

Lone inventors as the source of technological breakthroughs: myth or reality?

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Abstract: Why are lone inventors thought to be the sources of technological breakthroughs? The perception – or myth - persists despite a variety of contrary arguments for the benefits and pervasiveness of collaboration. By differentiating between non-collaborative and independent inventors, I demonstrate that while the average rate and success of creative effort is lower for non-collaborative inventors, the successes are much more variable. If assessments of success depend on the maximum of a distribution and not the rate or mean outcome, then a higher variance distribution could be judged as more creative, a source of breakthroughs, and a plausible basis for the “myth.”

Introduction

Are lone inventors more creative and more likely to be the sources of technological breakthroughs? The idea first became popular in the early industrial revolution as journalists and the public associated important inventions with particular individuals, for example, the telephone with Alexander Graham Bell, electric power transmission with Nikola Tesla, and the airplane with the Wright brothers (Hughes, 2004 pgs. 55, 18, 57, respectively). Most historians agree, however, that the rise of the corporate research and development laboratory in the early 20th century marked the end of the “golden age” of the lone inventor (Mowery and Rosenberg, 1998; Hughes, 2004). Lone inventors were increasingly dismissed as kooks and charlatans when their wild claims proved false. As a result of these trends, it has become increasingly common to refer to the “myth” of the lone inventor (Basalla, 1988).

The myth dies hard, however, and controversy continues in the technology, creativity, and popular literatures. Schumpeter lauded the lone inventor early in his career but later acknowledged the growing importance of corporate invention (Schumpeter, 1934; 1942). Lone inventors are often cited as the source of discontinuous breakthroughs (Tushman and Anderson, 1986; Mokyr, 1990, pg. 295); referring to the golden age of invention, Hughes reports that, “Independents invented a disproportionate share of the radical inventions.” (2004 pg. 53) Sociologists and historians of technology have argued for the iterative and social continuity of creative search, however, and documented the surprisingly collaborative nature of the supposedly lone inventors of the golden age (Merton, 1942; Basalla, 1988; Hargadon, 2003). Investigations of creativity have

described many advantages of collaboration (Sutton and Hargadon, 1996; Milliken, Bartel, and Kurtzberg, 2003; McFadyen and Cannella 2004). Yet a recent compendium on collaborative creativity acknowledged that the research basis for collaborative creativity remains, “somewhat weak,” (Paulus and Nijstad, 2003, pg. 4) and related research illuminates the many problems of working with others (McGrath, 1984; Mullen, Johnson, and Salas, 1991; Diehl and Stroebe, 1987; Runco, 1995; Paulus and Brown, 2003). Accounts of lone creativity and breakthroughs remain common in journalism and literature (Morison, 1966; Schwartz, 2002; Evans, 2005), even as managerial prescriptions for collaboration have increased in popularity (Leonard and Swap, 1999). Noble prize author John Steinbeck wrote that:

Our species is the only creative species, and it has only one creative instrument, the individual mind and spirit of a man. Nothing was ever created by two men. There are no good collaborations, whether in music, in art, in poetry, in mathematics, in philosophy. Once the miracle of creation has taken place, the group can build and extend it, but the group never invents anything. The preciousness lies in the lonely mind of a man. (1952, pgs. 130-131)

If the story of the lone inventor were indeed a myth, then why does it persist so stubbornly? First, it is simply easier to attribute causality and credit to a single person (Basalla, 1988). Popular audiences in particular prefer a heroic explanation and the reality of exhaustive iterations and tangled webs of attribution remains a less attractive story line. Lone inventors also get all the credit for an invention, while collaborators by definition suffer from the identification problem (Kasof, 1995). Second, lone inventors find the myth helpful in their efforts to attract resources; Edison is often held up as a masterful example of this strategy. Third, psychological research has contributed most of our research on creativity and has until recently focused on the characteristics of highly

creative persons, at the expense of contextual and social influences (Amabile, 1996; Simononton, 2003; Paulus and Nijstad, 2003, pg. 3). Fourth, western beliefs in the creativity of lone inventors are bolstered by monotheistic religions and creation stories (Barron, 1995). Finally, it may simply be that the age of the heroic lone inventor has passed, to be replaced by the corporate research laboratory (Mowery and Rosenberg, 1998; Hughes, 2004). Surprisingly, and with the exception of a study focused on tennis racket technology (Dahlin et al, 2004), no research has systematically investigated these ideas or the relationship between lone inventors and breakthroughs.

How can the lone inventor be both less creative and the disproportionate source of breakthroughs? I propose that the myth of the lone inventor persists because of attention to different aspects of a distribution. Like remembering the most enjoyable point of a vacation and forgetting the less memorable parts (Kahneman, 2000), people may remember an inventor's best work and forget about the failures. Furthermore, if the creative variability of lone inventors is higher, relative to their mean outcome, then the argument that lone inventors are the source of breakthroughs becomes entirely plausible. This could occur even if the average outcome of the lone inventor's efforts is worse than collaborative inventors.

To establish these ideas, I develop a new and ultimately social definition of creativity and creative success by combining ideas and definitions of creativity from prior research. I define generative creativity as the first assemblage of a new combination. Separate from the generation of the new combination, I measure its success by the number of times

other inventors use it in future creative search. I also differentiate between independent inventors – those that do not work for corporations – and individual or non-collaborative inventors, who may or may not work inside a corporation. With these definitions, the data indicate that non-collaborative inventors create fewer new combinations, that those new combinations are less likely to be used again, and that the variability of future use is much greater. Non-collaborative inventors are less handicapped in generating new combinations when working in well-documented technologies with more extensive prior art. Future use of their new combinations is also more likely and more variable when they cite the scientific literature. A 10% sample of U.S. inventors from 1975 to 1998 provides empirical support for the arguments.

