CROWDSOURCING AND INDIVIDUAL CREATIVITY OVER TIME:
THE DETRIMENTAL EFFECTS OF PAST SUCCESS

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Abstract

Several organizations have developed online crowdsourcing platforms that tap into the "wisdom" (creative ideas for new products and services) of a large "crowd' of non-experts (consumers). The crowdsourcing model seems very attractive because consumers are intrinsically motivated to freely contribute their creative ideas, but little is known about the effectiveness of these approaches. Two years of panel data from Dell's IdeaStorm system are used to empirically explore the relationship between individual creativity, productivity, and past success. Estimation results from random effects and conditional fixed effects logit models reveal that individual creativity is positively related to current effort, but negatively related to past success. Thus, productive individuals are likely to have creative ideas, but are unlikely to repeat their early creative success once their ideas are recognized as being creative. These findings highlight some of the difficulties in maintaining an adequate supply of creative ideas from existing crowdsourcing applications, and emphasize the need for a greater understanding of the reward and feedback mechanisms in these systems.

[Keywords: Innovation, Ideation, Intrinsic Motivation, Marketing]

1. INTRODUCTION

The need for innovation is consistently a top business priority among CEOs (Barsch, et al. 2007; Andrew, et al. 2010; IBM 2010). Innovation is generally believed to be the successful implementation of creative ideas (Amabile 1996; George 2007). For an idea to be creative, it must be both novel and potentially useful to the organization (Amabile 1988; 1996; Sternberg and Lubart 1995). Not surprisingly, recommendations on how to effectively manage creativity have received much attention in the popular press (Nussbaum, et al. 2005; Catmull 2008; Pink 2009) as well as academic literature (see the reviews by Shalley, et al. 2004 and George 2007).

Given the necessity of generating creative ideas *repeatedly*, firms have traditionally relied on an internal staff of professional inventors (Ernst, et al. 2000; Schulze and Hoegl 2008; Poetz and Schreier 2010). There are strong reasons for adopting this approach, particularly related to the importance of domain expertise and technical knowledge in developing successful innovations (Amabile 1996; 1998; Poetz and Schreier 2010). While it is well known that the creative output of inventors is highly skewed—a relatively small number of inventors are responsible for the both the quantity and quality of patents owned by a company (Ernst, et al. 2000; Simonton 2003; 2004; Singh and Fleming 2010)—recent research questions whether these few star inventors can maintain their performance over time (Goncalo, et al. 2010). Audia and Goncalo (2007) empirically find that inventors with past success in obtaining patents in the hard disk drive industry tend to become more specialized over time, i.e., individuals with prior creative experience are likely to continue generating creative ideas that are increasingly incremental over time. They caution that allocating more resources to the firm's most prolific inventors may eventually lead to technological obsolescence.

Many organizations are now outsourcing creativity in an attempt to get fresh ideas (Surowiecki 2004). One approach that is receiving substantial attention is "crowdsourcing," a neologism created by *Wired* magazine contributor Jeff Howe (Howe 2006; 2008). As he defines it, crowdsourcing is the act of taking a task once performed by an employee and outsourcing it to a large, undefined group of people in the form of an open call. Several firms have implemented online crowdsourcing systems that tap into the "wisdom" (e.g., creative ideas for new products and services) of a large "crowd" of non-experts (e.g., consumers). For example, Dell (computer hardware), Starbucks (coffee), and Threadless (tee-shirts) were all recently in the headlines for their online efforts in having thousands of consumers suggest, discuss, and vote on new product ideas (Ogawa and Piller 2006; Sullivan 2010). Companies are very interested in these Web 2.0 approaches because consumers presumably have specialized knowledge about their own problems with existing products, and they are intrinsically motivated to freely contribute their new product ideas (Lakhani, et al. 2007; Brabham 2008; Fuller 2010). While there is good reason to believe that individuals can generate ideas that are novel and useful under the right conditions (von Hippel 2005; Bagozzi and Dholakia 2006; Magnusson 2009; Poetz and Schreier 2010), less clear is the nature of crowd creativity over time. Do relatively few consumers propose the creative ideas? Do individuals in the crowd continue to propose creative ideas over time? Do their proposed ideas diverge from previous ideas? These questions are empirically explored in this paper using two years of panel data from Dell's IdeaStorm crowdsourcing system.

To address these questions, it is necessary to understand the role of past success in repeatedly generating creative ideas. In this context where ideas are voluntarily supplied by consumers, motivation crowding provides a useful theoretical framework (Frey 1997). Motivation crowding is a well-established social psychology theory that has wide empirical support (Osterloh and Frey 2000; Frey and Jegen 2001). The crowding-out effect occurs when extrinsic rewards (which can include non-monetary payments such as "gold-stars" or external evaluation; Shalley, et al. 2004) undermine intrinsic motivation. As applied to crowdsourcing, this theory implies that past success in proposing ideas that are externally recognized as being creative will subsequently lead to *fewer* creative ideas. As individuals with past success attempt to generate ideas that will excite the organization, they end up proposing less divergent ideas (i.e., intrinsic motivation is crowded-out by extrinsic evaluation). Thus, past creative efforts have a detrimental effect on crowd creativity.

The empirical evidence for crowding-out in this paper differs from existing research which argues that past creative success causes individuals to generate even more ideas, but that these later ideas do not break new ground (Audia and Goncalo 2007; Conti, et al. 2010; Goncalo, et al. 2010). Instead, individuals in the crowd are unlikely to repeat their early creative success once their ideas are recognized as being creative. Effectively managing crowd creativity thus focuses on continually getting new ideators who then generate creative ideas for a limited time and giving appropriate feedback that does not undermine consumers' intrinsic motivation for proposing creative ideas.

The present paper also has several methodological improvements over related studies of inventors and their patenting activity (Audia and Goncalo 2007; Conti, et al. 2010). First, creative ideas that were actually implemented are studied in this research (although novel and potentially useful, most patents are never commercialized; Silverberg and Verspagen 2007). Second, both creative and non-creative ideas are considered in this research (prior research only considers granted patents, which does not include patent applications that were never granted[1]). Third, past creative success in this paper is based on reported implementation dates (the existing research measures past creative success using patent application dates rather than patent grant dates[2]).

2. THE THEORETICAL FRAMEWORK

In this section, the underlying theoretical foundation for the empirical work is discussed. Three hypotheses involving crowdsourcing and individual creativity over time are developed. All of

[1]Audia and Goncalo (2007) note that up to half of all patent applications are rejected.

[2]This means that the measures of past success used by existing studies may reflect information that is actually unknown to inventors. For example, suppose an individual has patent applications at time t_1 and t_2 ($>t_1$), and learns at t_3 ($>t_2$) that their first patent is granted. With respect to the second patent, using patent application dates rather than grant dates means that this individual would be considered to have had a successful past experience (at t_1) even though this information is actually only confirmed after the second patent application (at t_3).

these hypotheses are conditional on an individual having proposed an idea. The first two hypotheses involve the positive relationship between an individual's likelihood of proposing a creative idea and their creative productivity. The third hypothesis is concerned with the detrimental effects of past success in generating creative ideas.

