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Collective Intelligence of Market-Categories in Entrepreneurial Ecosystems: Evidence of Population-Level Learning in Mobile Applications

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In this paper, we examine how groups of organizations engage in population-level learning in entrepreneurial ecosystems. We specifically analyze how within- and across-group characteristics of organizational groups shape learning, and thereby extend the literature on population-level learning that has focused mostly on within-population leaning. We argue that a group of new organizations may develop collective intelligence, in which population-level learning stemming from both the audience of consumers and fellow producers enhances innovation in groups. These persistent differences are facilitated by active feedback from within the audience (within-group learning sources) and member organizations' diversification into other groups (across-group sources), but the effect of latter decreases after a certain point, indicating a curvilinear relationship. Our longitudinal analysis of Apple's mobile application ecosystem supports these claims. Different market-categories indicated a significant, persistent heterogeneity in the aggregated performance across several different criteria, and this heterogeneity was facilitated by active audience feedback. Diversification of member organizations also showed a positive influence on group-level heterogeneity, yet its effect decreased after a threshold. This paper contributes to the literature on population-level learning by showing the importance of examining across-group learning sources, and by introducing a new collective intelligence framework for analyzing organizational groups. In addition, we provide a framework through which persistent heterogeneity in entrepreneurial ecosystem innovation can be understood.

1. INTRODUCTION

Entrepreneurial ecosystems – defined here as a community of new organizations focused on the creation of new products and services – are receiving increasing attention because of their importance in producing innovations that lead to job creation and economic growth (Franke & Shah, 2003; Schoonhoven & Romanelli, 2001). A good example is the entrepreneurial ecosystem surrounding the production of mobile applications ("apps"), which has experienced impressive success in just a few years (Bresnahan, Yin, & Davis, 2015). While strategy and organization scholars have so far focused on the innovative outcomes of individual firms in an ecosystem (Adner & Kapoor, 2010; Gawer & Henderson, 2007; Ozcan & Eisenhardt, 2008), less progress has been made in explaining the persistent differences in innovation across ecosystems or sub-markets of an ecosystem. For example, there are well known category differences in Apple's mobile ecosystem, with Games, Lifestyle, and Travel categories generating more than twice the successful applications of Music, Productivity, and Sports categories (Bresnahan et al., 2015). Existing explanations of these differences focus on the limiting case of geographically clustered ecosystems where agglomeration economies take effect (Porter, 1998) or markets where IP policy plays a strong role in limiting imitation (Teece, 1986), as in biotechnology, leaving geographically distributed ecosystems with weak appropriation regimes like mobile apps relatively unexplored. In this study, we seek to address this issue. Why are the organizations in some ecosystem-markets more innovative than others?

Our research draws on theories on population-level learning and collective intelligence. Population-level learning refers to the outcome of "systematic change in the nature and mix of routines *in a population* of organizations as a result of experience" (Miner & Haunschild, 1995: 115). Based on the premise that learning is collective as well as individual (Gavetti & Warglien, 2015), this theory specifically focuses on how and when specific types of routines or practices become widely shared by an interaction among organizations in the population (Ingram & Baum, 1997; Ingram & Simons, 2002). The theory suggests that the outcomes of the population-level learning can be both adaptive or maladaptive (Levitt & March, 1988; Miner & Raghavan, 1999), making this theory particularly suitable for our purpose.

We integrate this theory with recent analytical developments in the literature about collective intelligence of teams. By doing so, we seek to address two concerns in population-level learning theory. First, while population-level theory emphasizes the change in shared routines or "norms" among organizations as a key driver as well as consequences of the population-level learning (Lant & Phelps, 1999; Miner, Kim, Holzinger, & Haunschild, 1999), it has been difficult to find evidence of persistent learning differences across populations, perhaps because of the difficulties of identifying suitably large and comparable data from which population-level inferences can be made without reference to few, large idiosyncratic organizations that account for most learning. In addition, the consequences of the learning can be best examined when a multitude of performance criteria are considered together, since the effect of learning might exhibit, or even at odds with each other, depending on which dimension of outcomes is examined in a study (See Argote, 2013; Greve, 2003 for reviews).

The literature on collective intelligence can provide a solution to these problems. This research stream, developed by Anita Woolley, Tom Malone, and colleagues, showed that specific groups of individuals outperform others across a wide variety of performance metrics, above and beyond what the intelligence of group members explains (e.g., Engel, Woolley, Jing, Chabris, & Malone, 2014; Woolley, 2011; Woolley, Chabris, Pentland, Hashmi, & Malone, 2010). They develop a methodology to capture the latent collective intelligence inherent in a variety of metrics, based on experimental data in teams. By extending this approach to a panel of new organizations, we examine the impact of population-level learning across market-categories in an entrepreneurial ecosystem.

We first develop a theoretical framework about why population-level adaptation or collective intelligence might exist among entrepreneurial firms in the ecosystem, and what producer- and audience-side factors might explain its emergence. Then, we test the theory using a rich dataset on

Apple's mobile application ecosystem, in which thousands of (mostly) small startups develop applications for the iPod, iPhone and iPad devices. This context is ideal for our purpose for a several reasons. First, we can observe the population of the apps and firms – both survived and failed ones. Thus, we can satisfy an important criterion for examining the population-level learning (Miner & Anderson, 1999). In addition, the dynamics of distinct market-categories of apps and firms can be observed, which segment producers and the audience into distinct markets and (sub)populations (e.g., Lounsbury & Rao, 2004; Porac, Thomas, Wilson, Paton, & Kanfer, 1995; Zuckerman, 1999). For example, producers and audiences hold different expectations and needs for apps in the category of Games vs. those in Productivity or Social Networking. By comparing the dynamics of these populations in the same platform, we can control for the unobservable contextual and period influences that may affects their learning (Baum & Berta, 1999). Finally, we can analyze what characteristics of audiences and producers in each population can explain their differences in collective learning, since we can systematically observe the detailed feedback from audiences as well as firms' activities across distinct populations.