Three insights and an evolutionary rubric

Some of the controversy over the creative efficacy of the lone inventor can be traced to simple identification and definition. Namely, does the lone inventor refer to an independent inventor - one who does not work for a (typically) large corporation - or a non-collaborative inventor - one who works in social isolation - regardless of whether they work for a corporation? Table 1 illustrates a two by two of these possible configurations, for three-year time periods during the careers of U.S. inventors. As can be seen, almost 20% of the observations of corporate inventors represent non-collaborative work. And over a third of the observations of independent inventors represent collaborations. Hence the first insight; independent and non-collaborative creativity are different phenomenon and subject to a very different set of influences and should not be conflated.

The typically skewed distribution of creative output must also be considered when explaining who invents breakthroughs. Almost all creativity, such as the number of patents or papers in a lifetime of work, follows an extremely skewed distribution. Even more importantly, the quality or impact of that work also follows a skewed distribution. Citations to an inventor's work, for example, usually follow a negative binomial distribution. This becomes important because, in the contest for a breakthrough, the only outcome of interest is the far right outlier (March, 1991). As a result, understanding what drives the higher moments of such a distribution becomes crucial. Methodological problems also increase, since outliers often violate the heteroscedasticity assumptions of most statistical models. Finally, since people tend to remember the last and most extreme aspects of a series of episodes (Kahneman et al. 1993, Kahneman 2000), they may assess a person's creativity by considering the most extreme outcome. Hence the second insight; if lone inventors' work is more variable, their best work may be more creative, even if their average work is less so.

Revisiting the definition of creativity provides the third insight. I propose a definition that results from the combination of four ideas in research on creativity (Fleming, Mingo, and Chen, 2006): creativity is novel and useful (Stein, 1963; Amabile, 1996); novelty is a new combination (Simonton, 1999); the definition and measurement of usefulness remains necessarily social (Gardner, 1993; Csikszentmihalyi, 1999; Simonton, 1999); and the generation of novelty should be separated from its evaluation (Osborn, 1957). Little creativity research has combined these four ideas, which probably reflects the difficulty

of measuring new combinations and usefulness separately with the non-archival methods that are popular in creativity research. Novel technologies can almost always be traced to combinations of prior technologies (Gilfillan, 1935; Basalla, 1988). Science, music, language, art, design, manufacturing, and many other realms of creative endeavor can be described as search across a combinatorial space (Romer, 1993; Hargadon and Sutton, 1997; Weitzman, 1999). Generating a new combination provides no guarantee of its usefulness or success, however. Such usefulness is best determined from a social perspective, as Csikszentmihalyi (1999) argues, “To be creative, a variation must somehow be endorsed by the field...Creativity involves social judgment.” Creative individuals can incorporate their own prior work, but their influence will be limited unless others pick up and build on their ideas. As Simonton (1999: 7) argues, “Homage is paid when the discoveries and inventions of the past are used to construct the miracles of today, whether they be drugs, telephones, computers, automobiles, bridges, jet airliners, or rockets.”

These three insights can be fitted within an evolutionary framework of creative thought and ultimate influence (Campbell, 1960; Simonton; 1999). People generate new ideas through combinatorial thought trials. They then subject these trials to psychological and often social selection processes. The original inventor and other inventors retain the best ideas for use and incorporation into further combinatorial search. This model inherently separates novelty, which is defined as any new combination, and success, which is measured by popularity in future combinatorial search. Most definitions of creativity recognize the importance of both novelty and usefulness, but few separate them explicitly

in theory and measurement. For example, experts are often asked to rate ideas for creativity (Amabile, 1996; Burt, 2004) and citations are often used to rate the importance of patents or papers (Trajtenberg, 1991; McFadyen and Cannella, 2004). Separation is useful, however, in that generating ideas is a very different process from their evaluation and diffusion. Separation also avoids the normative bias that all creativity is good by definition, even though much – even most of it – is useless.

Following this reasoning and providing the third argument, I will define two phases of creativity and label them as *generation* and *use*. The empirical test of the ideas will measure generation as the first appearance of a novel combination and its success as the incorporation of that novel combination in future combinatorial search by other inventors. Theorizing will focus upon the differences between collaborative and non-collaborative inventors and consider the influence upon the first moment for the generation of new combinations and the first and second moments for their future use.

Theory

If we restrict our consideration to the initial idea and define *generative* creativity as the assemblage or rearrangement of new combinations, then creativity should be increased by exposure to a wide variety of ideas and components that have not been previously combined. The argument is old. Burt (2004: 351) lists its previous proponents, including Smith (1766), Mill (1848), Simmel (1922), and Merton (1948). Exposure can be increased in a variety of non-social ways, through changes in domain-focus to literature and new education. However, much—even most—exposure occurs through social

interactions with other creative individuals (Katz and Lazarsfeld, 1955; Allen, 1977). If generative creativity requires the creation of new combinations, then collaboration confers an advantage because each contributor brings a different perspective and different set of combinatorial components to the search process. A wider combinatorial search space will provide greater opportunities for novelty, even controlling for the increased resources and productivity of additional inventors.

H1: Non-collaborative inventors create fewer new combinations, relative to collaborative inventors.

Collaboration also increases the likelihood that new combinations will be more successful because they will 1) be subjected to more rigorous selection processes and 2) diffuse more easily to future inventors for retention in future use. While collaboration increases an inventor's exposure to recombinant potential, it also aids an inventor during the selection phase of the inventive process. Consider an evolutionary model of creativity where inventors create and then immediately test their ideas and new combinations within their own minds (Campbell, 1960). Most new ideas are rejected almost immediately while some are retained for future search. Individuals, however, both non-experts (Runco and Smith, 1991) and experts (Simonton, 1985) are notoriously bad evaluators of their creative products. The arguments resonate with anecdotal descriptions by extremely successful lone inventors; they readily admit and joke about their inability to predict which of their inventions would become breakthroughs (Schwartz, 2004, pg. 144).

When selecting which ideas to develop further, the sole inventor is at a disadvantage, because collaborators can subject the idea to greater variety of potential applications, thought experiments, and virtual tests. Collaborative inventors often report a division of labor between those who generate and those who criticize: “You wanted Charlie in the conversation, because he would tell you when you were full of it.” (Kenney, 2006) The two inventors of the Hewlett Packard thermal ink-jet were a prolific empirical tinkerer who generated prototypes and a very methodical engineer who explained, documented, and criticized (Fleming, 2002). Collaborators will develop different conceptions of the invention and how it might be used and will provide a more comprehensive screen for the idea. As a result, more poor ideas will be developed and patented by the lone inventor and fewer of these ideas will be used again in the future.