2.1 Creative Productivity

Creativity is normally defined as the generation of ideas that are both novel and potentially useful to an organization (Amabile 1996; George 2007). Ideas are considered to be novel if they are relatively new compared to other ideas available to the firm and useful if they are potentially valuable to the organization in the short or long run (Shalley, et al. 2004). While many people only link creativity with radical breakthroughs that may diverge from a company's existing way of doing business, from this definition creativity can also encompass ideas for incremental improvements to existing products and services (Mumford and Gustafson 1988; Shalley, et al. 2004). No assumptions about the relative value of divergent versus incremental ideas are made in this research—depending on the circumstances, both incremental and divergent ideas can be important (Helfat 1994; Sorensen 2002).

Much of the creativity literature focuses on identifying the traits of highly creative individuals and the contextual factors associated with creative success (Zhou and Shalley 2003; Shalley, et al. 2004; George 2007). The seminal work on scientific creativity argues that an individual's creative productivity (and impact) is highly related to their total output (Simonton 2003; 2004). For example, future Nobel laureates can be predicted based on the number of citations to their work (Ashton and Oppenheim 1978) and the single best predictor of citations is the total number of publications (Cole and Cole 1973). In the aggregate, creative productivity follows a skewed distribution (Lotka 1926; Huber 1999)—for any discipline, the vast majority of (significant) contributions are made by only a few individuals. Importantly, all of these results seem to apply to any form of creativity (Simonton 1997; Huber 2000).

Generally speaking, the periods during an individual's career with the most high-impact work are those with the largest total output. This empirical finding has been termed the equal-odds ratio—i.e., the ratio of high-impact work to total output is uncorrelated with total output (Simonton 1997). In other words, quality is a probabilistic function of quantity (Simonton 2003). Thus, the absolute number of ideas generated by an individual in a time period should be positively related to their likelihood of having a creative idea in that time period.

H_1: *An individual's likelihood of proposing a creative idea is positively related to the quantity of ideas they generate.*

In addition to total output, an individual's creative productivity is also a function of their domain-relevant knowledge (Amabile 1988; 1996). This domain-relevant expertise includes factual knowledge, technical understanding, and practical experience. The larger the set of domain-relevant knowledge, the more alternative ideas can be obtained by combining, recycling, recombining, and further developing these pieces of information (Hargadon and Sutton 1997). Domain-relevant expertise is the "raw material" for creative ideas (Amabile 1988). Highly creative scientists manage their domain-relevant knowledge by working on several independent projects at the same time (Simonton 2003). These projects are generally very diverse (breakthrough versus incremental; empirical, theoretical, literature review; pilot studies versus completing final results) and allow for "cross-talk" among projects (Miller 2000). Individuals that are able to identify novel business opportunities for new technologies also tend to have broad prior knowledge (Shane 2000). Thus, creative individuals have a diverse knowledge base that evolves over time.

With respect to crowdsourcing new product ideas, domain-relevant knowledge can grow through active participation in the community. Online discussions of consumer problems and possible solutions may well lead to greater factual knowledge and technical understanding as well as a deeper appreciation of practical considerations. Consumers with broad exposure to previously suggested ideas should be more likely to have a creative idea than individuals with little or no awareness of what other people are submitting. Reading and commenting on others' ideas can reduce duplication and, more importantly, can be the seeds for even more creative ideas.

H_2: *An individual's likelihood of proposing a creative idea is positively related to their exposure to others' ideas.*

2.2 Creativity and Motivation Crowding

Recent research argues that previous creative success is detrimental to future creative efforts. This hypothesis was originally proposed by Audia and Goncalo (2007), and expanded on in Goncalo, et al. (2010), and is based on the organizational learning theory of exploration-exploitation (March 1991). Exploration (like divergent creativity) refers to new ideas that break from established ways of thinking, while exploitation (like incremental creativity) involves improvements to existing solutions. According to this theory, exploration occurs at the beginning of the innovation process when few creative ideas have been proposed. Exploitation is favored once creative ideas have been identified because more certain results can be obtained by reusing and recombining existing knowledge. Audia and Goncalo (2007) employ this theory to understand creativity among an internal staff of professional inventors. They empirically show that past success in obtaining patents leads inventors to be more productive in generating patents, but these patents tend to be less divergent over time.

Crowdsourcing new product ideas presents a different situation. Most crowdsourcing platforms allow consumers to engage in a variety of activities including proposing new product ideas, expressing their preferences by voting, commenting on ideas, and obtaining feedback on their ideas in discussion forums. Participation is voluntary and individuals are able to demonstrate their expertise through active involvement. Reasons given for participating in a crowdsourcing community include a desire to have fun, develop creative skills, take on a challenge, and solve problems (Lakhani, et al. 2007; Brabham 2008). Thus, crowdsourcing is intrinsically appealing for consumers that join these communities (Fuller 2010).

Intrinsic motivation is noteworthy because many studies link it to individual creativity (see the reviews by Zhou and Shalley 2003; Shalley, et al. 2004; George 2007). Intrinsic motivation is defined as engaging in an activity for its inherent enjoyment and satisfaction rather than because of external pressures or rewards (Ryan and Deci 2000). Not all tasks are intrinsically motivating, and people are not necessarily intrinsically motivated for the same tasks. As summarized in Amabile's (1988; 1996) intrinsic motivation principle of creativity, "People will be most creative when they feel motivated primarily by the interest, enjoyment, satisfaction, and challenge of the work itself…people who are primarily intrinsically motivated will be more likely to generate truly creative ideas than people who are primarily extrinsically motivated" (Amabile 1988, pp142-143). Intrinsic motivation is of great interest since it can be self-generating and self-perpetuating (Deci 1975; Hackman and Oldham 1980).

Individuals are likely to experience high levels of intrinsic motivation when working on complex tasks (i.e., those with high levels of variety, significance, identity, autonomy, and feedback; Hackman and Oldham 1980). Complex jobs should increase an individual's excitement about their work and their interest in contributing, and this excitement should encourage creativity (Shalley, et al. 2004). With respect to proposing new product ideas, crowdsourcing has many of the characteristics of a complex job. Because intrinsic motivation drives participation, it is expected that individuals within the crowd can generate creative ideas.