This study makes three important contributions. First, this paper is one of a few papers that examine the population-level performance or fitness changes. Empirical studies on the tradition of population-level learning has focused on the consequences at individual firms such as performance implications of imitation of other firms (e.g., Baum & Ingram, 1998; Ingram & Simons, 2002; Madsen & Desai, 2010; Schwab, 2007). This skewed attention is problematic, since the "outcomes (of population-level learning) are not the simple sum of independent actions" (Miner et al., 1999: 190) and learning at one level may be unrelated to or inconsistent with learning at another level (Argote, 2013; Lounamaa & March, 1987). Second, we extend the burgeoning literature on collective intelligence to the population of organizations and develop the methods to examine the theory on a panel data of groups of organizations. By doing so, we can explain how learning from one group may or may not diffuse to other groups, unlike the assumption made in the literature of only within-group interaction and learning. Finally, we suggest a new framework through which entrepreneurial ecosystems can be understood, and what factors can foster healthier entrepreneurial ecosystems.

2. THEORY AND HYPOTHESES

Entrepreneurial Ecosystem, Population-level Learning, and Collective Intelligence

The concept of business ecosystem importantly extends a traditional focus of organizational studies on a focal firm to upstream suppliers and downstream complementors and buyers in examining innovation and strategies (Adner & Kapoor, 2010, 2015; Adner, Oxley, & Silverman, 2013; Baldwin, 2012; Iansiti & Levien, 2004; Kapoor & Lee, 2013; Teece, 2007). This perspective also departs from a concept of the value chain in that it focuses on interactions among firms in the ecosystem, whereas the latter focuses more on bargaining power and the focal firm's ability to capture more value compared to other firms in the value chain (Adner & Kapoor, 2010: 309). In this sense, this perspective emphasizes the importance of more holistic approach that includes diverse aspects of value creation. However, studies so far largely focused on the specific part of the system, and examined how outcomes and strategic behaviors of a specific firm is influenced by its dependence with other firms in the system (e.g., Adner & Kapoor, 2010; Ozcan & Eisenhardt, 2008). The holistic approach is particularly important to understand an entrepreneurial ecosystem, in which (mostly) small-sized entrepreneurial firms compete. In this system, it becomes particularly important to secure the viability and success of the entire population of the firms in achieving success for each member firm (Navis & Glynn, 2010; Santos & Eisenhardt, 2005), beyond the usual importance of population dynamics on firm-level heterogeneity in performance (Demsetz, 1973; Nelson & Winter, 1982). This implies a necessity of developing an approach to examine performance of the entire system to comprehend entrepreneurial ecosystems, rather than each firm.

Among various organizational theories, population-level learning theory provides a particularly valuable tool for understanding different outcomes of entrepreneurial ecosystems. This perspective examines how specific learning (or change in routines) are derived from interactions with other firms in the population, and how learning becomes shared among them and, as a result, the fitness of the population changes over time (Ingram & Simons, 2002; Miner & Haunschild, 1995). Unlike classical organizational ecology theory (Hannan & Freeman, 1989; Hannan & Freeman, 1977), which assumes that population-level changes are derived from births and deaths of organizations, this perspective consider both imitation and selection as a driver of change in population (Miner & Anderson, 1999; Miner & Raghavan, 1999)—thus in line with an adaptation perspective (Cyert & March, 1963; Levinthal, 1991; Levitt & March, 1988). Particularly valuable to our purpose of understanding performance heterogeneity among and within entrepreneurial ecosystems, this perspective argues that outcomes of learning can be both positive and negative. For instance, firms can imitate others' practices or actions that appear desirable but are in fact unrelated to outcomes, resulting in the population's embrace of a suboptimal practice (Levitt & March, 1988).

There are, in large, two types of learning considered in this theory (Miner et al., 1999). Interorganizational population-level learning indicates learning of an organization that is influenced by the shared experiences and changes by many organizations in a population, while collective population-level learning indicates fully collective actions, outcomes, institutions, and/or routines that have meaning only at a population-level. Organizational studies in the learning tradition have devoted most of attention on the former type of vicarious learning, albeit the basic premise of population-level learning theory that learning at population level is not equal to, or even inconsistent with, the sum of individual firm's learning (Gavetti & Warglien, 2015). Rather, the topic of dynamic change in performance of the entire population or fitness has been examined by simulation studies drawn from a tradition of evolutionary economists (e.g., Gavetti & Levinthal, 2000; Levinthal & Posen, 2007).

There can be a couple of constraints that prevent a further development of studies on the tradition. A difficulty of obtaining a comprehensive data on the population of organizations is an obvious one. However, there are two other, interrelated reasons. While population-level learning emphasizes the change in routines shared among participating firms or norms as a key milestone of learning, it is extremely difficult to examine such changes in empirical data. In addition, it is important to examine how changes in norms can exhibit in multiple different dimension simultaneously, because selection and imitation – the two key mechanism of population-level learning—may have distinctive effect on each dimension of outcomes and thus might only be effectively understood by examining multitude of them together (Argote, 2013; Greve, 2003).