Collaborative combinations are also more likely to be used in future creative search because they will diffuse more widely and easily. As Nijstad and Paulus (2003) describe, “Creativity is socially defined...ideas need to travel in order to reach the important others who can judge their merits.” Unlike the sole understanding of the solitary inventor, collaborations give rise to a more distributed understanding of a new combination. Furthermore, assuming an inventor’s collaborators are themselves more likely to communicate and collaborate with others in turn, there will be a greater number of social paths that enable the diffusion of the idea.

Uncertainty about an inventor’s reputation will also impede diffusion of a sole inventor’s ideas. Building upon Coleman’s (1988) arguments for the value of cohesive social

capital, reputation will arise much more quickly in a collaborative situation. A sole inventor's reputation, regardless of whether it is positive or negative, will remain less certain. Increased uncertainty will increase the risk to others of adopting the inventor's ideas and slow the diffusion of those ideas. For both these reasons—more rigorous selection processes and easier diffusion and retention — non-collaborative combinations will be used less in future creative search.

H2: The new combinations created by non-collaborative inventors are less likely to be used again in future inventive search, relative to collaborative inventors.

A focus on breakthroughs motivates consideration of the variability in usage as well. The variability in future usage of collaboratively generated new combinations will be lower than the variability of lone inventor combinations, for two reasons. First, collaborative selection processes will be more effective than those of an individual inventor (Sutton and Hargadon, 1996; Rowat et al., 1997). The inventor of the aluminum tennis racket, Styrofoam egg cartons, and plastic milk bottles reported that, “The problem with the loner is that if you don't sift, you are liable to spend much time going down dead ends.” (Brefka, 2006) Collaborative inventors will develop and patent fewer dead ends and this will lighten the distribution on the lower end. Breakthroughs are probably also less likely to be patented, due to skepticism and pressures for conformity, but since breakthroughs remain so rare, most of the influence will be felt upon the bottom of the distribution.

Second, the greater uncertainty that surrounds lone inventors will increase the possibility of contagion processes. Inventors confront great uncertainty in the decision to adopt a combination for further refinement (Podolny and Stuart, 1995). In the absence of

objective information on the value of the new combination, inventors look to other inventors for clues. If other inventors have incorporated a new combination, even if only through chance, it increases the likelihood that the same new combination will be adopted again, relative to another new combination that has never been adopted. Although they did not consider non-collaborative inventors, Dalhin et al (2004) found that patents by independent inventors – those not employed by a corporation - tended to be over represented amongst very poorly or very highly cited patents.

H3: The variability in future usage of new combinations invented by a non-collaborative inventor will be higher, relative to collaborative inventors.

These arguments imply additional observable implications. Following the reasoning in hypothesis 1, that solitary inventors will lack opportunities for social exposure to new combinations, we would expect that lone inventors would be more disadvantaged when these opportunities were most important. This is most likely to occur when technologies are new and poorly documented. In these situations, tacit knowledge that has yet to be codified will be crucial – and typically available only through social communications. In contrast, if technologies are well codified and much prior art has been accumulated, solitary inventors should be less disadvantaged by the lack of collaborators.

H4: Non-collaborative inventors create even fewer new combinations when they work in technologies without prior art.

After a new combination has been invented, and again following our logic for hypothesis 2, it must reach others in order to be assessed and used. Solitary inventors will remain at a disadvantage unless they can rely upon non-social channels. Referencing the scientific literature strengthens the effectiveness of non-social channels (Sorenson and Fleming,

2004; Sorenson and Singh, forthcoming). When technologies reference science, they diffuse faster because the basis of the invention will be more accessible via public, published, and non-social sources. While reference to science will help all inventors, this will be of differential advantage to solitary inventors, who cannot rely upon collaborators to diffuse the technology.

H5: New combinations by non-collaborative inventors are more likely to be used again if they cite science.

Following the reasoning in hypothesis 3, that the variability of future use will be higher for non-collaborators, referencing the scientific literature should decrease variability for such inventors. This occurs because referencing science lessens the uncertainty around the inventor's solitary reputation. Referencing science, especially if it has appeared in a high status journal, will reassure potential adopters that the technology is built upon a sound basis. The technology will also be more easily understood by future adopters, such that the quality will be known and more easily accessed. These mechanisms will weaken the contagion effects caused by the greater uncertainty of a non-collaborative reputation. Weakened contagion effects will decrease the variability in future use of a new combination.

H6: The variability of usage will be lower for non-collaborative inventors if they cite science.

Data and Methods

I test the hypotheses by modeling the collaborations and creativity of patented inventors. Patent data provide a superior methodological opportunity for a variety of reasons. First, they can provide a clean separation of the generation and success of creative ideas and new combinations. Second, they provide the time and breadth necessary to identify breakthroughs and collect enough data to estimate the influences upon the mean and variability of such rare events. Finally, they afford observation of larger collaborative networks that have demonstrated strong influences upon the diffusion of ideas (Singh, 2005; Sorenson et al. 2006).

The raw data for the analyses come from all U.S. utility patents granted from 1975 to July 2002, inclusive (Hall, Jaffe, and Trajtenberg 2001; USPTO, 2002). Each patent record contains the patent number, the date of application and grant, all inventors' last names (with varying degrees of first and middle names or initials), inventors' home towns, detailed information about the patent's technology in class and subclass references (over 100,000 subclasses exist), and the owner or assignee of the patent (generally a firm, and less often a university or government, if not owned by the inventor). Because inventors are not uniquely identified, I applied an inventor-matching algorithm to determine each inventor's patents and other inventors with whom the focal inventor had coauthored (for details, see Appendix A).

