McDonald, R., & Eisenhardt, K. 2014. ***Competiing in New Markets and the Search for a Viable Business Model.*** Working Paper.

Pahnke, E. C., McDonald, R., Wang, D., & Hallen, B. 2014. Exposed: Venture Capital, Competitor Ties, and Entrepreneurial Innovation. ***Academy of Management Journal***, 58(5): 1334-1360.

Rindova, V.,& Kotha, S. 2001. Continuous Morphing: Competing through Dynamic Capabilities, Form, and Function. ***Academy of Management Journal***, 44(6): 1263-1280.

Staw, B. M. 1981. The Escalation of Commitment to a Chosen Course of Action. ***Academy of Management Review***, 6: 577-587.

Stern, I., & Henderson, A. D. 2004. Within-Business Diversification in Technology-Intensive Industries. ***Strategic Management Journal***, 25: 487-505.

Tanriverdi, H., & Lee, C.-H. 2008. Within-Industry Diversification and Firm Performance in the Presence of Network Externalities: Evidence From the Software Industry. ***Academy of Management Journal***, 51(2): 381-397.

Thompke, S. 2003. ***Experimentation Matters: Unlocking the Potential for New Technologies for Innovation***: Harvard Business Press.

Yin, P.-L., Davis, J. P., & Muzyrya, Y. 2014. Entrepreneurial Innovation: Killer Apps in the iPhone Ecosystem, ***American Economic Review, Papers and Proceedings***, 104(5): 255-59.

Table 1: Data Description

Comments data (July, 2008 - December, 2011).

name	description	format
appid	app id from iTunes	num
version	version which is commented	string
star	star rating accompanying a comment	num
comment_date	date on which comment was posted	date

Detailed app data (September, 2010 - December, 2011).

name	description	format
id	scrape id	num
appid	app id from iTunes	num
url	app url on iTunes	string
name	app name on iTunes	string
price	app price on the scrape day	num
categoryname	app category on the scrape day	string
cversion	current version	string
updated	the date on which current version was released	date
released	the date on which app was released	date
size	size in MB of the current version	num
utcsecs	Unix timestamp of scrape	num
artistid	artist id assigned by iTunes	num
developer	name of the developer	string

AppAnnie Top 300 Ranking data (July, 2008 - December, 2011).

name	description	format
appid	app id from iTunes	num
listtype	type of ranking (free, paid, grossing sales)	string
date	date of the ranking	date

Notes. Variable description refers to initial (raw) data.

Table 2: Variable Description

name	description
Outcome variable	
Diversification	Indicator variable which equals one if the second app by the developer is in the different category than the first one.
Explanatory variables (commitment)	
Time to decision	Time between the release of the first app and the release of the second app.
The number of versions	The number of versions of the first app before the release of the second app.
App size	The size of the first app at the time the second app is released (after Sept 6, 2010) or size on Sept 6, 2010 (otherwise).
Explanatory variables (feedback)	
Score	The average rating of the first app before the release of the second app (no comments get zero).
No feedback	Indicator variable taking the value of one if the first app did not receive any comments before the release of the second app.
Bad feedback	Indicator variable if the first app received at least one 1-star rating before the release of the second app.
Good feedback	Indicator variable if the first app received at least one 5-star rating before the release of the second app.
The number of 1 star ratings	The number of 1-star ratings received by the first app before the release of the second app.
The number of 5 star ratings	The number of 5-star ratings received by the first app before the release of the second app.
The number of 1-2 star ratings	The number of 1-2-star ratings received by the first app before the release of the second app.
The number of 4-5 star ratings	The number of 4-5-star ratings received by the first app before the release of the second app.
Top 300 ranking	Indicator variable taking the value of one if the first app entered Top 300 ranking (paid, free, or grossing sales) before the release of the second app.
Variance	The variance of the score variable, measures consistency of the feedback.
Control variables	
The number of comments	The number of comments for the first app before the release of the second app.
App price	The price of the first app at the time the second app is released (after Sept 6, 2010) or price on Sept 6, 2010 (otherwise).
Category-cohort FE	A set of indicator variables which take the value of one for a group of developers who released their first app in a given category on a given month in a given year.