To address these constraints, we attend to a burgeoning literature on collective intelligence in teams. Over the past few years, researchers have shown that some groups are more 'intelligent' than others, above and beyond what the intelligence of group members can explain (e.g., Engel et al., 2014; Woolley, 2011; Woolley et al., 2010). Extending a concept of general intelligence in individuals to the group level (Spearman, 1904), studies based on this theory develop a theory about why collective intelligence may exist in human groups, and what factors may predict the emergence of collective intelligence. Using an empirical strategy developed to detect and measure collective intelligence based on experimental data, they consistently found that specific groups outperform others across various of performance dimensions (e.g., Engel et al., 2014; Woolley, 2011; Woolley et al., 2010). In addition, these studies found that this shared capacity is derived from the active information sharing among group members, which facilitates learning among them.

Although some effort has been made to generalize collective intelligence from teams to large organizations in which, presumably, not all participants collaborate or are known to each other (Woolley, Aggarwal, & Malone, 2015), to our knowledge there has not been any effort to consider whether groups of organizations might be shown to exhibit collective intelligence. In this paper, we present an exploratory attempt to develop a theory on collective intelligence of entrepreneurial ecosystem, and test based on a panel data on Apple's mobile application ecosystem. By doing so, we seek to provide 1) a theoretical explanation of the differential capacity of distinct entrepreneurial ecosystems and market-categories in an ecosystem, 2) an analytical framework to examine the multitude of performance dimensions that can capture the outcomes of the population-level change in shared norms, and 3) an initial study to extend the theory of collective intelligence to a group of organizations.

We first explore the emergence of collective intelligence in the Apple mobile application ecosystem. We then examine the audience- and producer-side factors underlying population-level learning that might influence the emergence of collective intelligence.

Population-level Learning in Entrepreneurial Ecosystem

Entrepreneurial ecosystems consist of a variety of mostly small organizations that share technological architecture and institutional norms. These organizations include those in different part of value chain system, but are typically orchestrated by a few central firms like Apple, Microsoft, Intel, and Cisco, which provides the key platform and set the rules for participating and operating to complementor organizations (Gawer & Henderson, 2007). A hallmark of platform-based ecosystems are low entry barriers, which are the consequence of common-use technologies and complementary assets that are maintained by platform-owners (Gawer, 2014; Teece, 1986). As a result, entrepreneurial ecosystems are typically characterized by rapid entry and experiments by entrepreneurs to search for the most commercially successful innovations (Bresnahan et al., 2015).

This combination of the hyper-competition among participating firms (without a clear domination among themselves) and the shared platform technology increases the motivation of participating entrepreneurs to be attentive to other companies and try to learn from them. There are a number of reasons why vicarious learning among entrepreneurs in the population might be active in the ecosystems. First, a technological or institutional structure shared among them (e.g., Application Program Interface provided by Apple, Google, and Twitter) enable a variety of learning modes, including via direct experience of competitors' products and even reverse engineering. Descriptions of all applications are listed on Apple's iTunes platform, including evaluations and comments by users. In addition, protective actions patents are often not applicable in this software-based setting (Boudreau, 2011; von Hippel & von Krogh, 2003), thus, entrepreneurs are motivated to publish their companies and search for alternative rapidly according to the change in other competing products and audiences' changing needs (Siggelkow & Rivkin, 2005). Furthermore, in many ecosystems, the search for superior performance configurations (or at least a solution applied in better performing products) is made possible by users' rating system and the observability of product performance (Greve & Taylor, 2000; Levinthal, 1997). Therefore, to some extent, these features of entrepreneurial ecosystems are comparable to those of human teams that facilitate active information sharing (Engel et al., 2014; Woolley et al., 2010). We thus suggest that population-level learning that is comparable to collective intelligence can emerge in entrepreneurial ecosystems, even without the proscribed roles or formal authority structures that facilitate collective intelligence in teams and organizations.

We argue that the competition and vicarious learning from other competitors in an entrepreneurial ecosystem will be importantly confined by market categories within the ecosystem. Platform owners or central firms typically provide a classification of products in the ecosystem in order to help consumers navigate the products in the system. These categories, often defined by the core (perceived) attributes of products, mediate cognition and perception of both producers and consumers as they shape expectations and evaluation, and thus determines a reference group of rivals (Porac et al., 1995), interaction among companies (Kennedy, 2008), and a breadth of strategic alternatives from which firms can choose (Hsu & Grodal, 2015). Given that entrepreneurial ecosystems are highly interdependent systems without physical boundaries or authorities to guide each member's behavior (Bresnahan et al., 2015), market categories will be particularly important to determine the separate population within the ecosystem.

Overall, we argue that members will actively observe others in the same market-category to learn about their behaviors and practices, and to outcompete them, based on which structure and governance of categories of ecosystems emerge. As organizations developing learning capabilities, new organizations might adopt the routines and practices underlying these capabilities and improve the learning as well. This learning can exhibit in a wide variety of tasks and performance criteria related to product development such as adoption, innovativeness, and commercialization. However, since organizations tend to specialize in market-categories, these learning capacities may differ across them. We therefore hypothesize the existence of a single latent factor, c, that will predict a variety of performance measures of the market-categories in entrepreneurial ecosystems, above and beyond what quality of the firms participating in the categories can predict. The group of organizations in each market-category will have a single value this factor, c, that explains market-category performance.