I split the data into three-year time periods for each inventor's career. Similar archival approaches have used five-year windows (McFadyen and Cannella, 2004); I found no

substantive differences for window size and chose the smaller size to maximize observations. The models analyzed non-overlapping windows, starting with 1975-1977. I did not use patents applied for after 1998 because the grant date can lag the application date by many years and result in missed observations. In addition, the use variable needs time for observation. All variables were calculated by application date within the three-year time period. The database includes 2,058,823 inventor career-period observations and 2,862,967 patents. Approximately half the inventors resided outside the U.S. and were not considered because foreign names and inconsistent address data made their unique identification much more difficult.

I also take a random sample of inventor careers (I sample entire careers, not three year windows) in order to avoid network autocorrelation. Many variables are the same for a set of connected inventors, for example, the number of their patents and collaborators, whether their organization is a firm or university, or the age of their technology. Hence, observations of connected inventors will be dependent. Since this violates the most basic assumption of independent observations in statistical estimations, I sampled 10% of the population, which resulted in 53,570 observations of 35,400 inventors. Sampling makes it much less likely that connected inventors will be included and avoids overestimating the degrees of freedom. Hence, I avoid spuriously high p values and estimate coefficients more conservatively.

I also interviewed a small sample of Boston area inventors who 1) demonstrated the highest variance in whether their patents were assigned to a firm, 2) had at least one three

year time period in their career when none of their patents were assigned to an organization (that is, they owned them personally), 3) demonstrated the highest variance in collaboration, and 4) had a least one period in which they did not collaborate with anyone. Hence, I interviewed a non-representative sample of prolific inventors and was not attempting to validate hypotheses. The inventors probably represent a greater number of university based inventors as well, given the many universities in Boston. Of 14 inventors who met the cutoff criteria, I have so far been able to reach and interview Paul Brefka, George Kenney, and Brian Seed. I asked a broad set of questions about their inventive experiences and only after I had recorded their responses, did I explain my ideas on the topic. Appendix B contains the interview questions.

Dependent Variables

New combinations: The models use the number of new subclass pairs in an inventor's patents as a measure of generative creativity or variation. The subclasses come from the U.S. Patent Office's organization of all technology into approximately 100,000 categories. The patent office also periodically updates its classification system and subclass assignments for all patents back to the system's founding in 1790 (I used the 2004 concordance). To calculate the measure, I stepped through the assignments and identified the first appearance of a previously uncombined pair of subclasses. I then summed this indicator measure for all patents during the focal inventor's three-year window. The future use models include the ln of this variable as a control.

Future uses of the combination: The second dependent variable counts how many times future inventors (besides the focal inventor and the focal inventors' collaborators – including those usages as well only strengthens the results) use the inventor's new combinations. When a new combination is used twice within a single three-year window, only the first usage is counted as a new combination; the second adds to the future uses variable. Given recent concerns about prior art citations as a measure of inventive success or diffusion (Alcacer and Gittleman, 2005), the count of future usage provides a cleaner and more easily interpreted variable than citations. Citations remain difficult to interpret theoretically because they conflate generative variation and future usage. Appendix C explains the dependent measures in detail.

Explanatory Variable

Lone: All inventors that did not collaborate with any other inventors during the three year time period are identified by an indicator variable.

Control Variables

Independent: I identified independent inventors by including the proportion of patents in the three year window that were unassigned (patents without assignees are owned by the individual inventor).

Ln of number of patents: The models include the ln of the number of patents by the inventor during the three-year window. (All count variables were logged to account for their exponentiated entry into the count models.) This controls for the increase in raw

resources that result from collaboration, that is, there are simply more minds and hands to complete the work. This variable also controls for effort and patenting strategies; for example, if an individual chose to include all her creativity or claims in one patent, or split them across multiple patents.

Ln of new subclasses: The variation models include the ln of the number of new subclasses in the inventor's patents. The number of new combinations variable only counts new combinations; that is, a new subclass by itself does not constitute a new combination (the results are insensitive to the inclusion of the variable). Yet, the appearance of a new subclass obviously creates new subclass pairs.

Ln of non-patent references: The models include the ln of the number of non-patent references made by the inventor's patents. Most of these references are to peer-reviewed science and can be interpreted as an awareness of the scientific literature. Awareness of the scientific literature makes the search process less random, particularly with interdependent components; identifies new components of recombination (Fleming and Sorenson, 2004); and enables faster diffusion of technical knowledge across organizational, technological, and geographic boundaries (Sorenson and Fleming, 2004).

Ln of university patents: The models include the ln of the number of the inventor's patents assigned to a university, because collaborative structure in university labs may differ from that in private firms.

Ln of backward citations: The models include the ln of the number of backward citations made by the inventor. A larger value of this variable corresponds to a greater amount of prior art in the technological area.

Ln of number of assignees: The logged count of the number of assignees during the three year window controls for the inventor's career movement across firms.

Ln of focal inventor's experience: The models include the ln of the cumulative total of unique subclasses that the focal inventor has worked in prior to the current time period. This controls for inventors who already have a wide breadth of experience and recombinant potential before possibly collaborating.

Time and career period indicators: All models include indicator variables for time period and career period of the inventor, in both the mean and variance estimations. Time period indicators control for differences in patenting processes and in the time that combinations are at risk of usage in further application. Career period indicators control for differences in productivity, creativity, and risk aversion over a career.

Selection hazards: There exists severe selection bias in the usage models, because a new combination cannot be used again unless it is first invented. To control for selection bias, I estimated a first-stage selection model (Heckman, 1976) and entered the inverse Mills ratio in the usage models. The first stage used variables the same variables for estimating

generative creativity, and the usage models included the ln of the number of new combinations. Tables 2 and 3 provide descriptive and correlation statistics.

Models and Results

Both dependent variables demonstrate skewed count distributions. Use of linear regression on such distributions can result in inconsistent, biased, and inefficient estimations. Count models provide more accurate results and, given that the variance was greater than the mean in both distributions, negative binomial models provide more accurate estimation of errors. Given that my theory implies predictions for the second moment as well as the first, I estimated a mean-variance decomposition model (King, 1989; see also Fleming, 2001). Like the basic negative binomial model, this model estimates a relationship between the mean and variance of an over-dispersed count distribution. Rather than simply assuming a constant relationship between the mean and variance, however, the decomposition model allows estimation of substantive influences upon the relationship. All dispersion models estimated robust errors to correct for the lack of independence across repeated observations of the same individual.