Table 3: Summary Statistics (separately for diversified and non-diversified developers)

Div	No		Yes	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Time to decision	96.80	130.21	122.73	143.08
The number of versions	1.65	1.53	1.53	1.34
App size	14.78	53.60	6.73	28.71
Score	2.47	2.12	2.27	2.11
No feedback	0.38	0.48	0.41	0.49
Bad feedback	0.24	0.43	0.23	0.42
Good feedback	0.51	0.50	0.47	0.50
The number of 1-star comments	3.36	104.90	2.01	34.94
The number of 5-star comments	12.67	228.21	6.99	108.58
The number of 1- and 2-star comments	4.69	142.95	2.83	50.11
The number of 4- and 5-star comments	17.39	346.43	9.65	155.54
Variance	0.55	0.99	0.53	1.01
Top 300 Ranking	0.04	0.19	0.02	0.12
The number of comments	24.28	491.52	13.77	213.20
App price	2.33	16.61	1.44	6.65
Observations	19888		15543	

Notes. The Summary Statistics are at the level of developer (information about the first app).

Table 4: Fixed Effects Regressions (full sample)

	Probit	AME	Probit	AME	Probit	AME	Probit	AME
DV	Div	Div	Div	Div	Div	Div	Div	Div
Time to	0.000993***	0.000360***	0.00100***	0.000363***	0.00100***	0.000364***	0.00100***	0.000364***
decision	(0.0000598)	(0.0000214)	(0.0000598)	(0.0000214)	(0.0000597)	(0.0000214)	(0.0000597)	(0.0000214)
Versions	-0.0849***	-0.0308***	-0.0828***	-0.0300***	-0.0856***	-0.0310***	-0.0857***	-0.0310***
	(0.00686)	(0.00246)	(0.00697)	(0.00250)	(0.00686)	(0.00246)	(0.00686)	(0.00246)
App size	-0.00266***	-0.000966***	-0.00267***	-0.000968***	-0.00268***	-0.000970***	-0.00268***	-0.000971***
	(0.000280)	(0.000101)	(0.000280)	(0.000101)	(0.000280)	(0.000101)	(0.000280)	(0.000101)
No	0.0106	0.00383	0.0325	0.0118	0.0845***	0.0307***	0.0846***	0.0307***
Feedback	(0.0379)	(0.0138)	(0.0262)	(0.00951)	(0.0165)	(0.00604)	(0.0165)	(0.00604)
Rating	-0.00811	-0.00294	0.0178	0.00646	-0.00206	-0.000747	-0.00203	-0.000735
Variance	(0.00873)	(0.00317)	(0.0128)	(0.00464)	(0.00829)	(0.00301)	(0.00829)	(0.00301)
Top 300	-0.336***	-0.118***	-0.324***	-0.114***	-0.333***	-0.117***	-0.335***	-0.117***
Ranking	(0.0496)	(0.0164)	(0.0501)	(0.0167)	(0.0498)	(0.0165)	(0.0497)	(0.0165)
Score	-0.0177*	-0.00641*						
	(0.00817)	(0.00296)						
Bad			-0.0519+	-0.0188+				
Feedback			(0.0303)	(0.0109)				
Good			-0.0658*	-0.0239*				
Feedback			(0.0266)	(0.00959)				
1-Star					-0.000412	-0.000150		
Rating					(0.000335)	(0.000122)		
5-Star					-0.000248	-0.0000901		
Rating					(0.000297)	(0.000108)		
1-2-Star							-0.000633	-0.000229
Rating							(0.000954)	(0.000346)
4-5-Star							-0.000459	-0.000167
Rating							(0.000827)	(0.000300)
Comments	0.00000590	0.00000214	0.00000560	0.00000203	0.000176	0.0000638	0.000449	0.000163
	(0.0000178)	(0.00000647)	(0.0000180)	(0.00000652)	(0.000176)	(0.0000640)	(0.000757)	(0.000275)
Price	-0.00793***	-0.00287***	-0.00796***	-0.00289***	-0.00795***	-0.00288***	-0.00795***	-0.00288***
	(0.00222)	(0.000806)	(0.00223)	(0.000808)	(0.00223)	(0.000807)	(0.00223)	(0.000806)
Cons	-0.210		-0.230		-0.285		-0.285	
	(0.238)		(0.236)		(0.235)		(0.235)	
Category X Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
Obs	35431	35431	35431	35431	35431	35431	35431	35431
logL	-22468.4	-22468.4	-22467.5	-22467.5	-22470.0	-22470.0	-22470.3	-22470.3

