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Relation-specific creative performance in voluntary collaborations: A micro-foundation for competitive advantage?

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Abstract

A fundamental question in the strategy literature is how sustainable competitive advantage can be generated within one firm and yet difficult to copy by another. We offer one solution to this conundrum by way of relation-specific performance that is developed in creative projects ? where the individuals involved have significant latitude on the intended objectives as well as their collaborators on these projects. Because higher-level cognition is involved in navigating such projects from conception to implementation, there is heightened relation-specificity in their performance ? as measured by how widely they are adopted by third-party users. This relation-specificity means that any performance improvement as a result of repeated collaborative efforts of a group of individuals is difficult to emulate or sustain outside of this specific group. This thus offers one way to simultaneously address several important critiques of the resource-based view of the firm. We rely on a novel set of data on user-written Facebook applications to demonstrate the relation-specificity of creative performance.

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ABSTRACT

A fundamental question in the strategy literature is how sustainable competitive advantage can be generated within one firm and yet difficult to copy by another. We offer one solution to this conundrum by way of relation-specific performance that is developed in creative projects – where the individuals involved have significant latitude on the intended objectives as well as their collaborators on these projects. Because higher-level cognition is involved in navigating such projects from conception to implementation, there is heightened relation-specificity in their performance – as measured by how widely they are adopted by third-party users. This relation-specificity means that any performance improvement as a result of repeated collaborative efforts of a group of individuals is difficult to emulate or sustain outside of this specific group. This thus offers one way to simultaneously address several important critiques of the resource-based view of the firm. We rely on a novel set of data on user-written Facebook applications to demonstrate the relation-specificity of creative performance.

Key Words: Voluntary collaborations, teams, learning, creativity, performance

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INTRODUCTION

A fundamental question in the strategy literature is how sustainable competitive advantage can be generated within one firm and yet difficult to copy by another. For instance, the resource-based view (e.g., Barney 1991, Mahoney and Pandian 1992) postulates that the rare resources mobilized by a firm give rise to its competitive advantage, yet if the rarity of these resources is known ahead of time, they would be priced so high as to neutralize any competitive advantage (Priem and Butler 2001). Building on the evidence of firm-specific knowledge (Helfat 1994; Wang et al. 2009), this study proposes and shows evidence of the development of such knowledge – specific to those individuals who develop it (i.e., 'relation'-specific) – in an entrepreneurial setting prior to the start of a formal business venture. We regard such development as a precursor of how certain individuals choose to work by their own volition with the same partners (possibly under a formalized setting at a later time) and how the process through which performance improves can be difficult to copy for other firms.

Our reasoning is as follows: for projects that require much high-level cognitive thinking, a constant exchange of ideas or an artful combination of resources to refine an initial 'product' concept (such as starting a new business venture), repeated engagement with the 'right' partner over time can lead to significantly superior performance compared with collaborating with others or working alone. Precisely because such performance is a result of an exchange of ideas between two individuals or among a group of individuals, the performance improvement achieved can be difficult to transfer outside of this set of relations: one individual from this group working alone on the next project is unlikely able to replicate the superior performance achieved as a group, even if he/she works with another partner.   As we shall demonstrate, this performance improvement extends beyond familiarity among one another: given the same extent of prior collaborations, collaborating with one partner may lead to significantly different results than collaborating with another.

We focus on the performance in terms of (third-party) user adoption of creative projects (hence ‘creative performance’) – where individuals voluntarily sign on to develop a project, decide on its objective or functionality, and implement it for others to use or adopt for a combination of expressive, esthetic or utilitarian purpose. The potentially esthetic aspect of the final product of these projects includes what scholars have termed ‘cultural products’ (Hirsch, 1972:641). In a broad sense, these projects also include instances of entrepreneurs starting new ventures – they need both good vision and execution to succeed (Bricklin 2001). Creative projects inherently have high variance in performance (and therefore difficult to predict and price *a priori*), thus requiring much thoughtful planning – beyond exploitative searches – to deliver superior performance.

The contexts in which repeated exchanges of ideas and/or resources can generate relation-specific performance improvements likely involve a higher-level cognitive element than mere task repetition. If task repetition is key to performance improvements, as in contract software programming, medical surgery and financial analysis, (e.g., Huckman and Pisano 2006; Espinosa et al. 2007; Groysberg, Lee and Nanda 2008), relation-specific performance improvements can still arise based on the degree of familiarity of the collaborating individuals (since familiarity improves coordination and hence repeated tasks). We argue that this form of relation specificity is only a ‘weak’ form because any partner with whom a focal individual has had the same level of prior collaboration should achieve comparable performance.

In situations where the outcome is ambiguous and no established procedures are evident, individuals likely have to adjust their ideas as they proceed with their investigations. In this way, each round of feedback becomes more important in shaping the final outcome, and the performance improvement becomes entwined with the specific collaborative relation. As the exchange of ideas involve more than experience-based proficiency, performance improvements attained as a result may be attributed to specific individuals – not merely their prior history of collaboration (‘team familiarity’). In this sense, we describe this form of relation-specificity as a stronger form than performance based on team familiarity alone.

Since distinctive performance in creative projects can be difficult to replicate outside of such collaborative relations, it can serve as a micro-foundation to a sustainable distinctiveness in the creative capacity of the formal organization borne out of these relations. In this manner, this process simultaneously addresses several important critiques of the resource-based view (e.g., why such valuable resources were not properly priced in the first place), and offers an alternate explanation on why individuals would – beyond organizational efficiency (Williamson, 1981) – continue to voluntarily work with one another in the form of formalized organizations.

The rapidly growing reach of the internet, specifically ‘web 2.0’ platforms such as Facebook provides new, profitable opportunities for individuals to explore, and some publicly available information provides a rare opportunity to study how individuals capitalize on opportunities they conceptualize on their own, and at times, collaborate with one another in a comparable context. The user-developed Facebook applications (or simply, ‘apps’) provide us with a novel data set of how individuals or groups of individuals pursue their recognized opportunity in the novel, unstructured domain of social media. We compile a unique data set on the collaboration history and performance of Facebook apps developed within the first calendar year that such apps were allowed to be posted and downloaded by other Facebook users.