The relationship between mean and variance in the decomposition model can be modeled in a variety of ways. Cameron and Trivedi (1986) propose the negative binomial II parameterization (or Negbin II model) where the variance/mean ratio is linear in the mean. By contrast, the Negbin I holds the variance/mean ratio constant. I verified the applicability of the Negbin II by regressing predicted counts on the quantity $(\text{residuals}^2/\text{predicted})$. The coefficient and intercept were positive thus supporting the

Negbin II parameterization (Cameron and Trivedi 1986). Also consistent with Cameron and Trivedi's argument, Negbin II models demonstrated much more significant log likelihoods than Negbin I models. Finally, the Negbin II specification is more robust to distributional misspecification than other parameterizations (Cameron and Trivedi 1986). STATA Version 9 estimates both the mean μ_i and dispersion parameter α by the method of maximum likelihood. Equation (1) describes the resulting variance, conditional on the mean and explanatory variables.

$$\text{Var}(y_i | \mathbf{x}) = \mu_i \left(1 + \frac{\mu_i}{\nu_i}\right) = \mu_i + \alpha \mu_i^2 \quad (1)$$

Results

Table 4 reports generative creativity models and table 5 reports the future usage of that creativity. Model 1 reports the basic negative binomial results for the generation of new combinations. As might be expected, the number of new combinations correlates very strongly with the number of patents and new subclasses during a 3 year time period. The size of the indirect network, reference to science publications, number of university patents, amount of prior art, and wide previous experience also correlate positively and significantly with new combinations. Inventors that patent with multiple firms, however, appear to generate fewer new combinations. Independent inventors also appear to generate 10% fewer combinations than corporate inventors.

Moving to the predicted relationships, the estimates support the first and fourth hypotheses, that non-collaborative inventors will generate fewer new combinations and that they will be at the greatest disadvantage when working in technologies with less prior art. Model 2, which includes the interaction between no collaboration and prior art

citations, demonstrates a strong effect: non-collaborative inventors are 27.2% less likely to invent a new combination.¹ This is only partially moderated by working with old technologies; if a non-collaborative inventor works at a standard deviation above the mean of the number of prior art citations, she will invent 10.2% more new combinations than if she had worked collaboratively, all else equal. Taken together, these results support the argument that non-collaborative inventors remain isolated from social sources of new ideas and that this isolation hurts them most when working with new and undocumented technologies.

Moving to consideration of the control variables in the future use predictions, the number of new pairs demonstrates a very strong influence, as would be expected. The number of patents, number of new subclasses, size of the indirect network, references to science, and number of university patents all demonstrate a positive correlation with future use. The number of assignees that the inventor works for, the inventor's breadth of experience, and the selection hazard demonstrate no significant relationship. The number of backward citations correlates negatively with future use, which makes the generative strategy of working in well-documented technologies less attractive; even if a non-collaborative inventor creates a greater number of new combinations by working in fields with extensive prior art, those new combinations do not appear to be any more likely to be successful.

¹ Effect sizes are calculated as the exponential of the coefficient, for example, $1 - e^{(-0.3176)} = 27.2\%$. For continuous variables, the calculations are made for a one standard deviation change of the independent variable.

As predicted in hypothesis 2, new combinations by non-collaborative inventors are less likely to be used, on average, by others in the future. Hypothesis 3, which argued that the variability of that usage would be higher as well, also receives support, as illustrated by the positive coefficient for non-collaboration in the dispersion estimation. These effects, from model 6, are moderate: the average use of non-collaborative new combinations is 11.6% less and the coefficient of variation is 8.6% greater. Hypothesis 5, that citation of science would moderate the negative influence of not collaborating on future use, is also supported, though at the $p < 0.1$ level of significance. When this interaction is considered, the 11.6% drop in future use is essentially halved, to 5.2%. Hypothesis 6, that science should decrease the variability in use, is disconfirmed. When a non-collaborative inventor cites science, the future use of their combinations becomes more variable, relative to collaborative inventors who use science (science by itself has a large negative effect on variability, as expected). This effect is only marginally, significant, however, at the $p < 0.1$ level of significance. Independent inventors also suffer from an average of 22.2% fewer uses of their combinations, though the variability is not significantly different from zero.

Figures 1 and 2 illustrate the differences in the predicted distributions of future use of solitary vs. collaborative inventors. The upper left of Figure 1 illustrates how non-collaborators are much more likely to strike out completely, that is, they are almost 60% more likely to invent a new combination that never gets used again. The predicted probability of non-collaborative inventors quickly drops below the line of collaborative inventors, indicating that inventions of approximately average future use (the mean of

future use is 18.55), collaborative inventors are the more likely inventors. Well before one standard deviation (207 for future use), however, the non-collaborator's line again crosses the collaborative line. As illustrated in figure 2, when predicted future use is above 141, the new combination was more likely to have been invented by a non-collaborative inventor.

These results, while statistically significant, remain primarily descriptive. Establishing causality will remain difficult, however, in the absence of a natural experiment or instrumental variables for collaboration and working outside of a firm. Experimental approaches to address this problem will also be problematic, because it will be difficult to measure the number and breakthrough potential of a subject's ideas. Archival approaches still provide superior capabilities to measure breakthroughs, because they allow the passage of time and enable natural assessments to take place. Estimating dispersion parameters with archival approaches will also be difficult, given the need for additional power in estimating the second moment.

Discussion

The results provide managerial implications because many lone inventors work for firms, as indicated by the cross tabulation of Table 1. The results do not completely support the growing popularity of collaboration to increase creativity, however. Indeed, if a firm desires a highly skewed breakthrough and can afford the increased rate of failures, by these results it would do better to isolate its inventors. This argument gains even greater credibility if the opportunity costs of collaboration are taken into account. Put in other

words, inventors that work together are missing the opportunity to work alone; the aggregate output of the group must be might be less than the sum of individual outputs. Providing plausibility for this argument, a regression of new combinations per inventor demonstrates striking advantages to working alone.