But creative ideas only occur when an individual finds the task intrinsically interesting and is working in an environment where extrinsic constraints do not undermine intrinsic motivation (Amabile 1988; Ryan and Deci 2000). Most interesting is that there are many situations when extrinsic rewards get in the way of intrinsic motivation. For example, many well-intentioned summer reading programs offer prizes to children who read books from an approved list. Desiring to win the prizes, children accumulate points by getting the books marked off as quickly and easily as possible (often only superficially "reading" the books). While the prizes may trigger some additional reading in the short run, it is very unlikely that the children will continue reading at a high level after the prizes are no longer available (Deci and Flaste 1995). Thus, external rewards (including recognition and evaluations; Shalley, et al. 2004) can have detrimental effects on intrinsic motivation and individual creativity.

Introduced into the economics literature as motivation crowding[3] (Frey 1997), the notion that an external reward can crowd-out intrinsic motivation has wide empirical support (Deci, et al. 1999; Osterloh and Frey 2000; Frey and Jegen 2001). The social psychology foundation for motivation crowding rests on Cognitive Evaluation Theory (CET) (Deci and Ryan 1985; Ryan and Deci 2000). According to CET, a feeling of competence during a task generally enhances intrinsic motivation because the basic psychological need for competence is being satisfied. However, feelings of competence will not increase intrinsic motivation unless a sense of autonomy is also present (i.e., there is an internal perceived locus of control). Thus, intrinsic motivation for an activity can only be maintained or enhanced if the individual experiences perceived competence (or self-efficacy) and believes their behavior to be self-determined rather than forced by some outside intervention.

In this context, extrinsic rewards can have two possible aspects: a "controlling" and an "informing" aspect (Osterloh and Frey 2000). If the external intervention is perceived to be controlling, then the feeling of self-determination shrinks and intrinsic motivation is likely to be reduced. If the external intervention is perceived to be informing, then the feeling of competence rises and intrinsic motivation will increase. A comprehensive meta-analysis of empirical studies

[3]This effect is also closely associated with "the overjustification hypothesis" (Lepper, et al. 1973), "the hidden costs of reward" (Lepper and Greene 1978), and "the corruption effect" (Deci 1975).

involving external rewards confirms that virtually every type of expected tangible reward contingent on task performance undermines intrinsic motivation (Deci, et al. 1999). Not only tangible rewards, but also threats, deadlines, directives, competitive pressure, and surveillance are perceived to be controlling and found to be associated with lower levels of creativity (see the review by Deci, et al. 1999). In addition, research generally finds reduced creativity when an individual expects a judgmental (i.e., critical) evaluation of their work (Zhou and Shalley 2003; Shalley, et al. 2004).

Many crowdsourcing applications allow for the evaluation of proposed ideas. For example, Dell, Starbucks, and Threadless publically acknowledge the ideas that they decide to implement. However, these firms do not report the rationale for their decision, nor do they offer any developmental feedback (e.g., encouragement or advice on how to improve the suggested ideas). Because the feedback from many crowdsourcing systems is more judgmental than developmental, external feedback from these organizations will most likely be viewed as being controlling. This feedback is associated with lower intrinsic motivation and a smaller chance of having another creative idea. In addition, generating an idea that the organization wants to implement is a rare event (these firms have only implemented a few hundred ideas from the several thousand ideas received; Sullivan 2010). To the extent that an individual sets a personal goal to achieve the distinction of having proposed an implemented idea, intrinsic motivation to continue generating creative ideas decreases once the goal is attained (i.e., only engaging in a task to reach the goal; Rawsthorne and Elliot 1999). Thus, an individual's prior success in proposing creative ideas that are recognized as being creative should be negatively related to their likelihood of generating another creative idea.

H_3: *An individual's likelihood of proposing a creative idea is negatively related to their past success in generating creative ideas.*

3. DATA

Data for this study comes from the publically available information on Dell's IdeaStorm web site. According to their web site, "The goal is for you, the customer, to tell Dell what new products and services you'd like to see Dell develop." IdeaStorm has won a number of awards including the 2008 PR Innovation of the Year and the 2008 Award for Collaboration and Co-Creation by the Society for New Communications Research. IdeaStorm is lauded as being an excellent, best-in-class crowdsourcing application (Howe 2008; Sullivan 2010).

To participate, individuals must join (at no cost) the IdeaStorm community by selecting an anonymous username (you do not have to be a Dell customer to join). Like most crowdsourcing applications, information on demographics and personal characteristics are not collected (the IdeaStorm community is a "large, undefined" crowd). Ideastorm members can propose ideas as well as comment and vote on the ideas of others. To cut down on duplicate ideas, contributors are encouraged to first search the IdeaStorm site for similar ideas. In addition, the IdeaStorm team and community members patrol the web site for duplicate ideas (which are then merged together). Overall, Dell seems to be happy with the general quality of ideas (Killian 2009)[4].

IdeaStorm was officially launched in February 2007. Information on all of the ideas proposed between its inception and June 2009 was collected. In order to allow a time buffer for community activity around an idea to stabilize, ideas generated during the last four months were dropped from the analysis. Over the two year period February 2007 – February 2009, 4,327 individuals generated a total of 8,514 ideas.

[insert Figures 1 and 2 about here]

[4]One metric that speaks to idea quality is the number of proposed ideas that are already offered by the firm. During the two year period of this study, only 94 ideas (or around 1% of all ideas proposed) were found to have already been offered by Dell.

Monthly counts of proposed ideas are shown in Figure 1. During the first few weeks after the web site was unveiled, ideas poured into IdeaStorm. From a peak of almost 1,200 ideas during the first month, the number of suggested ideas rapidly declined over the next six months, eventually steadying at a constant level. As shown in Figure 2, the number of individuals proposing ideas exhibits a similar exponentially declining time pattern. Figure 2 also suggests that a large fraction of the ideas in any time period are generated by new members. The reason for this is that most people offer just one idea. From Table 1, over 75% of all individuals propose only a single idea during this two year time period. While a small number of consumers very actively suggest ideas (three people suggested more than 200 ideas), these results indicate that most individuals in the crowd do not repeatedly generate ideas over time.

[insert Table 1 about here]

The IdeaStorm team reads each idea within 48 hours of posting to ensure that it meets Dell's terms of use and eventually makes a decision for each idea on whether or not to implement it. During this two year period, 344 ideas (or 4% of all ideas proposed) were implemented[5]. Individuals that have an idea accepted by Dell (about 5.7% of all ideators) receive a pen in an engraved box (Sullivan 2010); no monetary compensation is awarded. Implemented ideas are also publically discussed by Dell administrators in their "Ideas in Action" blog, and are appropriately tagged on the IdeaStorm web site.

Monthly counts of proposed ideas that were implemented are shown in Figure 1. Not surprisingly, a relatively large number of implemented ideas were generated in the initial months after IdeaStorm was launched when a lot of ideas were submitted. While very few consumers propose more than one idea that is implemented (although one person did suggest 28 ideas that were eventually implemented), Table 2 confirms that the vast majority of individuals (almost 95%)

[5]Another 236 ideas (or 2.8% of all ideas proposed) were tagged as being under review or having been reviewed (and not implemented).

never propose an idea that Dell wanted to implement during this two year period. Thus, it seems that relatively few individuals generate the creative ideas.