The remainder of the paper is organized as follows: we develop our theory and hypotheses next, followed by a discussion on the context of Facebook apps, and our data and methodology. After these, we show our econometric results, and discuss their limitations and implications.

THEORY AND HYPOTHESES

To foreshadow our theoretical development, we seek to understand the nature of relation-specificity in projects where individuals have the choice of either working alone or collaborating with others by first describing two basic elements of such specificity: mutual selection and collaborative idea generation as key characteristics in voluntarily collaborating groups. Based on these characteristics, voluntarily collaborating groups is not necessarily the norm in contexts where individuals can work alone – and hence the prevalence of lone or lead entrepreneurs in business ventures. Our focus on individuals working together identifying an opportunity, solidifying toward a goal for their creative project and ultimately implementing it provides a magnified view of how Mahoney and Michael's (2005) subjectivist theory of entrepreneurship (Kor et al. 2007) may unfold in a real setting.

We next explore a weak form of relation-specific performance – a consequence of team familiarity in the learning literature (e.g., Boh et al. 2007). Performance improvements based on increased team familiarity are specific to a particular pair or group of individuals because of their history of collaboration – something that cannot be replicated immediately for all other potential collaborators. We then explore a strong form of relation-specific performance that goes beyond team familiarity: for a focal individual who ultimately collaborates with others, there exists a favorite partner such that repeated collaborations with this partner would improve performance more than repeated collaborations with another individual. Meanwhile, we frame our hypotheses around the concept of creative projects – allowing the individuals involved to have considerable latitude on the ultimate objective, actual implementation and the overall 'look and feel' of the final product or services. This adds an additional dimension to individuals simply working to fulfill a pre-determined need or work request in typical work-related tasks in the learning literature.

The Collaboration Choice when Working Alone is also Viable

To understand the motivation behind individuals working together when they could otherwise work alone (and many entrepreneurs in successful businesses do work alone, or take on a leadership role in team composed of subordinate-like members), we need to look at settings whether individuals working together do so voluntarily – not because one or more of them are hired by one another. Unlike studies on teams in the work environment, where most of the team members are pre-assigned (e.g., Edmondson 1999), we draw on a small stream of literature on voluntary collaborations based on scientific and academic researchers.

Scientific and academic researchers generally have considerable autonomy as to what they want to achieve in their research projects, as well as with whom to collaborate – akin to our context of creative projects. Studies on the collaboration choices of these researchers point to 'strong pragmatism' as the primary motivation (Melin 2000). That is, individuals seek out and evaluate their prospective partners based on who would deliver better results with their skills, networks or access to resources. Between the two most-cited reasons for collaboration – work-related resources and reputation, the former have far more influence on the decision whether to work alone or to collaborate with others (Whitley 2000; Beaver 2001; Birnholtz 2007).

The pragmatic attitude on the choice between working alone versus collaborating with others is a double-edged sword in the sense that it applies to all the individuals in question. For an individual to collaborate with another on a project, both sides have to be convinced that collaborating with each other would offer better results than working alone. This mutual selection means that, if the collaboration decision is purely meritocratic, an average project idea that excites two individuals sufficiently to be collaborating with each other is likely to generate more desirable results than a project that is undertaken by a solo individual.

In addition to the mutual selection argument, the collaborative efforts likely yield better-quality ideas in the context of creative projects. A creative project is ‘a search for novelty’ (Lampel et al. 2000:266) – a departure from past routines and closely related to innovation (see Crossan and Apaydin, 2010, for a review). While creativity itself is difficult to define (Amabile 1996), creative ideas typically originate from novel combinations of elements of pre-existing ideas (Hatch 1998; Simonton 1999; Fleming, Mingo and Chen 2007). Paulus and Yang (2000), and Vera and Crossan (2005) conclude that the larger and more diverse skill set in a group allows more combinations of ideas – suggesting a higher capacity of creative development than a lone individual. As such, having someone to constantly inject a different perspective is conducive to the formative stage of idea generation (Staw 1995). In this regard, Dencker et al. (2009) show that changes in the product line of new firms statistically improve their survival odds. This can be summarized as follows:

Hypothesis 1 (H1): In general, creative projects involving a single individual working solo attain lower performance than those involving more individuals voluntarily collaborating with one another.

The pragmatic consideration on whether or not to collaborate with an individual is complicated by concerns about information confidentiality and benefit distribution. Jointly pursuing an opportunity with someone else necessitates the sharing of commercially sensitive information with a partner. Meanwhile, acquiring and maintaining an equitable sharing of net benefits from and allocation of upfront investment to a collaborative project can further increase the threshold to enter a collaborative venture for an individual who could otherwise work alone. Indeed, in spite of the increasingly large demands on resource requirements and hence stronger pressure for collaborations, half of the inventors in Fleming et al.'s (2007) survey of U.S. utility patents were developed by a solo inventor. Other studies such as Reagans and McEvily (2003) confirm how a cohesive team – where information is better shared than a non-cohesive one – is conducive to contract research and development work. Trust and prior working relations can ease these concerns, but at the same time the lack thereof can complicate Hypothesis 1. On the one hand, a focal individual may choose to decline a collaboration opportunity even if it is likely to be profitable, simply because the level of trustworthiness of the prospective collaborator is unknown. Since researchers typically observe only collaborations and not attempts to collaborate, this scenario is difficult to detect – but generally resulting in far more solo projects than collaborative ones. On the other hand, for a focal individual with familiar collaborators, he or she may gravitate toward his or her trusted collaborators for constructive feedback and may well involve their collaborators in the project as a result of such interactions in the past instead of seeking new partners or working alone. In this case, we would observe that among those individuals who readily collaborate with others, creative projects undertaken solo may not perform that much worse than collaborative ones.