Hypothesis 1: *There will be a single collective intelligence factor for a (sub)population of entrepreneurial ecosystem that predict a variety of the (sub)population-level performance dimensions.*

Feedback from Audiences and Population-level Learning

Next, we attend to producer-side factors that can influence vicarious learning in order to test the mechanism that explains differences in c. We specifically predict that more active feedback from audiences to the entrepreneurs in the population will facilitate the emergence of its collective intelligence. Audiences, including consumers and critics, can be an important medium through which organizations learn about markets. In most markets, both audiences and producers tend not to know the optimal configuration of product attributes a priori. Rather, they develop their understanding and expectations about the products through the repetitive process of learning by doing and using (Rosenberg, 1982; Shah & Tripsas, 2007). Active feedback from audiences will convey rich information flow about what customers except from the products, need to achieve from using them, and feel from the focal products, providing a valuable resources based on which experiential learning can be facilitated (Argote, 2013). In addition, feedbacks often include the direct or indirect comparison with other competing products in the same population, and thus make producers knowledgeable about products that are delivering higher satisfaction to audiences-- which amounts to help them learn about performance landscape (Levinthal, 1997).

Overall, active feedbacks from audience will increase the likelihood of continual improvement of the products receiving products through better knowledge both about their own products and about other better competitors. Such improvement from active information will be diffused to other products so much as vicarious learning is prevalent in the population, further facilitating the emergence of population-level learning. We thus hypothesize the positive influence of the amount of comments received by entrepreneurs in the population on the emergence of collective intelligence or collective learning among themselves.

Hypothesis 2: *The collective intelligence of a (sub-)population in entrepreneurial ecosystems will have a positive relationship with the number of comments received by the products in the (sub-)population.*

Population Spanning Diversification by Firms and Population-level Learning

In addition to audience-side factors, producer-side factors can also affect the population-level learning in the ecosystem. We specifically investigate the extensiveness of firms' diversification to other populations in the system. Although there is a certain common knowledge, each category or population is subject to distinct set of skill, knowledge, and requirement, including consumer expectation, required skill sets, accumulated experience and knowledge about consumers and markets. Literature on learning, social networks, and creativity has shown the positive influence of access to diverse information and knowledge sets (e.g., Ahuja, 2000; Burt, 2004; Taylor & Greve, 2006). Importantly, those studies have demonstrated spillover effects created from accessing diverse information (e.g., Ahuja, 2000; but see Burt, 2010), since this information may offer distinctive value during the innovation process. Actors that span knowledge boundaries might apply attributes of products that are drawn from other populations yet unconventional in the focal population (Fleming & Waguespack, 2006; Rosenkopf & Nerkar, 2001), and those new practices might spill over to others through vicarious learning and imitation. This suggests that diverse population spanning activities of producers might have a positive influence on the emergence of collective learning.

However, we argue that this positive effect will be attenuated as diversification activities become too prevalent. First, too diverse information may cause absorptive capacity problems for small, resource limited companies (Cohen & Levinthal, 1990). Similarly, literature on distal learning suggests that as a distance from learning source and destination increases, the average effectiveness of learning tends to decrease (Greve, 1999; March & Simon, 1958). Vicarious learning may also decrease especially when spanning activities are diverse as well as prevalent, since firms facing such heterogeneous information might lose confidence over the information (Rhee, Kim, & Han, 2006). Finally, literature on market categories suggest that excessive boundary-spanning might blur the boundary of a population itself, confuse the audiences and producers, and even cause devaluation of the category as a whole (e.g., Hsu, 2006; Zuckerman, 1999). This suggests that following Hypothesis.

Hypothesis 3: *The collective intelligence of a (sub-)population in entrepreneurial ecosystems will have an inverted U-shaped relationship with the degree of the (sub-)population-spanning diversification by the firms in the (sub-)population.*

3. CONTEXT

Our main observations came from data on a population of 395,873 apps produced by 115,200 firms observed every two days (on average) on iTunes (the United States market) between September 6, 2010 and August 31, 2011 (we continue to track these apps until December 31, 2011). Apps for the iPhone must be officially released and distributed through a single channel, the iTunes store, from the birth of the iPhones.[1] This allows us to observe the entire population of apps, properly measuring how collective-level performance changes over time. We aggregated the data into weeks (67 weeks in total) in order to increase the comparability across different observations.

There are 20 categories for apps 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. Table 1 represents the number of apps for each category. We excluded Books and News from our sample because these apps are typically digital versions of print or web content (e.g., New York Times or bible) and thus it is unlikely to expect vicarious learning and observation among themselves in the App Store.

— Insert Table 1 about here —

We also excluded 8,945 observations that we could not identify release date of apps or firms of the apps, since these are necessary for calculating our variables. The final sample thus consists of 322,290 apps, from which we construct a panel of 1,206 category-week level observations (18 categories over 67 weeks).

We combined this database with several others for constructing variables. To examine user comments and ratings on our sample apps, we traced back the data on them to a genesis of the App Store on July 10, 2008. Also, we supplanted the data with the daily lists of apps that were the most 300 downloaded and with highest grossing apps (based on sales of the apps plus in-app purchases) from July 1st 2009. We gathered the data on rankings from App Annie (www.appannie.com), the data source that is extensively used by app developers, venture capital firms, and analysts.

4. ESTIMATION

To test an existence of collective intelligence of app categories (Hypothesis 1), we drew upon the approach developed in Woolley et al. (2010) for measuring collective intelligence of groups. This approach centers around a factor analysis to extract the latent factor explaining diverse performance metrics. While the paper is based on experiments, however, we have a panel data structure where

[1] Although there is the possibility of illegal "jailbreaking" the phone to utilize non-approved apps, the size of this market is considered to be negligible compared to the official app market.

we can observe both cross-sectional and dynamic change within and across categories. To exploit this structure fully, we used a dynamic factor analysis.