[insert Table 2 about here]

In addition to titling their idea and giving a description, consumers can tag their idea based on 39 different categories (e.g., new product ideas, laptops, sales strategies). Each idea can be classified in up to three categories; typically, however, ideas are assigned a single category. Similar to Audia and Goncalo (2007), these idea categories will be used to measure the extent to which an idea diverges from an individual's previous ideas—i.e., ideas that are in at least one new category for an individual are considered to be divergent. As suggested by Table 1, individuals tend to propose less divergent ideas as the number of ideas they submit increases. The same general pattern is found for consumers suggesting ideas that were implemented (see Table 2). Thus, prolific ideators are less likely to propose divergent ideas than consumers with only a few ideas.

4. THE EMPIRICAL STUDY

In this section, the three hypotheses developed in the second section are formally examined. To do this, an unbalanced panel data set was constructed based on two years of daily IdeaStorm data at the individual level (February 2007 - February 2009). Here, observations are only included in the data set if an individual *i* proposes at least one idea in time period *t* (note that an individual can have more than one idea in any time period). This data set involving 7,158 observations is much more comprehensive than other case studies involving IdeaStorm information that only consider a few ideas proposed during the first month after launch (DiGangi and Wasko 2009).

4.1 Measures

Proposing a Creative Idea. As noted earlier, creative ideas are both novel and potentially useful to an organization (Amabile 1996; George 2007). Previous studies typically measure creativity using objective counts of productivity (e.g., patents, research papers) or ratings provided by external "judges" (Zhou and Shalley 2003; Shalley, et al. 2004). IdeaStorm and similar crowdsourcing applications are somewhat unique in that the firm's implementation decisions are reported, i.e., ideas that are novel and *actually* useful are implemented. Thus, the primary dependent measure analyzed in this research is y_{it}, a binary[6] variable where a value of one indicates that individual *i* proposed an idea in time period *t* that was eventually implemented (otherwise zero). In addition, implemented ideas that diverge from an individual's other implemented ideas are also analyzed. In this case, y_{it}, is a binary variable where a value of one indicates that individual *i* proposed an idea in time period *t* that was eventually implemented and assigned to at least one new category for that individual (otherwise zero).

Creative Productivity. Following the existing literature (see the review by Simonton 2003), the productivity of an individual in a specific time period is based on the total number of ideas they submit in that time period. *Idea quantity* is defined to be the number of ideas generated by individual *i* in time period *t*. Across all consumers in the IdeaStorm data set, 359 (almost 10%) had two or more ideas in a single time period (one person proposed 14 ideas in the same day)[7]. Support for $\mathbf{H_1}$ is obtained if the estimated coefficient for *idea quantity* is positive and significant.

The stock of an individual's domain-relevant knowledge from the IdeaStorm community is measured based on their activity in commenting on the ideas of other community members. This strict measure is used because information on whether or not an individual reads an idea is unavailable (here, it is presumed that an idea is read before a comment is given). Like ideas, comments are tracked by commenter and date. To construct *past exposure to others' ideas* (defined as the cumulative number of different ideas, other than their own, individual *i* commented on before

[6]In less than 0.2% of all observations, an individual proposed more than one implemented idea in the same time period (8 observations had two, and 2 observations had three, implemented ideas). For the IdeaStorm data, count model estimation results parallel those of the logit model to be discussed.
[7]The submission date is assumed to be the same as the date when the idea was conceived. Although it cannot be completely ruled out, there is no evidence that individuals actually generate many ideas over the course of several days and then submit them in batch during one day. Active IdeaStorm members login to the community every day, and use automatic activity updates through their IdeaStorm dashboard, RSS, Twitter and Facebook feeds.

proposing an idea in time period *t*), comment dates were compared with dates of submitted ideas. Over 25% of all consumers commented on at least one idea before proposing their own idea (two people commented on more than 100 ideas). $\mathbf{H_2}$ is supported if the estimated coefficient for *past exposure to others' ideas* is positive and significant.

Past Success. In line with Audia and Goncalo (2007) and Conti, et al. (2010), the measure of past success in this research is based on the cumulative number of creative ideas proposed before time *t*. Here, creative ideas are those that are actually implemented by the organization. In practice however, it can take some time after an idea was initially submitted to decide if it merits implementation. Updates posted as comments (which are dated) are used to determine the specific date when an idea was implemented. For example, on May 29, 2008 IdeaStorm member "jervis961" proposed an idea titled "Don't put the Dell logo upside down on Mini Inspiron" (it seems that the earlier logo on the cover looked upside down when viewed by someone using the laptop). However, it wasn't until September 4, 2008 that vida_k (the Dell IdeaStorm Manager) posted a comment "Changed status to **IMPLEMENTED**" under this idea. In this case, *past success* (defined as the cumulative number of ideas proposed by individual *i* that was known to be implemented before time *t*) is constructed based on implementation dates, not submission dates. Monthly counts of implemented ideas by submission and implementation date are shown in Figure 3. As the previously proposed ideas are filtered, there is a slight upward trend over time in the number of reported ideas that were implemented—the mean time between submission and reported implementation is just over six months. If the estimated coefficient for *past success* is negative and significant, then $\mathbf{H_3}$ is supported.

[insert Figure 3 about here]

Control Variables. Several variables to control for possible effects due to individual or situational factors are included in the analysis. To control for the possibility that past success is simply due to greater productivity (Simonton 2003; 2004), *prior experience in generating ideas* (defined as the cumulative number of ideas generated by individual i before time t) is included in the analysis. An individual's *entry time* (defined based on their first submitted idea) is used to control for any effect of system aging on creative output. Any effects of differences in the variety of ideas proposed by an individual over time are controlled by including *past idea diversity* (defined using an entropy measure over the idea categories: $-\sum_j p_j \ln(p_j)$, where p_j is the proportion of all submitted ideas in category j by individual i before period t) in the analysis. To control for the possibility that the ideas proposed by some community members are given special attention, *top contributor* (a dummy variable with value one if individual i is on the published list of top 20 idea contributors, zero otherwise) is included in the analyses[8]. To be on the top contributor list, an individual's ideas must receive a large number of votes from other community members. According to their web site, IdeaStorm administrators carefully consider the most popular ideas as signaled by community votes. Finally, category dummies are included to control for any inherent differences in the propensity for creative ideas across topics, and monthly time dummies are used to account for any other unobserved time-varying effects.