Relation-Specific Performance Based on Team Familiarity

The effect of working with familiar faces (including those in cyberspace) is one important contributor to relation-specific performance improvements, as demonstrated in many studies (e.g., Reagans et al. 2005; Boh et al. 2007). However, Espinosa et al. (2007) show how the performance-enhancing effect of task familiarity – the experience of an individual in delivering similar predetermined goals – declines as task complexity increases, but how its importance increases when team coordination is more challenging. Both Reagans, Argote and Brooks (2005), and Huckman, Staats and Upton (2009) underscore how the cumulative experience of a group of individuals working together – and not just working in the same company – promotes effective coordination and teamwork.

Groysberg, Lee and Nanda (2008) indirectly use team familiarity to explain in part the often long-term decline in performance exhibited by star financial analysts. In that study, team familiarity mitigates the adverse performance impact brought about by a change of institutions for star financial analysts – those who move with the rest of their former work teams suffer less significant performance deteriorations. Studying the quality of cardiac surgeries, Huckman and Pisano (2006) document how the performance of freelance cardiac surgeons at a specific hospital improves with recent increases in his or her surgical volume at that hospital but not with surgical volume at other hospitals. This highlights the importance of institution-specific factors on performance, possibly the rest of the operating team and equipment capability. Similar effects of familiarity on performance have been documented on repeated interactions between organizations (e.g., Rowley et al. 2000; Argyres and Mayer 2007; Vanneste and Puranam 2010).

The effect of team familiarity to performance contributes one form of relation-specificity in performance in the sense that for a focal individual, collaborating with a more familiar individual (in terms of prior collaborations) will translate into higher performance than collaborating with a less familiar individual. We describe this form of relation-specific performance as 'weak' because the performance is ultimately tied to familiarity – or prior collaborations – between specific pairs (or groups) of individuals. That is, if a focal individual has had equal collaborative experience with two other individuals, he or she should expect comparable performance when he/she collaborates with either one of these two individuals. The relation-specific performance based on team familiarity can thus be summarized as follows:

Hypothesis 2 (H2): The number of prior collaborative projects with the same partner has a positive impact on performance.

Working with Different Partners Brings Different Results

Task and team familiarity are two pillars of performance improvement in the literature of organizational learning, in a range of study contexts ranging from software programming to medical surgeries. A unifying characteristic in these diverse contexts is that they involve tasks with pre-determined goals, such that individuals can perfect their skills through repeated practice. For instance, software programmers examined in Boh *et al*. (2007) worked on modification requests generated by someone else in a telecommunication firm. Reagans *et al.* (2005) examine the performance of specific joint replacement surgeries: total knee replacement and total hip replacement – both with established surgical routines.

In the general context of creative[1] projects, individuals are involved not only in searching and implementing a solution to a well-defined problem, but more crucially, also in the design as to what they want to achieve in the first place. Software developers working on creative projects may initially decide to design a program that broadcast the travel itinerary of a user on his or her website, but then change their minds to design instead a program to broadcast the same information only to specific individuals with close ties to this user – simply because the latter may be considered to have better prospects for business users, and not necessarily because the latter is technically simpler or more cost-effective to accomplish.

The recognition of where demand may originate, and how an existing idea can be tweaked to improve performance require the kind of meta-level thinking that goes beyond mere repetition. Just as there is no rule-book to success for budding entrepreneurs, there are no established routines for creative projects, or simply to be creative in general (Amabile et al. 1996). In studying how individuals improve their performance in playing simple board games, Schilling *et al*. (2003) draw on earlier works to show how individuals have the capacity to develop abstract schemas underlying different tasks, and attain implicit learning – the recognition of 'critical co-variations in the environment' – even though they may not be aware of these (e.g., Graydon and Griffin 1996; Wulf and Schmidt 1997). They note that as an individual specializes in repeatedly playing the same game he/she may accrue specialization benefits, but he/she is likely forfeiting some deeper cognitive processing from playing a different game.

Studying the network ties of patent developers, Fleming et al. (2007) highlight one avenue through which new ideas are generated and incorporated in patents: novel combination or rearrangements of ideas, technologies, processes, etc. (Simonton 1999). They find that

[1] We follow the definition of creativity in the extant literature as 'the generation of domain-specific, novel, and useful outcomes' (Tierney and Farmer 2002).

individuals occupying certain positions in a network of collaborations increase their productivity in developing patents, although they may not help much in the diffusion and use of these patents. Studying how children build miniature towers, Reagans, Argote and Miron-Spektor (2011) showed how constant information sharing and collaboration may not always lead to performance improvements, especially before each individual has developed specialized knowledge. These two studies project a less uniform and potentially asymmetric view of team familiarity.

Putting these findings together, we see how the meta-level perspective that is crucial for a commercially successful creative project to develop may be possible only with certain combinations of individual collaborators – such that 'unexpected mental connections' can be made (Schilling 2005). Perhaps because of differences in prior experience, resources available or communication hurdles, different partners may bring about different changes to an original idea – resulting in different levels of performance. In other words, for a focal individual who readily collaborates with others, there may be at least one 'favorite' collaboration partner with whom performance improvement over successive business ideas is much higher than the corresponding performance when collaborating with other 'non-favorite' partners. There are two possibilities in which this performance difference can play out, as phrased in these hypotheses:

Hypothesis 3a (H3a): For a focal individual, collaborating with his/her favorite partner results in better performance.

Hypothesis 3b (H3b): For a focal individual, repeatedly collaborating with his/her favorite partner results in better performance than repeatedly collaborating with others.