Notes. In all columns outcome variable is Diversification, an indicator which equals one if the second app by the developer is in the different category than the first one. Time to decision is the time between the release of the first app and the release of the second app. The number of versions indicates the number of versions of the first app before the release of the second app. App size is the size of the first app at the time the second app is released (after Sept 6, 2010) or size on Sept 6, 2010 (otherwise). Score is the average rating of the first app before the release of the second app. Apps with no comments receive a score of zero. No feedback is an indicator taking the value of one if the first app did not receive any comments before the release of the second app. Bad feedback is an indicator for the first app receiving at least one 1-star rating before the release of the second app. Good feedback is an indicator for the first app receiving at least one 5-star rating before the release of the second app. The number of 1 star ratings is the number of 1-star ratings received by the first app before the release of the second app. The number of 5 star ratings is the number of 5-star ratings received by the first app before the release of the second app. The number of 1-2 star ratings is the number of 1-2-star ratings received by the first app before the release of the second app. The number of 4-5 star ratings is the number of 4-5-star ratings received by the first app before the release of the second app. Top 300 ranking is an indicator taking the value of one if the first app entered Top 300 ranking (paid, free, or grossing sales) before the release of the second app. Variance is the variance of the score variable, measures consistency of the feedback. The number of comments is the number of comments for the first app before the release of the second app. App price is the price of the first app at the time the second app is released (after Sept 6, 2010) or price on Sept 6, 2010 (otherwise). Category-cohort FE are a set of indicator variables which take the value of one for a group of developers who released their first app in a given category on a given month in a given year. Robust standard errors in parentheses. $***, **, *, +$ indicate significance of coefficients at 0.1%, 1%, 5%, and 10% respectively.

Table 5: Fixed Effects Regressions (developers with at least 2 weeks between first and second app)

	Probit	AME	Probit	AME	Probit	AME	Probit	AME
DV	Div	Div	Div	Div	Div	Div	Div	Div
Time to	0.000805***	0.000293***	0.000815***	0.000296***	0.000817***	0.000297***	0.000817***	0.000297***
decision	(0.0000629)	(0.0000227)	(0.0000629)	(0.0000226)	(0.0000628)	(0.0000226)	(0.0000628)	(0.0000226)
Versions	-0.0835***	-0.0303***	-0.0803***	-0.0292***	-0.0845***	-0.0307***	-0.0846***	-0.0307***
	(0.00699)	(0.00251)	(0.00710)	(0.00255)	(0.00699)	(0.00251)	(0.00699)	(0.00251)
App size	-0.00256***	-0.000929***	-0.00256***	-0.000931***	-0.00257***	-0.000936***	-0.00257***	-0.000936***
	(0.000308)	(0.000111)	(0.000308)	(0.000112)	(0.000309)	(0.000112)	(0.000309)	(0.000112)
No	0.0145	0.00529	0.0358	0.0130	0.112***	0.0408***	0.112***	0.0408***
Feedback	(0.0414)	(0.0151)	(0.0288)	(0.0105)	(0.0189)	(0.00693)	(0.0189)	(0.00693)
Rating	-0.0117	-0.00426	0.0239+	0.00868+	-0.00379	-0.00138	-0.00376	-0.00137
Variance	(0.00922)	(0.00335)	(0.0135)	(0.00492)	(0.00873)	(0.00317)	(0.00873)	(0.00317)
Top 300	-0.340***	-0.120***	-0.324***	-0.115***	-0.338***	-0.120***	-0.340***	-0.120***
Ranking	(0.0505)	(0.0170)	(0.0510)	(0.0173)	(0.0508)	(0.0171)	(0.0507)	(0.0171)
Score	-0.0234**	-0.00849**						
	(0.00886)	(0.00322)						
Bad			-0.0694*	-0.0252*				
Feedback			(0.0320)	(0.0116)				
Good			-0.0975***	-0.0355***				
Feedback			(0.0287)	(0.0104)				
1-Star					-0.000372	-0.000135		
Rating					(0.000332)	(0.000121)		
5-Star					-0.000239	-0.0000869		
Rating					(0.000294)	(0.000107)		
1-2-Star							-0.000542	-0.000197
Rating							(0.000945)	(0.000343)
4-5-Star							-0.000400	-0.000145
Rating							(0.000820)	(0.000298)
Comments	0.00000784	0.00000285	0.00000749	0.00000272	0.000168	0.0000610	0.000392	0.000143
	(0.0000174)	(0.00000632)	(0.0000175)	(0.00000636)	(0.000175)	(0.0000636)	(0.000750)	(0.000273)
App price	-0.00769**	-0.00280**	-0.00775**	-0.00282**	-0.00772**	-0.00281**	-0.00772**	-0.00281**
	(0.00243)	(0.000882)	(0.00244)	(0.000886)	(0.00243)	(0.000883)	(0.00243)	(0.000883)
Cons	-0.0135		-0.0297		-0.110		-0.110	
	(0.223)		(0.221)		(0.220)		(0.220)	
Category X Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
Obs	28524	28524	28524	28524	28524	28524	28524	28524
logL	-18127.4	-18127.4	-18124.9	-18124.9	-18130.3	-18130.3	-18130.5	-18130.5