4.2 Estimation Approach

Panel logit models are estimated to test the three hypotheses because the dependent variable is binary. The individual-effects logit model is $\Pr(y_{it}=1 \mid \mathbf{X}_{it}) = \Lambda(\alpha_i + \mathbf{X}'_{it}\boldsymbol{\beta})$ where $\Lambda(z)=e^z/(1+e^z)$. As in Audia and Goncalo (2007), the basic estimation strategy in this paper is to use a random effects model to account for the possibility of unobserved individual-specific heterogeneity that may be a source of serial correlation. The random effects model specifies that $\alpha_i \sim N(0, \sigma_\alpha^2)$. This model assumes that the individual specific effects are uncorrelated with the independent variables.

[8] *Top contributor* is time-invariant and defined as of June 2009. This list was essentially determined based on the activity in the first few months after IdeaStorm was launched—the people on this list have not materially changed over time. The results are robust to the number of top contributors (e.g., 10 or 20).

Estimation results from random effects models use the variation across, as well as within, individuals. Here, the parameters $\boldsymbol{\beta}$ and σ_α are obtained using maximum likelihood estimation (after α_i is integrated out of the joint density function; Cameron and Trivedi 2009).

At the cost of a dramatically reduced sample size, fixed effects models are also estimated as a robustness check (Conti, et al. 2010). In this case, a conditional maximum likelihood estimator gives consistent results for the parameters $\boldsymbol{\beta}$. All time-invariant individual effects α_i are conditioned out of the model based on the total number of outcomes equal to one for a given individual over time (Cameron and Trivedi 2009). This model assumes that that the individual specific effects are correlated with the independent variables. Here, individuals that have y_{it}=1 (or 0) for all t are eliminated from the estimation sample, and time-invariant variables (including the constant) cannot be estimated. Estimation results from conditional fixed effects models rely on only the variation within individuals.

4.3 Results

Definitions for all the variables, along with summary statistics, are in Table 3. Because all of these variables (with the exception of *top contributor* and *past idea diversity*) are highly skewed, their log transforms are used in the estimations[9]. Due to the large number of individuals with just a single idea, a sub-sample of serial ideators (i.e., individuals that propose ideas on at least two separate occasions) is also considered to sharpen the conclusions. Among the 4,327 individuals in the sample, 704 are serial ideators.

[insert Tables 3 and 4 about here]

Random effects estimation results are in Table 4. As indicated by the significant Wald Chi-square statistics, these models provide a very good fit to the IdeaStorm data. Except for a significantly greater likelihood of ideas proposed in the first month after launch being implemented,

[9]One was first added to *past exposure to others' ideas* and *past success* since the log of zero is undefined. The results are robust to other offset values as well as the original variables.

the estimated coefficients for the time dummies do not reveal any pattern. The results for the category dummies across models suggest that ideas related to the Dell community, IdeaStorm, retail operations, Precision workstations and Vostro computers have significantly higher chances of being implemented. Not surprisingly, the unobserved heterogeneity parameter is significant in the random effects models (Table 4).

As reported in Table 4, three of the control variables are statistically significant in the random effects models. The positive estimated coefficient for *top contributor* suggests that known active participants have a higher likelihood of generating an idea that is implemented, while the negative estimated coefficient for *entry time* indicates that early entrants to IdeaStorm have greater chances of proposing an idea that is implemented than people joining later. These two results also hold for implemented ideas that are divergent. The negative estimated coefficient for *past experience in generating ideas* in Models 3 and 4 implies that cumulative past productivity leads to fewer implemented ideas that are divergent. This finding is consistent with the literature on cognitive framing that argues for a negative relationship between past experience and creativity (Smith, et al. 1993; Ward 1994; Smith 2003).

Strong support for $\mathbf{H_1}$ and $\mathbf{H_3}$ comes from the random effects results reported in Table 4. The positive and significant estimated coefficients for *idea quantity* confirm the important role of current productivity in individual creativity both in terms of implemented ideas as well as implemented ideas that are divergent. In line with motivation crowding theory, the negative and significant estimated coefficients for *past success* provides evidence of the detrimental effects of earlier creative efforts. Strong support for $\mathbf{H_2}$ comes from the reported results in Models 3 and 4 for implemented ideas that are divergent. Here, the positive and significant estimated coefficients for *past exposure to others' ideas* indicates that broad exposure to previously suggested ideas leads to more implemented ideas that are divergent.

4.4 Robustness Analyses

These results are robust to an alternative dependent measure that considers creative ideas that were implemented or reviewed. Thus, creative productivity and past success are also significantly related to a more conservative measure of creative ideas that got Dell's attention. As demonstrated by the results in Table 5, support for all three hypotheses is not limited to the random effects model and its assumptions. Conditional fixed effects models that remove all individual differences that are time-invariant also give strong support for $\mathbf{H_1}$, $\mathbf{H_2}$, and $\mathbf{H_3}$. These results show that variation across consumers is not necessary to verify these three hypotheses. Instead, the variation over time within an individual is most important to explain the relationship between individual creativity, productivity, and past success.

[insert Table 5 about here]

5. DISCUSSION

In this research, the nature of crowd creativity over time is empirically investigated. The relationship between individual creativity, productivity, and past success is studied in the context of Dell's IdeaStorm crowdsourcing system. Two years of panel data involving several thousand ideas and consumers provides strong support for the hypotheses developed in this paper. First, individual productivity is found to be positively related to creativity and innovation: individuals that are highly productivity in a single time period are more likely to propose creative ideas ($\mathbf{H_1}$) and individuals with broad exposure to others' ideas are more likely to have a divergent idea that is implemented ($\mathbf{H_2}$). Second, past success is found to be negatively related to individual creativity: individuals with past success in generating a creative idea are less likely to propose another creative idea ($\mathbf{H_3}$). Here, creative ideas include implemented ideas as well as implemented ideas that are divergent.

These results are generally consistent with the literature on scientific creativity which argues that individual creativity comes from having a large number of ideas (Simonton 2003; 2004). At the same time however, these results are distinct from research on the patenting activity of inventors which does not directly examine the role of individual productivity in a single time period (Audia and Goncalo 2007; Conti, et al. 2010). Moreover, the findings reported here extend this literature by confirming the importance of domain-relevant knowledge in generating creative ideas that are divergent, and by demonstrating that creativity is negatively related to previous creative success.

The fundamental premise guiding this research is that previous creative success is detrimental to future creative efforts (Goncalo, et al. 2010). Departing from existing explanations, motivation crowding (Frey 1997) is used to develop a theoretical framework for a setting where consumers voluntarily contribute their ideas for new products and services. The crowding-out effect occurs when extrinsic rewards (e.g., public recognition or acknowledgement) undermine intrinsic motivation. In a crowdsourcing application, public acknowledgement that an idea will be implemented is viewed as judgmental, and thus, controlling. As a result, this feedback will lead to lower intrinsic motivation and a smaller chance of having another creative idea. The strong empirical support for $\mathbf{H_3}$ is consistent with these arguments.