There is a subtle difference between Hypotheses 3a and 3b. Hypothesis 3a refers to a 'quantum leap' of performance whenever a focal individual collaborates with his/her favorite partner, and if confirmed, there may be a problem of endogeneity: the focal individual rationally chooses to collaborate with his/her favorite partner after their first collaboration because it clearly brings higher performance than collaborating with others (as shown in Schwab and Miner 2008) – the focal individual likely expects that this performance differential to persist upon choosing to continue the collaboration. Hypothesis 3b postulates a more gradual performance improvement, and if it is confirmed but not Hypothesis 3a, then it is only through repeated collaborations that a focal individual discovers the performance differential between collaborating with his/her favorite partner versus others. In this case, the focal individual may have some inkling on the performance potential of his/her favorite partner, but cannot be sure until he/she collaborates with the favorite and perhaps other partners for a few more times. This uncertainty may result because for a partner to meaningfully bring up new ideas in a creative context, one needs to understand the status quo – or where the focal individual is coming from, and vice versa. In the creative context of improvisational jazz, Barrett (1998: 606) emphasizes that 'learning to play jazz is a matter of learning the theory and rules that govern musical progressions. Once integrated, these rules become tacit and amenable to complex variation and transformation, much like learning the rules of grammar and syntax as one learns to speak.' In a similar way, a lack of prior collaborations can hinder the exchange of ideas between two individuals – even if the right collaborator is involved.

Our nuanced view that repeated collaborations with certain individuals can differentially improve the performance of creative projects with some compared with others is consistent with the latest findings on the effect of embedded, repeated exchanges between individual actors on firm performance. Traditionally, scholars believe that repeated transactions between individual actors tend to associate with positive performance (e.g., Rowley et al. 2000). More recent studies highlight evidence of the opposite: scarce resources can be misallocated to projects whose key personnel have had prior exchange relations with focal individual actors (e.g., Sorenson and Waguespack 2006). In other words, prior collaborations – even though they are sufficient to alter the decisions for individual actors – may not necessarily bring about improved performance because individuals enter into such collaborations with a biased view that past collaborations are a good indication of future performance. In a context where the performance of a business idea cannot be tightly controlled by a focal collaborator (e.g., it is determined by the reception of the public), it is possible to have an even stronger form of relation-specific performance:

Hypothesis 3c (H3c): For a focal individual, repeatedly collaborating with a non-favorite partner results in increasingly poorer performance.

In any case, we reduce any endogeneity concerns by choosing a context where past success is not likely tied to future successes because performance is measured by the number of downloads effected by users other than the developers, unlike traditional efficiency-related measures that are easily controlled by the individuals involved. Our survey of Facebook users reveal how the functionality and esthetics of a particular app remain the two most important factors influencing whether they would download it.

DATA

Few studies document how opportunities are recognized or creatively developed, largely because of a lack of data. From the perspective individual entrepreneurs, detailed studies of their experience can involve much idiosyncratic information that is difficult to generalize (Gruber 2010). Instead, we focus on a context in which individuals can voluntarily choose their collaboration partners, with publicly available information on performance: we assemble a novel data set from the emerging phenomenon of application (or simply 'app') development by individuals in the popular social networking website Facebook for our empirical support.

We choose data on user-written Facebook apps for several reasons. First, this is a context where individuals involved in one project can disband or re-group for the next – consistent with an established stream of papers on project-based work and collaborations (Ferriani, Cattani and Baden-Fuller 2009). Second, in the context of social networking, profit-minded individuals develop apps to reach as many users as possible (similar to movie production), much akin to atomistic entrepreneurs seeking profitable opportunities and working toward implementing them in a subjectivist's perspective of entrepreneurship (Mahoney and Michael 2005; Kor et al 2007). In particular, the user download performance is far more difficult for the developers to predict in advance than, say, how efficient their developmental effort would be. Since the downloading and installation of each App is voluntary for Facebook users, the number of installations, or downloads, of a particular App represents an independent measure of its utility or value. Much more so in Facebook apps than in motion pictures, users select which apps to download based on their functionality or esthetics, but not so much on who developed them. This alleviates concerns of endogeneity between the performance of a collaboration project and the choice of partners based on prior collaborations.

Third, unlike large-scale creative projects such as motion picture production, the performance of a Facebook app is not confounded by the influence of intermediaries like distributors or marketing agents (Jones 2001; Thornton 2002). Fourth, the performance of a Facebook app depends not so much on the technical know-how on API programming but more on how a specific app is used. While technical instructions on how to develop apps can be found in many places in the internet, some simple Apps displaying cartoon pictures have been downloaded by more than two million users (Richmond 2007). This calls for users to think hard about what kind of apps to develop – requiring much 'meta-level' thinking and exchanges of ideas – instead of learning to be technically proficient. Fifth, unlike other similar platforms such as Apple's iPhone apps, users do not pay a fee to download Facebook apps – thus the performance is not confounded with how expensive an app costs.

Research Context: Facebook Apps

Started in 2004 as a social networking site for students, graduates and faculty members of universities and colleges, Facebook expanded to U.S. high school students in 2005 and to every one over age 13 in 2006. The use of university or college e-mail addresses authenticated the identity of users and sets Facebook apart from its competitors, including Friendster and MySpace, where users often register using pseudonyms. Gradually, Facebook became the social networking site of choice (Hamilton 2007; Andriani 2008). According to industry estimates, nearly half the people who went online in the U.S. in late 2007 visited either Facebook or MySpace – two of the leading social network sites (Hamilton 2007). By early 2008, Facebook reportedly had close to 200 million active members (Nuttall 2009), while in early 2010, Facebook had 350 million active members (Facebook 2010).

In May 2007, Facebook opened an application programming interface ('API') to the public, and invited individual developers to create applications, or 'Apps', for Facebook users. Facebook was the first social network site to allow applications to be developed on its platform, and its Apps generated much excitement among internet entrepreneurs and venture capitalists alike (Richmond 2007). The API requires a different language from existing programming languages (developers have to learn the 'Facebook Markup Language' or 'FBML'), so practically every individual who wishes to develop an application must take time to learn the new programming language. While Facebook apps are downloaded free of charge to users, paid advertisements are just a click away from where apps are downloaded – and the revenue generated from these provides an important motivation for entrepreneurial app developers (Geron 2007). At least one California-based venture capital firm has reportedly raised US $300 million to develop Facebook Apps (Richmond 2007), and many other ventures have followed after our data was sampled (Hagel and Brown 2008). In general, most App developers do not make much money, but the allure of reaching a big audience and reaping sizable profits for relatively very little effort has encouraged many developers to dabble in Apps (Waters, 2010).