Even if they follow the implications of these results, managers should consciously expose their isolated inventors to recombinant opportunity and evaluate their output more carefully. Before dismissing the unusual combinations, a manager should take care not to throw out the potential breakthrough. Managers might accomplish this by using lone inventor inventions as the basis for brainstorming sessions amongst other engineers or by offering the work for sale outside the firm if it does not fit with the firm's current trajectory. Managers should act like collaborators to publicize and diffuse the lone inventor's work. Unfortunately, none of the interviewees described lone inventors as easy to work with. Uniformly, they indicated that managers needed to gain the lone inventor's commitment and then proceed to leave him or her alone. Consistent with the higher variance outcomes, such an approach does not bode well for product development schedules and might be best applied in an organizationally isolated search for breakthroughs.

The clearest and unsolicited message from the qualitative work was that lone inventors aren't. Every respondent indicated the importance of social stimuli, even if the interaction did not result in co-authorship of a patent. "Most of what I've done has been in collaboration – it's impossible to invent in a vacuum." (Kenney, 2006) Even those that

reveled in solitary work volunteered the importance of contact with individuals both within and beyond corporate boundaries. Paul Brefka, one of the most prolific and successful inventors in the sample, described it thus: “I like to be alone with a board, it’s a wonderful feeling. I can get totally immersed, with all communications cut off. Every now and then I come up for air, because you have to discuss and listen.” (Brefka, 2006) Interestingly, Brefka focused on what I have described as the selection stage and indicated that he depended upon others for ideas but himself for the “sifting.” “You can sift as an individual or a group... You collect from group but sift by yourself... I don’t have a different process for collaboration, for both individual and collaborative effort, I get exposed and then I retire.” Perhaps Brefka’s willingness to listen and sift explains his success. In particular, his personal ability to select the most promising combinations provides for a strong selection process in the absence of collaborative critique. To complement such abilities, he reported constantly seeking inputs from extremely diverse and time consuming sources. For example, before inventing musical technology, he observed musician Stevie Wonder at length. In light of these issues, the substantive variable of no collaboration should probably be interpreted as measuring a degree of isolation, despite the USPTO policy that every person who contributed anything to a patent be recognized as a co-inventor.

Conclusion

The “myth” of the lone inventor has remained uninformed by theory and large sample statistical study. I addressed this by developing the implications of an evolutionary model of inventive search by non-collaborative inventors. I differentiated between the

creative stage of generating new combinations and the social success of those combinations. Motivated by these arguments, I demonstrated that non-collaborative and independent inventors generate fewer new combinations. Furthermore, the usage of those combinations was less by other inventors in the future. Providing a firm basis for the “myth” of the lone inventor as the source of breakthroughs, the variability of usage was higher. Non-collaborative inventors can lessen the generative handicap by working in well documented technologies. Even better strategically, they appear to be almost as successful on average if they reference science. Furthermore, they are more variable, such that their probability of inventing a breakthrough is much greater. Most importantly, the research provides a framework for thinking about creativity and breakthroughs. The application of this framework to the process of solitary and collaborative invention resolves the “myth” of the lone inventor and illustrates when collaboration can result in less creativity.

Appendix A: Inventor Matching Algorithm

I refined the name matching algorithm from the procedure developed by Trajtenberg (2005).² Trajtenberg's algorithm includes matching criteria based upon an inventor's city, assignee, patent technology classes, shared co-inventors, citations and the SOUNDEX coding method applied to inventor names (the SOUNDEX algorithm corrects for phonetic misspellings). I included additional criteria for scoring based upon the population in which the inventor resides. Accordingly, a relatively common name in a zipcode with a very small population will receive a higher score than the same name in a zipcode with a larger population. Also, I utilized a combination of the U.S. Census Bureau's Frequently Occurring First Names and Surnames list and the occurrence of an inventor's name in the patent data base to create a ratio for scoring a possible name match. A name that occurs with relative frequency in the population, but only occurs once or twice in the patent data base will receive a higher score than a name that is more common in both the database and the US Census name list.

Appendix B: Interview questionnaire

- 1) Please give me a brief biography of your inventing career (do we have all your patents correctly identified?).
- 2) What technologies have you worked in?
- 3) How did you choose the problems you did?
- 4) Is the process of invention different when you collaborate as opposed to inventing alone? If so, then how? Has this changed over the course of your career?
- 5) Is the process of invention different when you work for a firm or organization as opposed to inventing independently? If so, then how? Has this changed over the course of your career?
- 6) Please tell me about the inventions that did not get patented. How are they different?
- 7) What were your most and least successful inventions? Can you explain the difference?
- 8) What are your thoughts on being managed as a lone inventor? And managing the lone inventor vs. a collaborative effort?

Appendix C: Subclass Description and Variable Example

Subclasses 326/31 (signal level or switching threshold stabilization) and 326/82 (current driving fan in/out or off chip driving) first appeared together in patent 5,136,185, which was applied for in 1991, assigned to Hewlett Packard Company, and granted to two inventors living in Silicon Valley. Subclasses 326/16 (test facilitate feature) and 326/56 (tristate feature) were also combined in that invention. Subclass 326/31 comprises electronic circuits that must switch and stabilize a single valid voltage level (high or low) in the presence of other driving circuits. Subclass 326/82 comprises circuits which drive or are driven by a large number of other circuits. These last two subclasses were combined to solve the problem of generating automatic test vectors that did not cause bus contention (buses are multiple sets of signals, usually connected to 16-bit or 32-bit

² Adam Juda, Matt Marx, and Debbie Strumsky all contributed to this effort.

registers; bus contention occurs when two circuits drive opposite voltages on a bus). Engineers design computer chips to avoid bus contention in normal operation, but automatically generated tests can manipulate the chip in abnormal ways, such that two circuits can fight for control. In worst cases, this damages the chip by connecting a direct path between power and ground. Even in the absence of damage, contention makes the test invalid. The first use of this new combination occurred five years later and a total of 10 appearances by the end of data collection in 2002.