Dynamic factor analysis takes account of panel data structures and potential autoregressive error terms (Forni, Hallin, Lippi, & Reichlin, 2000). It specifically decomposes variability of variables or metrics into average dispersion within times (cross-sectional dimension) and between times (time-series dimension). The cross-sectional dimension is examined through principal component analysis while the latter is through a linear regression model. Using the Stata procedure developed for this analysis (Federici & Mazzitelli, 2005), we extracted the latent components and checked their cross-sectional or *within-variance* (through comparing the proportion of variance of the performance measures explained by the factors) and temporal validity or *between-variance* (through regression analyses). Then we regressed another performance metric on the first component to further check the explanatory validity of the component, following Woolley et al. (2010). This tests for a common c factor, as predicted by Hypothesis 1.

Afterward, we regressed the computed first component on our predictor variable to test Hypotheses 2 and 3. Each category of app may have persistent but unmodelled differences at the category-level (such as different accumulated experience). Particularly in population-learning, the differences in the accumulated experience prior to data observation period are important. We thus included fixed effects for each category to capture time-invariant heterogeneity including accumulated experience (Ingram & Simons, 2002).[2] Given that the app store was experiencing rapid growth during the sample period (Yin, Davis, & Muzyrya, 2014), we need to take into account unobservable time effects. We thus added time fixed effects in our model. Finally, we use Huber/White robust standard errors to correct for heteroscedasticity.

5. MEASURES

Performance Metrics. To extract the collective intelligence factor, c, we used three performance metrics of categories that are critical in Apple's mobile application ecosystem: 1) the *proportion of apps ranked in top 300 download ranking* (adoption), 2) the *proportion of apps ranked in top 300 gross sales ranking* (commercialization), and 3) the *proportion of updates for app in a category* (viability). The first measure captures software adoption based on whether users actually downloaded apps to their devices. The second captures commercialization with a revenue metric (based on both sales of the apps plus in-app purchases). The third and final is a measure of viability of apps, an important criteria for maintaining consumers' attention and interests on the apps (Bresnahan et al., 2015; Yin et al., 2014).[3] The first two measures are based on the collection of daily lists of the top downloaded free and paid apps overall, and of the top grossing apps. From the lists, we calculated the total number of times that the apps in the category were ranked in these lists, and then divided the figure with the total number of apps in the category in each week. For the last measure, we attended to the release dates for each version of the apps, and then we calculated the total number of updates for the apps in the category for each week, divided by the total number of the apps in the category for each week.

To further check of validity of the constructed factor, we considered the *user ratings for apps* in the category as a criterion test. In the App Store, any consumer who downloads an app can rate the app from 1 to 5 "stars" (with 5 being the best) with a review to provide qualitative feedback about the app. We calculated average ratings for each app from the population of consumers' ratings for our sample. Then we aggregated these into each category and divided by the number of apps in the category.

Independent Variables. We included any comment with one or more word from the release of the apps in measuring the *number of comments received by apps* in the category. We first calculated the total number of comments received by the apps in the category, and then divided with the total number of apps

2 Nevertheless, the random-effects and population average models yielded the same results as fixed-effects.
3 In-app advertisements are not counted for the top grossing.

in the category. The *degree of category spanning* was measured as the average Herfindahl index of the firms producing any app in the focal category.

$$H = \sum_{i=1}^{18} s_i^2$$

where s_i is the proportion of apps in a category i relative to the total number of apps across 18 categories released by a firm. This measure ranges from $1/18$ to 1, with 1 indicates a complete focus on a category by a firm. We averaged this measure across all firms in a category.

As a robustness check, we tested two alternative measures of the category-spanning diversification: the *number of firms producing in the other category besides the focal category*, and the *number of categories spanned by firms in the focal category.* The former was measured by the number of firms that have released apps in other categories beside the focal category, divided by the number of firms in the category. The latter was measured by the total number of categories in which the firms in the category have released any app, divided by the number of firms. These alternative measures had little bearing on the findings (available upon request).

Controls. In addition to the independent variables, we controlled for other variables that may influence category performance and the emergence of collective intelligence at the category level. We paid particular attention to ruling out the quality differences between firms in the category as an alternative explanation for persistent performance differences among categories—a key difference that is needed to be made from collective intelligence (Engel et al., 2014; Woolley et al., 2010). We specifically used three different dimensions of the firms' capability. First, we controlled for the *firm app rating* to proxy the average group members' intelligence. This was measured by the running-average of ratings for the apps that were released by the firms for each week. We also controlled for the *number of apps' versions released by firms,* measured by the average number of distinct versions of apps released by the firms in the category, to capture the firms' cumulative experiences of releasing and revising their innovations. In the context, most companies tend to update their apps frequently not just to amend the errors but also to update the major part of their apps, including design, key features, and functions. Thus each version represents an appropriate unit to measure firms' experience. Furthermore, we also included the *average release times between apps of firms*, measured by the average number of days between different apps released by the firms, to capture the firms' cumulative ability to rapidly innovate. In addition to these measures of firm capability, we included the *change rates for the number of apps*, measured by the percentage difference of the number of apps in a category compared to the figure from the last week, in order to capture the effect of entry and elimination of members on the emergence of collective intelligence among themselves (Miner & Haunschild, 1995).

We lagged all independent and control variables by a week to enhance causality (the similar results were attained when lagged by two weeks). Also, we centered category spanning diversification to lower collinearity with squared term and ease interpretation.

6. RESULTS

Table 2 represents descriptive statistics and zero-order correlations between variables. Note that for regression analyses for testing hypotheses 2 and 3, we use only variables with number 6 to 12 (shaded area; as explanatory variables), with the variable number 1 (as dependent variable).