Notes. In all columns outcome variable is Diversification, an indicator which equals one if the second app by the developer is in the different category than the first one. Time to decision is the time between the release of the first app and the release of the second app. The number of versions indicates the number of versions of the first app before the release of the second app. App size is the size of the first app at the time the second app is released (after Sept 6, 2010) or size on Sept 6, 2010 (otherwise). Score is the average rating of the first app before the release of the second app. Apps with no comments receive a score of zero. No feedback is an indicator taking the value of one if the first app did not receive any comments before the release of the second app. Bad feedback is an indicator for the first app receiving at least one 1-star rating before the release of the second app. Good feedback is an indicator for the first app receiving at least one 5-star rating before the release of the second app. The number of 1 star ratings is the number of 1-star ratings received by the first app before the release of the second app. The number of 5 star ratings is the number of 5-star ratings received by the first app before the release of the second app. The number of 1-2 star ratings is the number of 1-2-star ratings received by the first app before the release of the second app. The number of 4-5 star ratings is the number of 4-5-star ratings received by the first app before the release of the second app. Top 300 ranking is an indicator taking the value of one if the first app entered Top 300 ranking (paid, free, or grossing sales) before the release of the second app. Variance is the variance of the score variable, measures consistency of the feedback. The number of comments is the number of comments for the first app before the release of the second app. App price is the price of the first app at the time the second app is released (after Sept 6, 2010) or price on Sept 6, 2010 (otherwise). Category-cohort FE are a set of indicator variables which take the value of one for a group of developers who released their first app in a given category on a given month in a given year. Robust standard errors in parentheses. $***$, $**$, $*$, + indicate significance of coefficients at 0.1%, 1%, 5%, and 10% respectively.

Table 6: Fixed Effects Regressions (developers with at least 4 weeks between first and second app)