To further understand these results, two possible reasons that help explain the detrimental effects of past success were considered: (1) individuals with past success propose fewer ideas and (2) individuals with past success propose less divergent ideas. The random effects and conditional fixed effects Poisson estimation results testing these premises are reported in the Appendix (Table A.1). Results indicate that *past success* is significant and negatively related to the number of ideas proposed by an individual that diverge from their prior ideas, but is not related to productivity (i.e., number of ideas generated by individual *i* in time period *t*). Thus, an individual's idea quantity is not affected by past success. However, as they attempt to generate creative ideas that will excite the organization, they actually end up proposing less divergent ideas that are not deemed useful.

5.1 Implications

These findings have some important implications for organizations managing similar crowdsourcing systems. As already noted, most consumers only propose a single idea (Table 1). Given the importance of productivity, it should not be too surprisingly that these individuals are unlikely to have a creative idea that is implemented—only about 3.9% of people in IdeaStorm with one idea had their idea implemented, while 14.9% of serial ideators had at least one idea that is eventually implemented. The reason for this is that individuals with a single idea are also significantly less likely to propose multiple ideas during the same time period (only 6.3% of the consumers that propose ideas in a single time period proposed multiple ideas, as compared to 35.7% of serial ideators who had at least one occasion in which they proposed multiple ideas), and comment significantly less often on other ideas (47.2% of the serial ideators commented on at least one idea, as compared to only 22.0% of the people with one idea). This basic finding that a small fraction of the community members accounts for the vast majority of creative ideas is consistent with the literature on scientific productivity (Lotka 1926; Huber 1999). Thus, the majority of creative ideas come from serial ideators who have not as yet had their creative ideas acknowledged by the organization. As their creative ideas are externally recognized however, serial ideators become less likely to subsequently propose further creative ideas. To ensure a continual supply of creative ideas over time, an organization needs to entice new members who become serial ideators. Even then, serial ideators only generate creative ideas over a relatively short period of time. As suggested by the declining proportion of new IdeaStorm members that become serial ideators shown in Figure 4, Dell's future supply of creative ideas may be drying up.

[insert Figure 4 about here]

5.2 Limitations and Future Research

Another approach for managing crowd creativity is to develop an online platform that does not undermine intrinsic motivation. The results in this paper suggest that the common use of commenting, voting, and publically reporting implementation decisions may be harmful to creative outcomes. Improving our understanding of reward and feedback mechanisms in crowdsourcing applications presents an excellent opportunity for future research. For example, several crowdsourcing systems such as Threadless and Innocentive offer monetary rewards for creative ideas, yet report that very few individuals win more than once (Jeppesen and Lakhani 2010). At the same time, thousands of software programmers willingly contribute their time to various open source software projects for no tangible rewards (von Krogh, et al. 2008). Future research might analyze secondary data involving actual crowdsourcing applications and/or construct experimental scenarios to determine the proper rewards and feedback to maintain (or increase) the crowd's creative output (e.g., Alexy and Leitner 2010). In addition, future research should consider the potential trade-off between encouraging intrinsic motivation and obtaining initial interest in joining and participating in the community. For example, publically acknowledging the ideas that Dell implements may weaken intrinsic motivation for active participants, but also could be an important reason why people join the IdeaStorm community in the first place.

Although Dell's IdeaStorm represents the gold standard for new product idea crowdsourcing applications, the generalizability of the specific results from this study may be limited. Future research might, therefore, attempt to confirm the relationship between creativity, productivity, and past success found in this paper in other settings besides computer hardware and software. The present study is also limited to the publically available data on the IdeaStorm web site. More refined measures of community activity (e.g., comment and vote valence) and idea creativity (e.g., perceptions of novelty, usefulness, and feasibility) might lead to other hypotheses and, consequently, a deeper understanding of the nature of crowd creativity over time.

5.3 Conclusions

Organizations are very interested in the crowdsourcing model because consumers are intrinsically motivated to freely contribute their creative ideas for new products and services. Many companies and entrepreneurs have rushed to develop these systems, even though very little is known about their effectiveness. Most crowdsourcing applications have not been in existence very long, so there is no established history of successes and failures. This empirical study of Dell's IdeaStorm system reveals that individual creativity is positively related to productivity, but negatively related to past success. As a result, productive individuals are likely to have creative ideas, but are unlikely to repeat their early creative success once their ideas are recognized as being creative. These findings highlight some of the difficulties in maintaining an adequate supply of creative ideas from existing crowdsourcing applications, and emphasize the need for a greater understanding of the reward and feedback mechanisms in these systems.

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Table 1
The Distribution of Ideas Generated in IdeaStorm
(N=4327)

Total Number of Ideas Proposed by an Individual	**Number of Individuals** (column %)	**Number of Individuals Proposing >0 Divergent Ideas** (row %)
1	3395 (78.5%)	3395 (100.0%)
2	456 (10.5%)	384 (84.2%)
3	179 (4.1%)	120 (67.0%)
4	95 (2.2%)	36 (37.9%)
≥5	202 (4.7%)	

Table 2
The Distribution of Implemented Ideas in IdeaStorm
(N=4327)

Total Number of Implemented Ideas Proposed by an Individual	**Number of Individuals** (column %)	**Number of Individuals Proposing >0 Divergent Ideas** (row %)
0	4082 (94.3%)	0 (0.0%)
1	216 (4.9%)	216 (100.0%)
2	17 (0.4%)	14 (82.4%)
3	2 (0.0%)	1 (50.0%)
4	2 (0.0%)	1 (50.0%)
≥5	8 (0.2%)	

Table 3
Variable Definitions and Summary Statistics
(N=7158)

Variable	Definition	μ	σ	Min	Max
Idea quantity	number of ideas generated by individual *i* in time period *t*	1.19	0.63	1	14
Past exposure to others' ideas	cumulative number of different ideas, other than their own, individual *i* commented on before proposing an idea in time period *t*	64.53	180.90	0	1207
Past success	cumulative number of ideas proposed by individual *i* that were known to be implemented before time *t*	0.36	1.70	0	27
Entry time	time of first submitted idea (days)	204.85	209.51	1	761
Top contributor	a dummy variable with value 1 if individual *i* is on the list of top 20 idea contributors, 0 otherwise	0.13	0.34	0	1
Past experience in generating ideas	cumulative number of ideas generated by individual *i* before time *t*	14.21	37.64	1	243
Past idea diversity	$-\sum_j p_j \ln(p_j)$, where p_j the proportion of all submitted ideas in category *j* by individual *i* before period *t*	1.01	0.91	0	2.97

Table 4
Logit Random Effects Estimation Results
(standard error in parentheses)