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Table 1: Cross tabulation of collaboration and patent assignments, for a 10% sample of U.S. inventors, 1975-1998, by three year career periods. If all patents are unassigned, they are owned by the inventor and arguably represent invention by an “independent.”

	Collaborative	Non-collaborative	Total
All patents assigned	70,283 65.58%	13,907 12.98%	84,190 78.56%
Some patents assigned	2,264 2.11%	449 0.42%	2,713 2.53%
No patents assigned	6,918 6.46%	13,346 12.45%	20,264 18.91%
Total	79,465 74.15%	27,702 25.85%	107,167 100.00%

Table 2: Summary statistics for a 10% sample of U.S. inventors, 1975-1998, by three year career periods.

Variable	Mean	Std.	Min	Max
newsubcp	7.524975	37.89694	0	4436
restusage	18.55179	207.0066	0	26649
focalusage	0.74146	14.24815	0	2387
lnnumpat	0.36733	0.58953	0.00995	5.332767
lnnewsbc	-4.588469	0.279157	-4.60517	1.388791
lnnetsize	2.619561	3.79915	0	11.8986
lnsciref	-2.757067	2.841714	-4.60517	8.086413
lnunivpat	-4.421917	0.929249	-4.60517	3.43431
ageprioart	3.653887	1.362421	0	6.71
lnfocpresubc	-1.849068	3.388594	-4.60517	6.376744
nopriorart	0.20943	0.406904	0	1
noass	0.189088	0.39158	0	1
degree0	0.258494	0.437809	0	1

Table 3: Correlation statistics for a 10% sample of U.S. inventors, 1975-1998, by three year career periods.

	newsubcp	restusage	focalusage	lnnumpat	lnnewsbc	lnnetsize	lnsciref	lnunivpat	ageprioart	lnfocpresubc	nopriorart	noass
restusage	0.438											
focalusage	0.468	0.199										
lnnumpat	0.241	0.104	0.118									
lnnewsbc	0.030	0.069	0.008	0.025								
lnnetsize	0.091	0.028	0.035	0.339	-0.003							
lnsciref	0.125	0.093	0.064	0.331	0.037	0.212						
lnunivpat	0.017	0.021	0.013	0.035	0.009	0.038	0.223					
ageprioart	0.013	0.015	0.009	0.043	0.011	0.027	0.195	0.033				
lnfocpresubc	0.097	0.032	0.039	0.336	-0.005	0.164	0.144	0.009	0.058			
nopriorart	-0.043	-0.037	-0.018	-0.128	-0.025	0.113	-0.202	0.001	-0.371	-0.029		
noass	-0.046	-0.033	-0.016	-0.202	-0.016	-0.277	-0.201	-0.095	-0.087	-0.165	-0.008	
degree0	-0.052	-0.035	-0.019	-0.204	-0.017	-0.407	-0.192	-0.080	-0.067	-0.094	-0.040	0.441

Table 4: Mean variance decomposition of new subclass combinations, from a 10% sample of U.S. inventors 1975-98. All models include time and career period indicators. n=107,167 observations of 67,731 inventors.

	Model 1	Model 2
Innumpat	0.8429*** (0.0213)	0.8494*** (0.0214)
Innewsbc	0.1937*** (0.0164)	0.1939*** (0.0164)
Innetsize	0.0214*** (0.0036)	0.0213*** (0.0036)
Insciref	0.0493*** (0.0036)	0.0499*** (0.0036)
Inunivpat	0.0272** (0.0098)	0.0266** (0.0098)
Inassignee	-0.0374+ (0.0201)	-0.0396* (0.0201)
Inbackcites	0.0985*** (0.0116)	0.0823*** (0.0126)
Infocpresbc	0.0724*** (0.0070)	0.0724*** (0.0070)
propnoass	-0.2571** (0.0930)	-0.2675** (0.0929)
degree0	-0.1269*** (0.0212)	-0.3176*** (0.0557)
InbackcitesXdegree0		0.0876*** (0.0219)
InscirefXdegree0		
_cons	2.6593*** (0.4568)	2.7025*** (0.4558)
dispersion parameter _cons	1.0437*** (0.0082)	1.0431*** (0.0082)
ln likelihood	-272401.25	-272378.08

Table 5: Mean variance decomposition count models of future usage of new subclass combinations by other inventors from a 10% sample of U.S. inventors 1975-98. All models include career and time period indicators in mean and variance estimate. n= 66530 observations of 45,532 inventors.

	Model 3	Model 4	Model 5	Model 6
lnnewsbcp	0.7528*** (0.0104)	0.7541*** (0.0104)	0.7609*** (0.0108)	0.7616*** (0.0107)
lnnumpat	0.2028*** (0.0544)	0.1421* (0.0553)	0.2035*** (0.0531)	0.2037*** (0.0531)
lnnewsbcp	0.2665*** (0.0362)	0.2442*** (0.0344)	0.2452*** (0.0329)	0.2437*** (0.0324)
lnnetsize	0.0396*** (0.0039)	0.0416*** (0.0039)	0.0389*** (0.0037)	0.0390*** (0.0037)
lnsciref	0.1215*** (0.0048)	0.1170*** (0.0048)	0.1247*** (0.0047)	0.1213*** (0.0047)
lnunivpat	0.0420* (0.0189)	0.0450* (0.0192)	0.0393* (0.0196)	0.0409* (0.0197)
lnassignee	-0.0156 (0.0221)	-0.0223 (0.0219)	-0.0220 (0.0222)	-0.0252 (0.0219)
lnbackcites	-0.1377*** (0.0163)	-0.1470*** (0.0148)	-0.1762*** (0.0155)	-0.1766*** (0.0155)
lnfocpresubc	-0.0085 (0.0081)	-0.0084 (0.0081)	-0.0080 (0.0081)	-0.0081 (0.0081)
propnoass	-0.6090*** (0.1008)	-0.6317*** (0.1001)	-0.6307*** (0.1018)	-0.6397*** (0.0999)
degree0	-0.1969*** (0.0343)	-0.1009+ (0.0557)	-0.1959*** (0.0352)	-0.1228* (0.0551)
lnscirefXdeg0		0.0278* (0.0134)		0.0245+ (0.0132)
dinvnewpairmills	0.1549 (0.1833)	-0.0579 (0.1597)	0.0767 (0.1561)	0.0689 (0.1559)
_cons	1.3360*** (0.3058)	1.4044*** (0.3031)	1.3354*** (0.2943)	1.3294*** (0.2922)
dispersion parameter				
propnoass			-0.0107 (0.0294)	-0.0082 (0.0294)
degree0			0.1517*** (0.0243)	0.2042*** (0.0374)
lnsciref			-0.0515*** (0.0033)	-0.0540*** (0.0034)
lnscirefXdeg0				0.0178+ (0.0094)
_cons	1.1747*** (0.0095)	1.1745*** (0.0095)	0.8344*** (0.1988)	0.8293*** (0.1983)
ln likelihood	-199460.78	-199453.65	-198792.87	-198782.19