— Insert Table 2 about here —

Some of the variables show mid- to high-range of correlation (0.409 - 0.799), indicating a potential collinearity problem.[4] Multicollinearity increases standard errors and makes it less likely that coefficients will be statistically significant. That is, strong correlations between explanatory variables—like those between *degree of category spanning* and its squared term—and between them and controls—like those between *degree of category spanning* and *number of apps' versions released by firms* or *change rates for the number of apps*—will work *against* us in finding any significant effect for hypotheses. To check this, we conducted three different tests. First, we reestimated all models by orthogonalizing variables. This technique subtracts the vector from its projection, partialling out the common variance among variables (Cohen, Cohen, West, & Aiken, 2003). In other words, it creates a set of new variables such that the "effects" of all other variables have been erased from each other. Many studies have used this technique for dealing with collinearity (e.g., Alcácer & Zhao, 2012; Ingram & Simons, 2002; Pollock & Rindova, 2003; Sine, Haveman, & Tolbert, 2005). We specifically used a modified Gram-Schmidt procedure using orthog routine in Stata 14. We found the same results from the orthogonalization. Furthermore, we did not observe any instability in the estimated coefficients when variables were added hierarchically or when the first- or last-week observations were dropped (Greene, 2012; Kennedy, 2003). Similarly, the parameter estimates were not substantially changed when we estimate our models on random subsamples from each category of the data (Greene, 2012). Thus, we concluded that collinearity might not cause a serious concern in our estimates.

In Hypothesis 1, we predict the existence of a collective intelligence factor (*c*) in categories of apps. The results from dynamic factor analysis and regression analysis based on the criterion metric support this Hypothesis. First, the average inter-item correlation for different performance metrics (items 2 to 4 in Table 1) is positive (r = 0.335). Next, dynamic factor analysis yielded one factor with an initial eigenvalue accounting for more than 83.71% of the cross-sectional variance for the performance metrics, whereas the next factor accounted for only 8.90%. In addition, the 'first' proposed factor captured a significant portion of the between-times variance (which is devoid of the cross-sectional variance) of two of three performance metrics; when we regressed the between-times variance on the proposed model, the model explained 84.62 percent of the variance of the proportion of apps ranked in top 300 downloads (i.e., R^2 = 0.8462) and 74.98 percent of the variance of the proportion of apps ranked in top 300 gross sales ranking (i.e., R^2 = 0.7498).[5] Furthermore, when the factor loadings for the different performance metrics on the first general factor were used to calculate a *c* for each category over time, this score significantly predicted the criterion metric of the average user ratings for apps (B=8.706, p = 0.000), above and beyond what the average cumulative ratings for the apps released by firms so far predicts (B=1.116, p = 0.005).

── Insert Table 3 about here ──

If *c* exits, what causes it? In Hypothesis 2, we predict that *c* will be facilitated by the lively audience-producer interactions through comments posted in the App Store. Table 3 represents the results of the relevant analysis. The findings in Models 2 and 4 strongly support Hypothesis 2. Specifically, the estimates suggest that as apps in the category receive more comments from audiences, the more likely *c* is to emerge even after controlling for the variables for firms' capabilities and changes in the number of apps, in addition to category- and time-fixed effects.

In Hypothesis 3, we also posit that more diversification activities by the firms in the category will facilitate the emergence of *c* to a certain degree, but then impede it. In Models 2 and 4 of Table 3, we found a strong support for this Hypothesis. The results suggest that the degree of category spanning diversification by firms has an inverted U-shaped relationship with *c*.

── Insert Figure 1 about here ──

[4] Variance Inflation Factor (VIF) were between 7 to 8 for all models except the full one, which showed 11.48. The recommended cutoff is 10 for VIF Neter, J., Wasserman, W., & Kutner, M. H. 1985. ***Applied Linear Statistical Models*** (2nd ed.). Homewood, IL: Irwin..

[5] The proposed model explains about 10 percent of the between-time variance of the number of updates for apps.

We plot this relationship in Figure 1 based on the estimates from Model 4 of Table 3. This graph was drawn based on the estimates for Games category—the category with largest number of apps.[6] Bars in the figure indicate 95% confidence intervals. The graph clearly shows that a positive effect of the degree of category spanning diversification on *c* decreases as the diversification increases further after a certain point.

A few other findings are noteworthy. Estimated coefficients from the *number of apps's versions released by firms* suggest that *c* tends to emerge more among more experienced firms. This is consistent with previous research on population-level learning, which suggests a positive effect of accumulative experience of other firms in the population on a firm's learning (Ingram & Baum, 1997; Ingram & Simons, 2002). In addition, categories with larger number of news apps were more likely to develop *c* among themselves compared to those that experienced a loss in members. This is also consistent with prior proposition in the population-level learning literature, which posits that new firms tend to incorporate new routines at time of founding—drawing on the experience of other firms—whereas existing firms that are unable to adept tend to be selectively eliminated (Argote, Beckman, & Epple, 1990; Baum & Ingram, 1998; Miner & Haunschild, 1995).

7. DISCUSSION AND CONCLUSION

Literature on organizational learning has provided a valuable understanding of how firm characteristics and different learning modes influence aggregated-level outcomes (Ingram & Simons, 2002; Miner & Haunschild, 1995). Yet it has been difficult to find evidence of persistent learning differences across populations, particularly whether groups (sub-populations) might learn from other groups (sub-populations), perhaps because of the difficulties of identifying suitably large and comparable data from which population-level inferences can be made without reference to few, large idiosyncratic organizations that account for most learning. Using a data on one of Apple application ecosystems, we seek to redress this neglect. The findings from dynamic factor analysis showed the existence of the group-level learning and collective intellgience, which persistently influence several important dimensions of group-level performance even after controlling for the average firms' performance in the group. The results also suggest that such group-level learning is not only influenced by active feedback from audiences to the firms in the group (*within-group learning source*) but also by the firms' experience of crossing-group diversification (*across-groups learning source*).