Variables	Implemented Ideas: Model 1 (All)	Implemented Ideas: Model 2 (Serial Ideators)	Implemented Ideas that are Divergent: Model 3 (All)	Implemented Ideas that are Divergent: Model 4 (Serial Ideators)
ln(Idea quantity) (**H**$_1$ +)	0.98[a] (0.22)	1.25[a] (0.27)	0.93[a] (0.24)	1.30[a] (0.29)
ln(Past exposure to others' ideas) (**H**$_2$ +)	0.16 (0.10)	0.19[c] (0.11)	0.22[b] (0.10)	0.27[a] (0.10)
ln(Past success) (**H**$_3$ -)	-0.46[b] (0.23)	-0.56[b] (0.25)	-1.04[a] (0.32)	-1.04[a] (0.34)
Controls				
ln(Entry time)	-0.43[a] (0.12)	-0.42[a] (0.13)	-0.39[a] (0.12)	-0.37[a] (0.13)
Top contributor	1.37[a] (0.41)	0.86[b] (0.41)	1.27[a] (0.39)	0.74[b] (0.38)
ln(Past experience in generating ideas)	-0.23 (0.24)	-0.20 (0.24)	-0.56[b] (0.25)	-0.60[b] (0.26)
Past idea diversity	-0.38 (0.28)	-0.34 (0.28)	-0.10 (0.29)	-0.00 (0.29)
Time dummies	yes	yes	yes	yes
Category dummies	yes	yes	yes	yes
Constant	-2.11[a] (0.43)	-1.97[a] (16.26)	-2.24[a] (15.23)	-2.02[a] (0.52)
Unobserved Heterogeneity (σ_α)	0.85[a] (0.18)	0.78[a] (0.19)	0.73[a] (0.20)	0.57[a] (0.24)
Log-likelihood	-1144.64	-601.88	-1058.38	-516.11
χ^2 (df)	275.03[a] (70)	188.90[a] (69)	259.08[a] (70)	176.33[a] (69)
N	7158	3535	7158	3535

[a]significant at 0.01 level (2-tail); [b]significant at 0.05 level (2-tail) ; [c]significant at 0.10 level (2-tail)

Table 5

Logit Conditional Fixed Effects Estimation Results

(standard error in parentheses)

Variables	**Model 1** (Implemented Ideas)	**Model 2** (Implemented Ideas that are Divergent)
ln(Idea quantity) (**H_1** +)	1.29[a] (0.32)	1.47[a] (0.39)
ln(Past exposure to others' ideas) (**H_2** +)	0.35[c] (0.22)	0.48[b] (0.23)
ln(Past success) (**H_3** -)	-0.95[a] (0.34)	-1.61[a] (0.47)
Controls		
ln(Past experience in generating ideas)	0.23 (0.38)	-0.09 (0.42)
Past idea diversity	-0.78[c] (0.41)	-0.48 (0.45)
Time dummies	yes	yes
Category dummies	yes	yes
Log-likelihood	-291.33	-213.05
χ^2 (df)	197.67[a] (66)	194.88[a] (66)
N	1546	1551

[a]significant at 0.01 level (2-tail); [b]significant at 0.05 level (2-tail) ; [c]significant at 0.10 level (2-tail)