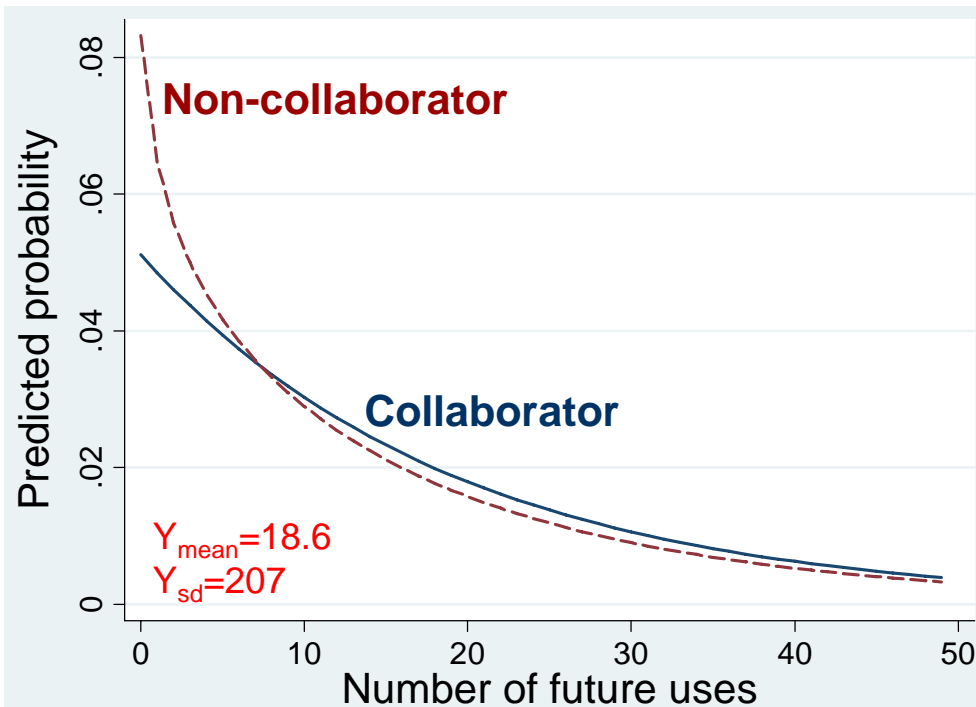


Figure 1: Predicted probabilities of future uses of new combinations of non-collaborative inventor (dashed line) vs. collaborative inventor, all else equal (and calculated at mean of outcome variable, 18.6). The graph indicates that non-collaborative inventors are much more likely to have complete failures at the far left side of the distribution.

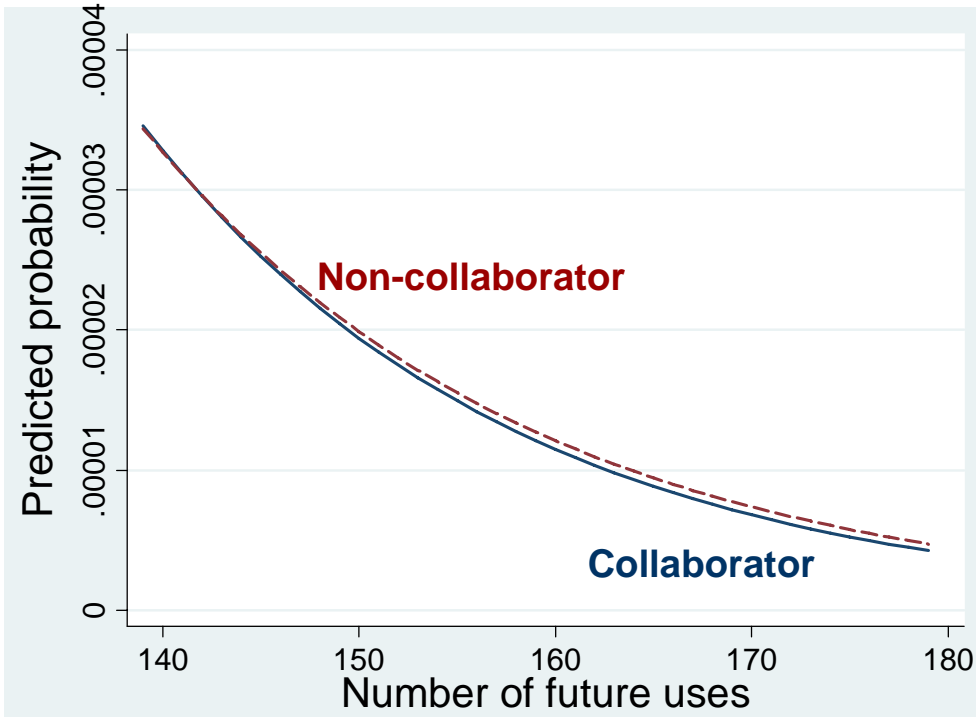


Figure 2: Predicted probabilities of future uses of new combinations of non-collaborative inventor (dashed line) vs. collaborative inventor, all else equal (and calculated at mean of outcome variable, 18.6). The graph indicates that non-collaborative inventors are more likely to invent combinations when those combinations are used more than 141 times.