	Probit	AME	Probit	AME	Probit	AME	Probit	AME
DV	Div	Div	Div	Div	Div	Div	Div	Div
Time to	0.000653***	0.000238***	0.000662***	0.000242***	0.000660***	0.000241***	0.000659***	0.000241***
decision	(0.0000668)	(0.0000243)	(0.0000667)	(0.0000242)	(0.0000667)	(0.0000242)	(0.0000667)	(0.0000242)
Versions	-0.0801***	-0.0292***	-0.0757***	-0.0276***	-0.0806***	-0.0294***	-0.0807***	-0.0294***
	(0.00711)	(0.00257)	(0.00722)	(0.00261)	(0.00710)	(0.00256)	(0.00710)	(0.00256)
App size	-0.00254***	-0.000928***	-0.00254***	-0.000927***	-0.00255***	-0.000932***	-0.00255***	-0.000932***
	(0.000332)	(0.000121)	(0.000331)	(0.000120)	(0.000332)	(0.000121)	(0.000332)	(0.000121)
No	0.0666	0.0244	0.0444	0.0162	0.120***	0.0438***	0.120***	0.0438***
Feedback	(0.0453)	(0.0166)	(0.0319)	(0.0117)	(0.0213)	(0.00783)	(0.0213)	(0.00783)
Rating	-0.0110	-0.00401	0.0318*	0.0116*	-0.00661	-0.00242	-0.00659	-0.00241
Variance	(0.00986)	(0.00360)	(0.0145)	(0.00531)	(0.00930)	(0.00340)	(0.00930)	(0.00340)
Top 300	-0.354***	-0.127***	-0.331***	-0.119***	-0.352***	-0.126***	-0.354***	-0.127***
Ranking	(0.0521)	(0.0178)	(0.0527)	(0.0182)	(0.0524)	(0.0180)	(0.0523)	(0.0179)
Score	-0.0128	-0.00466						
	(0.00966)	(0.00353)						
Bad			-0.109**	-0.0397**				
Feedback			(0.0344)	(0.0125)				
Good			-0.0906**	-0.0332**				
Feedback			(0.0315)	(0.0115)				
1-Star					-0.000292	-0.000107		
Rating					(0.000329)	(0.000120)		
5-Star					-0.000182	-0.0000665		
Rating					(0.000294)	(0.000107)		
1-2-Star							-0.000380	-0.000139
Rating							(0.000946)	(0.000346)
4-5-Star							-0.000273	-0.0000997
Rating							(0.000822)	(0.000300)
Comments	0.0000101	0.00000371	0.0000102	0.00000372	0.000133	0.0000485	0.000274	0.000100
	(0.0000170)	(0.00000620)	(0.0000171)	(0.00000624)	(0.000175)	(0.0000638)	(0.000753)	(0.000275)
App price	-0.0102**	-0.00374***	-0.0103***	-0.00377***	-0.0103***	-0.00375***	-0.0103***	-0.00375***
	(0.00312)	(0.00114)	(0.00314)	(0.00114)	(0.00312)	(0.00114)	(0.00312)	(0.00114)
Cons	0.430*		0.449*		0.378+		0.378+	
	(0.215)		(0.213)		(0.212)		(0.212)	
Category X Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
Obs	23453	23453	23453	23453	23453	23453	23453	23453
logL	-14969.5	-14969.5	-14964.1	-14964.1	-14970.0	-14970.0	-14970.2	-14970.2

Notes. In all columns outcome variable is Diversification, an indicator which equals one if the second app by the developer is in the different category than the first one. Time to decision is the time between the release of the first app and the release of the second app. The number of versions indicates the number of versions of the first app before the release of the second app. App size is the size of the first app at the time the second app is released (after Sept 6, 2010) or size on Sept 6, 2010 (otherwise). Score is the average rating of the first app before the release of the second app. Apps with no comments receive a score of zero. No feedback is an indicator taking the value of one if the first app did not receive any comments before the release of the second app. Bad feedback is an indicator for the first app receiving at least one 1-star rating before the release of the second app. Good feedback is an indicator for the first app receiving at least one 5-star rating before the release of the second app. The number of 1 star ratings is the number of 1-star ratings received by the first app before the release of the second app. The number of 5 star ratings is the number of 5-star ratings received by the first app before the release of the second app. The number of 1-2 star ratings is the number of 1-2-star ratings received by the first app before the release of the second app. The number of 4-5 star ratings is the number of 4-5-star ratings received by the first app before the release of the second app. Top 300 ranking is an indicator taking the value of one if the first app entered Top 300 ranking (paid, free, or grossing sales) before the release of the second app. Variance is the variance of the score variable, measures consistency of the feedback. The number of comments is the number of comments for the first app before the release of the second app. App price is the price of the first app at the time the second app is released (after Sept 6, 2010) or price on Sept 6, 2010 (otherwise). Category-cohort FE are a set of indicator variables which take the value of one for a group of developers who released their first app in a given category on a given month in a given year. Robust standard errors in parentheses. $***$, $**$, $*$, $+$ indicate significance of coefficients at 0.1%, 1%, 5%, and 10% respectively.