Figure 1
Number of Ideas over Time in IdeaStorm

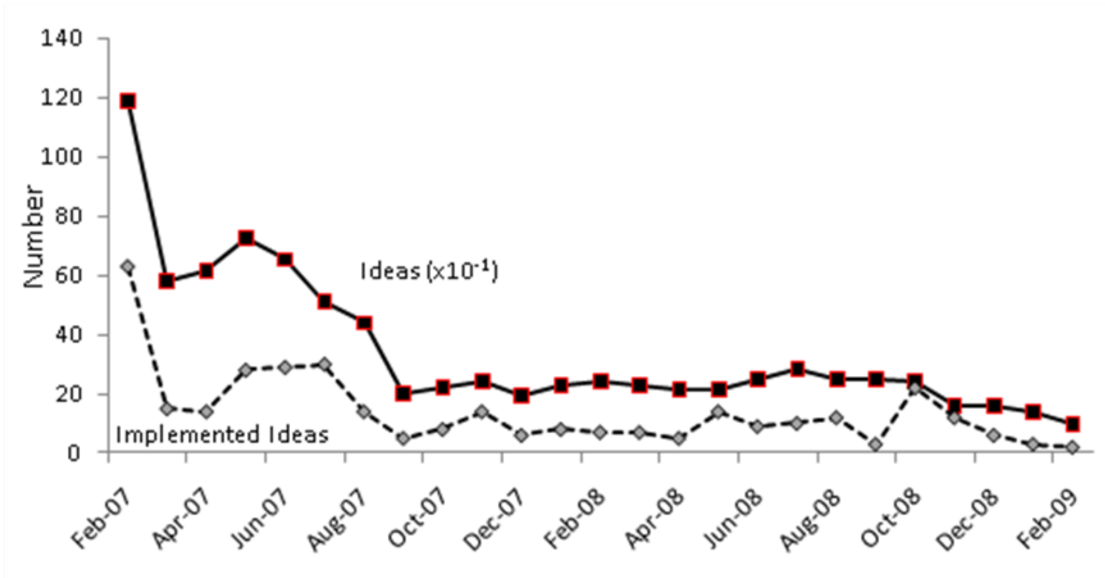


Figure 2
Number of Ideators over Time in IdeaStorm

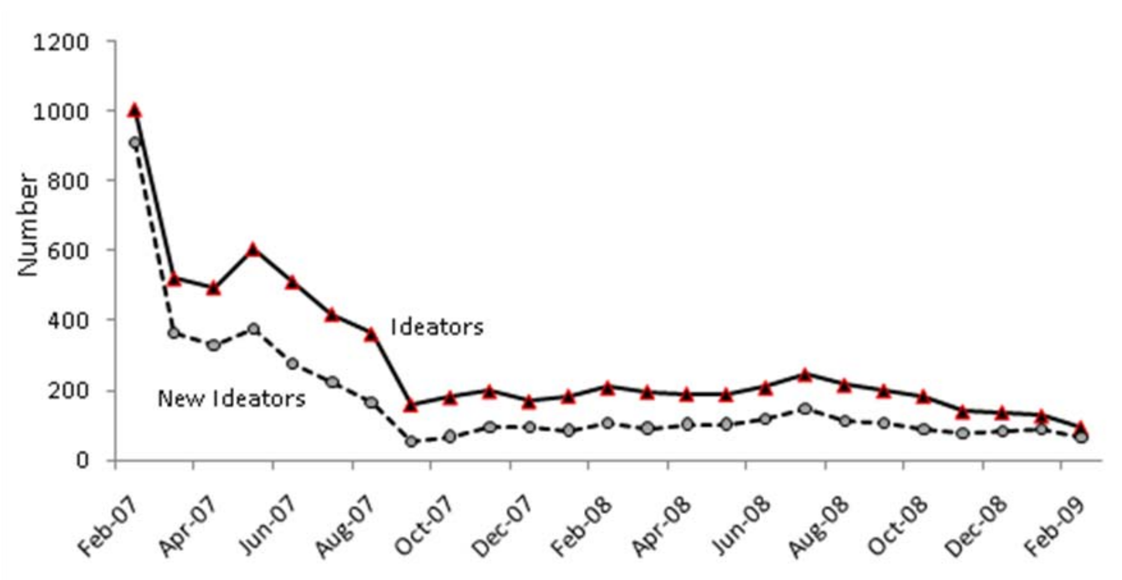


Figure 3
Number of Implemented Ideas over Time in IdeaStorm

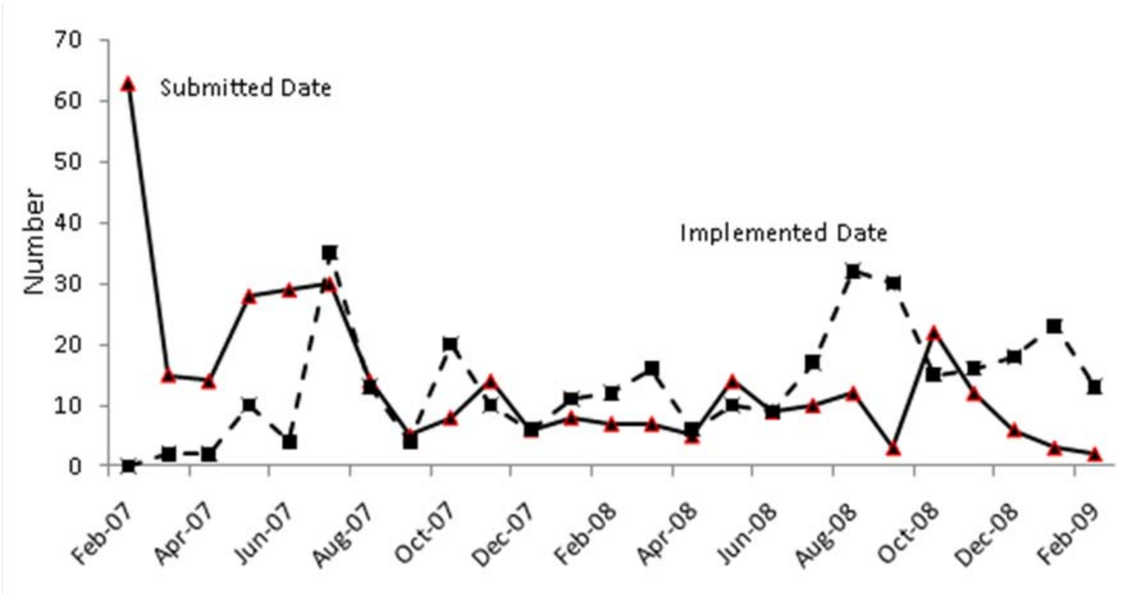
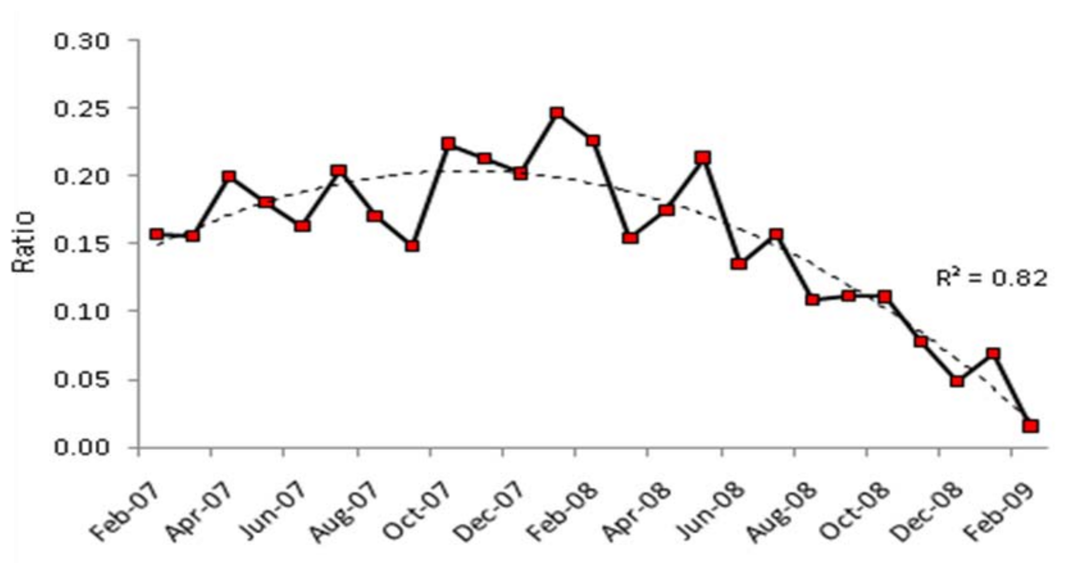


Figure 4
Proportion of New IdeaStorm Members that Become Serial Ideators



APPENDIX A

Table A.1
Poisson Count Model Estimation Results
(standard error in parentheses)

Variables	Random Effects: Model 1 (Number of Ideas in New Categories)	Random Effects: Model 2 (Number of Ideas)	Conditional Fixed Effects: Model 3 (Number of Ideas in New Categories)	Conditional Fixed Effects: Model 4 (Number of Ideas)
ln(Past success)	-0.54[a] (0.12)	-0.04 (0.04)	-0.40[a] (0.14)	0.05 (0.06)
ln(Idea quantity)	0.63[a] (0.05)		0.30[a] (0.10)	
ln(Past exposure to others' ideas)	0.01 (0.02)	0.02 (0.02)	0.00 (0.04)	0.07[b] (0.03)
ln(Entry time)	-0.01 (0.03)	0.03 (0.02)		
Top contributor	-0.22[c] (0.09)	0.02 (0.06)		
ln(Past experience in generating ideas)	-0.46[a] (0.06)	0.03 (0.04)	-0.54[a] (0.09)	-0.18[a] (0.06)
Past idea diversity	0.12[c] (0.06)	-0.04 (0.04)	0.18[b] (0.09)	0.07 (0.07)
Time dummies	yes	yes	yes	yes
Category dummies	yes	yes	yes	yes
Constant	-0.08 (0.11)	-0.45[a] (0.08)		
Unobserved Heterogeneity (α)	0.00 (0.00)	0.00 (0.00)		
Log-likelihood	-6664.47	-7836.15	-1817.33	-2822.29
χ^2 (df)	1528.19[a] (70)	1046.46[a] (69)	625.96 (67)	450.68 (66)
N	7158	7158	3535	3535

[a]significant at 0.01 level (2-tail); [b]significant at 0.05 level (2-tail) ; [c]significant at 0.10 level (2-tail)