Earlier incarnations of Facebook Apps (also called widgets or gadgets), provided by internet giants such as Yahoo!, Google and Microsoft, took the form of small clocks, weather reports, and news headlines users can install to decorate their web-pages. Other Apps integrate features of both traditional software and an online service, such as live data feeds from specific websites. Because downloading an app costs time and effort, users are generally not interested in downloading apps that do exactly what a prior app does – hence developing exact replicas of popular apps is not profitable for developers. Instead, they must develop something with a new functionality or sense of esthetics to appeal to other users. Within three months of the launch of the API, more than 7,000 Apps have been available for users to download. We focus on an early period of the Facebook app environment when developers did not have pre-conceived ideas of what would work and what would not in this environment – they had to learn and explore.

Study Focus: Facebook Apps by High-volume Individual Developers

We collected information on all Facebook Apps (11,837 in total) via a 'web crawl' at the end of 2007 – representing the first half-year of Facebook API (subsequently, the reporting of download statistics changed). Facebook users were generally willing to try Apps developed by novel programmers. Users typically download Apps based on their utility, including 'coolness' (Venkatesh and Davis 2000[2], and Venkatesh et al. 2003).

Facebook apps were either developed by corporate-like entities such as 'Watercooler Inc.' or individual developers, but not both. In our survey, about 40% of apps were developed by organized, corporate-like entities. Apps developed by these entities show no information on the actual individuals involved – we cannot ascertain the development history of the developers involved, or simply how many of them are involved. Thus, we sample only those apps developed by individuals. Of the Apps developed by individual developers (5,749 Apps in total), 75% were by single individuals, and 20% by groups of two.

Method

To ensure that we focus on those individual developers who are keen to maximize the creative performance of their Facebook apps, i.e., see their apps used by as many other Facebook users as possible, we include in our sample only a subset of individual developers who have been involved with at least five completed Facebook Apps at the time of data collection (we do include their first, second, third, and fourth apps). We refer to these individuals as 'high-volume' developers. We account for the bias introduced by this data selection procedure in an additional variable (DataSelectionBias) as per Heckman (1979) – using the same independent

[2] According to Venkatesh and Davis (2000), perceived usefulness and ease of use are excellent (and sufficient) predictors on whether users adopt and use a particular information system/program in a voluntary setting.

variables as in each regression but with one additional variable that is most pertinent to this selection (and not on general performance) – the date of the first apps released by the individual developers (since later releases of their first apps increase the likelihood of the apps not being included in our sample). The high-volume developers released 1166 apps developed by solo individuals, 240 apps developed by two individuals in collaboration, 60 apps developed by three or more individuals working together. Because some of the apps developed by three or more individuals did not list all the names of the developers, and there were relatively few of them, we restrict our app-based analysis to solo-developer apps and dual-developer apps for a crisp comparison. Each app constitutes one observation here.

We sent exploratory email surveys to a number of dedicated developers who had collaborated with others on Facebook apps, and asked for their reason for collaboration. They overwhelmingly cited practicality for inviting others or being invited for collaboration: their creative flair, technical or implementation expertise. This practicality may originate from known capabilities or resources of one another, but new ideas can also be developed over time.
In all, they highlighted how the demand for specific apps was not easy to predict – what 'worked' in previous apps may not work again, and new skills may be needed in new apps.

In all our analyses, our performance measure is based on the popularity of each app – consistent with how performance of creative projects like motion pictures are measured (e.g., Mezias and Mezias 2000; Schwab and Miner 2008; Cattani and Ferriani 2008). Facebook published two download statistics: i) the total number of users having downloaded an app, and ii) the number of active users for the app. Since these two statistics were highly correlated ($\rho > 0.8$), and that the range of downloads observed between the very popular versus the least popular apps is diverse, we use the natural logarithm of the total user downloads (LnUser). This is also a proxy measure for profit, since the higher the download for an app, the more likely the developer(s) would receive large revenue pay-offs through related advertising (e.g. Geron 2007).

To test for Hypothesis 1, we use the variable Solo to indicate if an app was developed by one individual only (equals 1, or 0 otherwise). As well, the following control variables are used:

PriorAppsofFocalDeveloper	measures the past experience of the developer(s) in terms of the (average) number of prior apps developed.
NumberCollegeNetworks	is the sum of unique college networks the developer(s) of the app belong(s) – since Facebook was set up as a college social medium, college network memberships may influence creative performance.
LnDaysAppReleased	measures the natural logarithm of the number of days a particular app has been released for downloads.
EarliestRelease	takes on the value 1 if the focal app is among a small number of apps initially released when Facebook first opened the app development interface to individuals – these Apps may set the standards on what to expect for users and future Apps.

Table 1 shows the mean, standard deviation and correlation statistics for the variables above. To enable easier access to different apps by users, Facebook set up 22 different categories under which apps can be listed (each app can be listed under up to two categories). As such, we incorporate dummy variables to account for the potentially different levels of popularity in these app categories. The apps included in our surveys were released over a half-year period, while Facebook's membership has also grown. To account for the potentially spurious effect of more downloads due purely to Facebook's increasing membership, we also incorporate period dummies for each 30-day period since the earliest app release date. We report the estimation results including these dummy control variables. The results are similar with or without these.

In addition to the app-based analysis, we focus on a subset of our data by selecting those 'high-volume' developers who have collaborated at least once in our sample. We then track their app development history and choices of partners. This procedure resulted in a total of 597 apps, (of which 240 were developed by two developers in collaboration, and 60 by three or more developers) developed by 84 focal developers. We derive an entire history of app development – solo or in collaboration with others, and examine the performance of each of these apps, examining whether those apps developed solo performed less well than collaboratively developed ones for this subset of developers.

Here we use each developer as a focal individual – equivalent to one 'observation'. As such, apps developed by more than one individual are represented more than once in this analysis. While this approach is commonly used in the study of social networks, we also replicate the same analysis randomly excluding certain focal individuals to ensure each app is represented only. As both approaches (excluding or including duplicate apps) yielded qualitatively similar results, we discuss our analysis based on the approach including each developer as focal individuals (with some apps replicated).