This study focuses on the collective-level learning and outcomes, yet future research can examine individual-level outcomes and the collective-level ones simultaneously. In the context of young communities like entrepreneurial ecosystems, growth of the entire ecosystem is important for individual organizations in it, given the competition with other similar communities for audiences' resource and support (Gawer & Henderson, 2007; Navis & Glynn, 2010). However, learning at aggregated-level is not always consistent with that at individual-level, and also there must be a certain degree of variation in strategies and performances of individual organizations in the group (Santos & Eisenhardt, 2005). It is important to examine how those different levels interact, and what strategies firms can use to contribute to the growth of a larger group while they still compete with others in the group.

Nevertheless, our study makes two important contributions to research on group-level learning. First, it shows the importance of considering firms' operations and behaviors occurring across-groups on the top of those occurring within-groups. Organizational research has a long-held tradition of analyzing how individuals and organizations cross sociological and economic boundaries, and how such activities affect important outcomes at firm- as well as group-levels (e.g., Henderson & Clark, 1990; Montgomery & Wernerfelt, 1988; Rao, Monin, & Durand, 2005; Schumpeter, 1934). However, research on group-level organizational learning (Ingram & Simons, 2002; Miner & Haunschild, 1995) has not considered such type of organizational operations in modeling the group-level outcomes. The results of this study suggest that this negligence might lead to a biased estimator of learning effect.

[6] The results from other categories showed the same inverted-U pattern.

Consider, for an example, a case where the cumulative production experiences of organizations in a group is measured to see its influence on the group-level outcomes. These cumulative experiences might include productions of different products, and such measures may produce upwardly biased estimation for the effect of experiences (when cross-boundary experiences are relatively low) or downwardly biased (when the cross-boundary experiences exceed a certain threshold). Hence, studies need to differentiate experiences and operations of companies in a group.

Second, we suggest a new way of measuring the outcomes of group-level learning of "collective intelligence" at the organizational level. While the literature on group-level learning emphasizes the change in shared routines or norms as a main driver of group-level outcomes (Miner & Haunschild, 1995; Miner et al., 1999), the difficulty of observing such a change has constrained systematic research based on archival data. By extending a theory on collective intelligence (e.g., Woolley et al., 2010), we took the opposite approach; rather than trying to measure the change in routine – which exhibits diverse performance dimensions – we seek to extract the change in routines from the change in several performance dimensions. Given the difficulty of observing change in routines (Ingram, 2002), we believe that scholars of organizational learning might be benefited from our approach.

Finally, our study also deepens research on entrepreneurial ecosystems (Gawer & Henderson, 2007; Kapoor & Agarwal, 2016) by examining the factors that might foster the growth of entrepreneurial ecosystems. Recently, more number of governments and corporations around the world are interested in fostering entrepreneurial ecosystem in order to facilitate innovation and economic growth, probably best epitomized by the "Startup America" dedicated to "growing entrepreneurial ecosystems." While literature on innovation have added valuable insights on the importance of ecosystem-based perspective for understanding the innovativeness of particular firms (Adner & Kapoor, 2010, 2015; Gawer & Henderson, 2007; Teece, 2007), less progress has been made on in explaining the persistent differences in innovation across ecosystems or sub-markets of an ecosystem (Bresnahan et al., 2015). We develop a framework through which such heterogeneity across ecosystems can be analyzed. Also, our study suggests the importance of facilitating active audience-producer feedback systems and diversification activities by producers (up to a certain point) for fostering the viability and commercial success of the overall systems.

April 25, 2016 Version

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Table 1: Number of Apps and Firms by Categories of Apps

Category Names	Number of Apps	Number of Firms
Books	53,318 (13.47%)	3,856 (3.35%)
Business	14,673 (3.71%)	6,781 (5.89%)
Education	32,818 (8.29%)	7,983 (6.93%)
Entertainment	42,096 (10.63%)	12,143 (10.54%)
Finance	7,675 (1.94%)	3,843 (3.34%)
Games	57,750 (14.59%)	14,721 (12.78%)
Health	9,913 (2.50%)	4,155 (3.61%)
Lifestyle	27,080 (6.84%)	10,122 (8.78%)
Medical	7,732 (1.95%)	2,765 (2.40%)
Music	17,215 (4.35%)	4,839 (4.20%)
Navigation	8,383 (2.12%)	2,642 (2.29%)
News	11,320 (2.86%)	3,778 (3.28%)
Photography	9,073 (2.29%)	3,630 (3.15%)
Productivity	10,882 (2.75%)	5,638 (4.89%)
Reference	15,628 (3.95%)	4,137 (3.59%)
Networking	7,469 (1.89%)	3,689 (3.20%)
Sports	14,230 (3.59%)	4,324 (3.75%)
Travel	22,977 (5.80%)	4,838 (4.20%)
Utilities	23,580 (5.96%)	10,427 (9.05%)
Weather	2,061 (0.52%)	909 (0.79%)
Total	395,873 (100%)	115,220 (100%)

Note: Based on a population of 395,873 apps and their developers observed on iTunes (the United States market) between September 6, 2010 and August 31, 2011

Table 2: Descriptive Statistics and Correlation Table (N=1,188)