To test for the remaining hypotheses, we devise a notion of the favorite collaboration partner as the one partner with whom a focal individual has most frequently collaborated – to the extent this is revealed in our sample. The fact that we do not know whom one's favorite partner is until we see the entire record of app development of a focal developer mirrors the uncertainty within the focal developer early on in his/her app development: he/she may not know whom his/her favorite partner is until after several actual collaborations with this partner and perhaps others. The variable WithFavPartner equals 1 if the focal developer is working with his/her favorite collaboration partner in the focal app, and 0 otherwise. If the estimated coefficient for this variable is statistically significant – meaning that simply performing with this partner elevates the performance of the apps for a focal developer (supporting H1), then we can infer that the positive performance of the first collaboration with the eventual favorite partner likely motivates the future collaboration choice of the focal developer. If the estimated coefficient is not significant – the performance differential between collaborating with one's favorite partner for the first time versus with others may not present a sufficiently clear motivation to affect the future collaboration choices of the focal developer. In our data, favorite partners are not always symmetric: that Adrian is the favorite partner of Barbara does not mean that Barbara is also the favorite partner of Adrian. In any case, the performance measure in our setting relies on users other than the developers themselves to download the focal app – comparatively much more independent of, or exogenous to, the performance of prior apps than traditional measures of team performance anchored in efficiency.

Moreover, these independent variables are used to test the Hypotheses 2 and 3:

PriorAppsWithPartner — measures the collaborative experience in terms of prior apps jointly developed with the partner(s) in the focal application.

PriorAppsWithFavPartner — measures the past experience of the favorite collaboration partner of a focal app in terms of the number of prior apps developed, if the favorite partner is involved in the focal app, and 0 otherwise.

PriorAppsWithNonFavPartner — measures the past experience of the collaboration partner of a focal app in terms of the number of prior apps developed, if the favorite partner is *not* involved in the focal app, and 0 otherwise.

In addition to the control variables identified earlier, we add one more variable to control for the experience of the collaboration partner(s) of a focal app:

PriorAppsofFavPartner — measures the past experience in terms of total prior apps developed of the favorite collaboration partner if he/she is involved.

Table 2 shows the mean, standard deviation and correlation statistics for these variables.

RESULTS

Table 3 shows the estimation results for all the solo and dual-developer apps to test for H1, with robust estimation and errors clustered around developers. The Hausman test cannot reject the possibility of random effects here, and thus random-effects estimates are used.[3] Model 1 shows the controls-only regression estimates. Interestingly, the estimated coefficient in this model shows a negative and statistically significant coefficient for the prior apps released by app developer(s). This runs counter to the traditional belief that more practice is associated with performance improvements, and suggests that the app development process may be more akin to an adaptive search process – with developers constantly searching for app niches that may promise high user downloads. It is possible that those developers whose first few apps are highly popular are more motivated to develop further apps, but the performance of the latter may mean-revert, or represent developers climbing down local performance peaks in search of others.

Model 2 adds the Solo variable, and its estimated coefficient is negative and statistically significant ($\alpha < 0.01$), showing how apps developed by solo individuals perform less well than apps developed by two individuals in collaboration with each other. This supports H1.

[3] Equivalent fixed-effects analyses have also been conducted and they yield qualitatively similar results.

The rest of the regression analyses were conducted on ‘high-volume’ developers who collaborate with others (i.e., excluding those developers with no history of collaboration with others), using each developer as a ‘focal individual’. As before, random effects are used based on the Hausman test, and robust estimation with clustered errors is used. Model 3 in Table 3 shows the controls-only analysis with each developer as a focal individual, and Model 4 adds in the Solo variable – whose estimated coefficient is negative but not significant. In this analysis – involving only those developers with a history of collaborating with others – those apps developed solo do not perform significantly less than others. This, in conjunction with the results in Model 2, suggests that the sub-par performance in solo apps in general may be due to the hurdles for solo individuals to find suitable collaborative partners.

Table 4 shows the results of the regression analyses based on each focal developer-app combination to test the remaining hypotheses. Model 4 is the same as the one in Table 3 above, and is reprinted for comparison. Model 5 adds the variable PriorAppsWithPartner, whose estimated coefficient is positive and significant ($\alpha < 0.01$). This shows how prior collaboration with partners in a focal app is generally associated with performance, supporting H2. Model 6 shows that the variable WithFavPartner has a positive but not statistically significant coefficient – rejecting H3a. This means that the performance of, say, the first collaborative app developed jointly with the eventual favorite partner is not definitively better than other apps, thus rejecting claims that the focal individual chooses to collaborate with the favorite partner for a second time as a result of the definitively distinctive performance.

Model 7 adds the PriorAppsWithFavPartner variable to Model 6, and shows its positive and statistically significant coefficient ($\alpha < 0.01$). This suggests that it is only through repeated collaborations with the favorite partner that the positive performance differential from working with others becomes significant – supporting H3b. Model 8 adds the PriorAppsWith-NonFavPartner variable to Model 6, and shows its negative and statistically significant coefficient ($\alpha < 0.001$), contrasting how repeated collaborations in the absence of one's favorite partner significantly contributes to a decline in performance – supporting H3c. That is, a strong form of performance relation-specificity is noted.

Model 9 includes all three variables: WithFavPartner, PriorAppsWithFavPartner, and PriorAppsWithNonFavPartner, with their estimated coefficients and significance qualitatively similar to those presented in Models 7 and 8. This shows how the performance-enhancing effect of team familiarity (PriorAppsWithPartner) can be a composite result of the performance-enhancing impact of collaborating with one's favorite partner and at the same time the performance-deteriorating impact of collaborating with others other than one's favorite partner. Meanwhile, the coefficient for WithFavPartner is still not statistically insignificant.

Separately, each regression model is run in an ordinary-least squares analysis to check for multicollinearity – which has not shown to be of an issue (Belsey *et al* 1980). As an extension, we also add variables denoting the degree of network overlaps as a proxy measure for cohesion in our regressions, but its estimated coefficient is not statistically significant.