	Variables	M	SD	Min	Max	1	2	3
1	Collective intelligence (*c*)	0.019	0.015	0.001	0.106	1		
2	Proportion of apps ranked in top 300 downloads	0.015	0.014	0	0.091	0.962	1	
3	Proportion of apps ranked in top 300 gross sales	0.007	0.008	0	0.056	0.905	0.814	1
4	Proportion of updates for apps	0.032	0.028	0	0.257	0.276	0.103	0.087
5	User ratings for apps	2.024	0.394	0.892	2.708	0.663	0.671	0.582
6	Number of comments received by apps	1.439	0.739	0.453	4.852	0.794	0.814	0.703
7	Degree of category spanning	0	0.199	-0.429	0.58	-0.262	-0.281	-0.133
8	(Degree of category spanning)^2	0.039	0.069	0	0.336	-0.055	-0.048	-0.049
9	Firm app rating	1.940	0.383	0.863	2.673	0.66	0.66	0.591
10	Number of apps' versions released by firms	4.388	1.449	1.516	11.085	-0.254	-0.267	-0.151
11	Avg. release times between apps of firms	0.062	0.482	-0.955	6.235	-0.015	-0.004	-0.004
12	Change rates for number of apps	49.939	12.090	22.23	94.346	0.581	0.556	0.482

	4	5	6	7	8	9	10	11	12
4	1								
5	0.097	1							
6	0.068	0.749	1						
7	-0.18	-0.468	-0.184	1					
8	-0.032	-0.425	-0.102	0.633	1				
9	0.101	0.975	0.077	-0.465	-0.409	1			
10	-0.145	-0.281	-0.075	0.799	0.485	-0.265	1		
11	-0.063	0.006	0.001	0.078	-0.053	0.004	0.075	1	
12	0.259	0.717	0.521	-0.735	-0.391	0.723	-0.604	-0.026	1

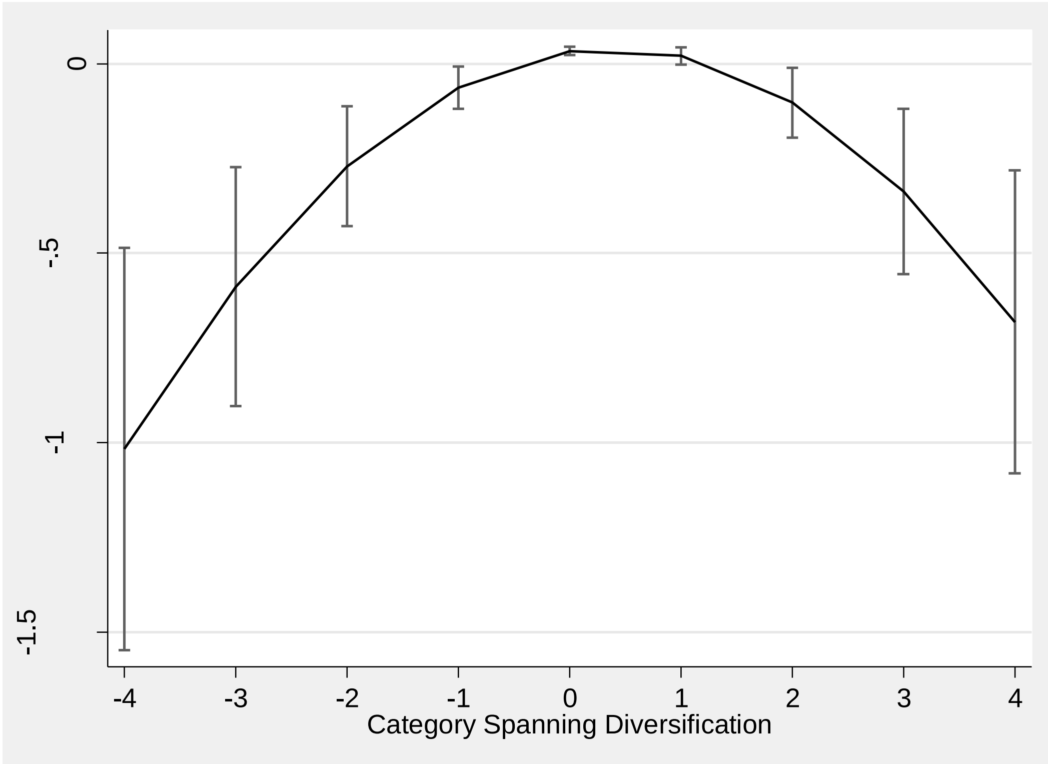
Note: Gray area indicates explanatory variables used for Table 3

Table 3: Predictors of Collective Intelligence of Categories

Variable	Model 1	Model 2	Model 3	Model 4
Predictors				
Number of comments received by apps (H2)		0.003* (0.001)		0.003** (0.001)
Degree of category spanning (H3)			0.042** (0.012)	0.042** (0.012)
(Degree of category spanning)^2 (H3)			-0.051** (0.014)	-0.055** (0.014)
Controls				
Firm app rating	-0.009* (0.004)	-0.012** (0.004)	-0.001 (0.005)	-0.005 (0.005)
Number of apps' versions released by firms	0.002** (0.001)	0.002* (0.001)	0.002** (0.001)	0.002* (0.001)
Avg. release times between apps of firms	0.001* (0.001)	0.001* (0.001)	0.001+ (0.001)	0.001+ (0.001)
Change rates for number of apps	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
Constant	0.014** (0.003)	0.010** (0.003)	0.021** (0.004)	0.017** (0.004)
Fixed effects for app categories	Yes			
Fixed effects for weeks	Yes			
R^2	0.896***	0.898***	0.900***	0.902***

Note: N=1,188 (18 categories X 66 weeks); *** p < 0.001; ** p < 0.01; * p < 0.05; † p < 0.1; robust standard errors in parentheses

Figure 1: Curvilinear Effects of Category Spanning on Collective Intelligence of Categories



Note: Bars indicate 95% confidence intervals; graph is based on observations from *Games* category; category spanning diversification was centered