DISCUSSION AND CONCLUSION

We set out to explore why individuals come to work with one another in groups that eventually become formal organizations rather than persisting as atomistic individuals. We postulate that the meta-level cognition required in developing successive creative projects may restrict performance improvements to the collaborating individuals (i.e., specific to that relation). By examining a novel data set from the how individual developers work alone or voluntarily collaborate with one another to write Facebook apps, we enrich our understanding on voluntary collaborations and find evidence supporting a strong sense of relation-specific performance.

While our finding reinforces the notion that creative projects developed by one individual perform less well as those developed by a group of individuals in general, our finding shows that this difference is not significant if we focus only on those individuals with a record of collaborations with others. This suggests that much of the inferior performance of solo creative projects may be due to the difficulties for the focal individual to successfully find a partner.

Our finding on the relation-specific performance improvements in creative projects extends beyond the notion of team familiarity. Given the same level of familiarity in terms of prior collaborations, repeatedly collaborating with one partner may still yield consistently superior performance than with others (or working solo). However, in one's first collaboration with a particular partner, a focal individual may not be able to reliably distinguish the performance of this collaboration from other projects, such that the relation-specific performance improvement (or detriment) may only be detected over repeated collaborations.

While we base our finding on only the first half-year of the launch of the Facebook application interface, we made attempts to record performance at the one-year mark, but by then, the performance statistics reported by Facebook have changed. Unable to reconcile our data with the new statistics, we tracked the performance of new apps released since December 2009 with the new statistics, and divided these into quartiles: A (top quartile of downloads), B, C, and D (lowest quartile). We found that those apps in the A quartile had a 66% probability of continuing to have more downloads than Apps in the B quartile two months later, and this probability decreased marginally to 58% another two months later. Apps in the A quartile had an 83% probability of better creative performance than apps in the C quartile two months later, and this decreased marginally to 76% another two months later. Finally, apps in the A quartile had an 89% probability of being better than Apps in the D (bottom) quartile two months later, and this decreased to 86% another two months later. In other words, the relative performance of Facebook apps has been reasonably persistent over time.

In this study, we measure performance on a quasi-profit measure, and unfortunately have no information on the cost or man-hour inputs into each app. In the context of Facebook apps, however, there is a sizable gap between the best-performing ones and the poorest-performing ones, with the former being downloaded hundreds of thousand times whereas the latter only a handful of times. The sheer revenue potential of being the one of the most popular apps far outweighs the cost of input resources required – developers are therefore rightly concerned about whether supra-normal performance can be achieved instead of small efficiency gains. In other context, however, efficiency gains as well as other pertinent measures of the quality of the 'product' may be required to provide a more rounded view of performance.

While we are able to demonstrate the relation-specificity of performance among Facebook app developers, future work can go further to identify the commonality in social networks among these developers, or their experience prior to Facebook. The effect of the latter is partially mitigated through the use of random-effects analyses with robust standard errors clustered around each developer. There is much potential for future research to better pinpoint the sources of relation-specific performance improvements as well as declines.

Certainly, not every individual can work with a random partner and achieve performance improvements over time. Amid reports of app developers forming their own companies to capitalize on the opportunities in this emerging technology, it is reasonable to believe that the relation specificity of creative performance can indeed serve as a compelling motivation for specific individuals to band together voluntarily and repeatedly. In the same vein, the same motivation may be behind specific individuals working together to formalize or corporatize their setting – they can produce better results together than working alone or with others.

Theoretically, relation-specific performance improvements, as witnessed in creative projects, can be a micro-foundation of competitive advantages of working together for a specific group of individuals. Because this performance is not easily replicated if the composition of the individuals involved changes – including situations where one individual in a successful, collaborative relation decides to venture out on his/her own, the performance improvement specific to a collaborative relation is to a large extent inimitable. Meanwhile, the true value of each collaborative relation is difficult to determine ahead of time, especially since its performance can become worse over time. The combination of these two characteristics suggests that the relation-specificity of creative performance can help mitigate an important critique to the resource-based view in strategic management (e.g., Barney 1991; Mahoney and Pandian 1992): that somehow, the value of the important resources contributing to a firm's inimitable competitive advantages is not known beforehand – otherwise other firms would start acquiring them (Priem and Butler 2001).

The manner in which otherwise atomistic individual developers searching for the 'next big thing' in Facebook apps, and strategizing and implementing their way to such opportunities is a vivid example of a subjectivist' perspective of entrepreneurship (Mahoney and Michael 2005; Kor et al. 2007). In doing so, our study adds an important dimension of how atomistic individuals – most capable of going alone in their creative projects – become collaborators over time in their discovery and implementation of profitable opportunities. In particular, the difficulty in transferring knowledge related to successful creative projects outside of the individuals involved is consistent with an earlier stream of work documenting difficulties in the transfer of standardized, codified business knowledge even among different divisions of the same firms (e.g., Szulanski 1996).

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Table 1. Statistics and Correlations for All Solo- and Dual-Developer Apps by ‘High-volume’ Developers

Maximum	Minimum	Mean	Std Dev			1	2	3	4	5
15.65	0	6.61	3.19	1	LnUser					
1.00	0	0.83	0.38	2	Solo	-0.14				
199.00	0	22.83	40.89	3	PriorAppsofFocalDeveloper	-0.18	0.14			
4.00	0	0.49	0.65	4	NumberCollegeNetworks	0.05	0.01	0.28		
5.15	0.69	3.90	1.03	5	LnDaysReleased	0.13	-0.06	-0.30	-0.07	
1.00	0	0.01	0.08	6	EarliestApps	0.08	-0.19	-0.05	0.12	0.10

Std Dev = Standard Deviation; correlations with absolute magnitude > 0.05969 are statistically significant at $\alpha < 0.05$, two-tailed test.

Table 2. Statistics and Correlations for All Apps by ‘High-volume’ Developers who Collaborate with Others

Maximum	Minimum	Mean	Std Dev			1	2	3	4	5	6	7	8	9	10
15.65	0	7.83	3.49	1	LnUser										
1.00	0	0.17	0.37	2	Solo	-0.08									
24.00	0	4.82	5.13	3	PriorAppsofFocalDeveloper	-0.11	0.09								
24.00	0	3.42	4.44	4	PriorAppsofFavPartner	-0.02	-0.35	0.60							
4.00	0	0.46	0.83	5	NumberCollegeNetworks	0.00	0.09	-0.15	-0.20						
5.15	0.69	4.04	1.05	6	LnDaysReleased	-0.06	0.16	-0.40	-0.54	-0.02					
1.00	0	0.05	0.21	7	EarliestApps	0.10	0.03	-0.21	-0.15	0.23	0.23				
24.00	0	2.37	3.55	8	PriorAppswithPartner	0.14	-0.30	0.57	0.86	-0.16	-0.63	-0.15			
1.00	0	0.78	0.41	9	WithFavPartner	0.16	-0.85	-0.11	0.41	-0.06	-0.23	-0.02	0.35		
24.00	0	2.35	3.56	10	PriorAppsWithFavPartner	0.14	-0.30	0.57	0.86	-0.16	-0.64	-0.15	1.00	0.35	
7.00	0	0.07	0.59	11	PriorAppsWithNonFavPartner	-0.25	-0.05	0.20	-0.09	-0.06	0.11	-0.02	-0.08	-0.21	-0.07

Std Dev = Standard Deviation; correlations with absolute magnitude > 0.08539 are statistically significant at $\alpha < 0.05$, two-tailed test.

Table 3. Random Effects Estimation of All Solo- and Dual-Developer Apps by 'High-volume' Developers

Dependent variable: LnUser								
N = 1406; 160 teams	Model 1		Model 2		Model 3		Model 4	
Predictor:								
Solo	-		-1.483**	(0.471)	-		-1.793	(0.605)
Controls:								
PriorApps	-0.017***	(0.004)	-0.017***	(0.004)	-		-	-
PriorAppsforFocalDeveloper	-	-	-	-	-1.457*	(0.068)	-0.122	(0.075)
PriorAppsforFavPartner	-	-	-	-	0.065	(0.050)	-0.006	(0.064)
NumberCollegeNetworks	0.728*	(0.299)	0.590†	(0.310)	-0.180	(0.256)	-0.228	(0.254)
LnDaysAppReleased	0.467*	(0.191)	0.445*	(0.189)	-0.104	(0.291)	-0.059	(0.301)
EarliestApps	2.082	(0.481)	2.248	(0.476)	1.034	(0.650	0.916	(0.662)
DataSelectionBias	0.103	(0.317)	0.207	(0.311)	-0.112	(0.173)	0.120	0.153
Intercept	3.752***	(0.749)	4.854***	(0.823)	6.897***	(1.466)	6.726***	(1.569)
Categories, Timing	Yes		Yes		Yes		Yes	
Within-team variance	2.026		1.977		1.674		1.665	
Variance due to team	48.25%		47.03%		34.54%		35.41%	
R^2 overall	0.1540		0.1684		0.2780		0.2815	
Log-likelihood ratio test	-		** from	Model 1	-		n/s from	Model 3

Robust standard errors with clustering around the individual developers reported in parentheses. † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 4. Random Effects Estimation of All Apps by Focal 'High-volume' Developers who Collaborate with Others

Dependent variable: LnUser

N = 689; 84 developers	Model 4		Model 5		Model 6		Model 7		Model 8		Model 9	
Predictors:												
PriorAppsWthPartner	-		0.336**	(0.113)	-		-		-		-	
WthFavPartner	-		-		0.754	(0.784)	1.130	(0.754)	0.180	(1.007)	0.505	(0.656)
PriorAppsWthFavPartner	-		-		-		0.357**	(0.124)	-		0.363**	(0.067)
PriorAppsWthNonFavPartner	-		-		-		-		-0.611***	(0.105)	-0.689***	0.200
Controls:												
Solo	-1.793	(0.605)	-1.524	(0.588)	-1.072	(0.857)	-0.457	(0.882)	-1.739	(1.086)	-1.191	(0.717)
PriorAppsforFocalDeveloper	-0.122	(0.075)	-0.121	(0.076)	-0.117	(0.078)	-0.110	(0.076)	-0.083	(0.054)	-0.073	(0.032)
PriorAppsforFavPartner	-0.006	(0.064)	-0.181*	(0.091)	-0.006†	(0.067)	-0.214*	(0.099)	-0.034	(0.054)	-0.249***	(0.058)
NumberCollegeNetworks	-0.228	(0.254)	-0.148	(0.241)	-0.228	(0.255)	-0.156	(0.240)	-0.231	(0.249)	-0.158	(0.179)
LnDaysAppReleased	-0.059	(0.301)	0.394	(0.300)	-0.066	(0.304)	0.415	(0.298)	-0.047	(0.299)	0.445	(0.301)
EarliestApps	0.916	(0.662)	1.11	(0.654)	0.900	(0.662)	1.086	(0.652)	0.893	(0.660)	1.091†	(0.595)
DataSelectionBias	0.120	0.153	0.131	(0.157)	0.104	0.154	0.104	(0.160)	0.115	(0.154)	0.118	(0.165)
Intercept	6.726***	(1.569)	4.285*	(1.694)	6.118***	(1.597)	3.246*	(1.636)	6.633***	(1.715)	3.746*	(1.718)
Categories, Timing	Yes		Yes		Yes		Yes		Yes		Yes	
Within-team variance	1.665		1.113		1.651		1.074		1.653		1.018	
Variance due to team	35.41%		19.88%		35.04%		18.84%		35.31%		17.38%	
R^2 overall	0.2815		0.3539		0.2850		0.3607		0.3089		0.3839	
Log-likelihood ratio test	-		** from	M3	n/a from	M3	**from	M3	*** from	M3	*** from	M3

Robust standard errors with clustering around the individual developers reported in parentheses. † p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001.