Dilemma of repeat collaborations in creative projects

Hiroyasu Inoue

Abstract

We focus on how repeat collaboration in creative projects affects the performance. Repeat collaboration has two contradictory aspects. One of them is a positive aspect: team development or experience. The other aspect is negative: team degeneration or abrasion. This contradiction causes the dilemma whether we should keep collaborating or not. The contradiction has not been quantitatively analysed.

We provided extensive and quantitative analyses of the dilemma in creative projects by using patent data of Japan and the United States. We proposed the three conditions to validate the existence of the dilemma quantitatively. First condition is the better impact of team patents is, the longer collaborations occur. Second condition is impact of consecutive patents decrease after hits a team makes. Third condition is at some point of consecutive patents, expectation of impact by switching teams is better than one of a consecutive production. We found these conditions arise in patents of Japan and the
United States. Therefore, we could validate the dilemma in creative projects quantitatively. Next, we proposed preventive strategies for abrasion. One is developing technological diversity and the other is developing inventor diversity. We found the two strategies are both effective through the validation on data.

**Keywords**

Team, Dilemma, Repeat collaboration, Patent, Invention, Creation

1 **Introduction**

Our globally connected societies require us to be aware of competitiveness in various range, such as individuals, companies, or countries [1]. To acquire competitiveness, knowledge creation has attracted the central interest instead of downstream process typified by manufacturing [2, 3, 4]. Since the central resource of the creation is knowledge workers [5], it is important to know how enhance their ability. Although there was a recognition that a genius can make great creations in the past [6], recent studies showed teams can generate better outcome than solos on average [7]. Besides, recent studies have revealed rising propensity for teams rather than solos [8, 9, 7]. If teams can make better performance, our next question is what quality of teams affects the performance.

We focus on how repeat collaboration in creative projects affects the performance. Repeat collaboration has two contradictory aspects. One of them is a positive aspect: team development or experience. There are studies to describe team development based on various models. Those studies described process in which team members adjust their relationships and performance to solve problems as a team [10, 11]. The other aspect is negative: team degeneration or abrasion. Previous studies found that repeat collaborations usually underperform in creative projects,
e.g., scientific research [12, 13, 14], consulting practice [15], and entertainment performances [13, 16, 17, 18]. Those interesting results were explained by ‘creative abrasion’ (a sequence of processes constituted by idea generation, disclosure/advocacy, and convergence), which is key to creative project performance [19]. Despite the both aspects of studies certainly constitute repeat collaboration, they contradict each other as mentioned first. This contradiction is not just a theoretical conflict. We even know this contradiction is the feeling we share. Works with familiar teammates assure stable results but do not set our expectations of big success, especially after a lot of collaborative works with the same team. On the other hand, building a new team accrues expectation of big success and risks to fail. This dilemma is descriptively discussed especially in innovation in companies as ‘Innovator’s dilemma’ [20]. This book, which has a lot of observed examples, showed how new companies with disruptive technologies redefine the competitiveness in markets and successful companies cannot adjust themselves to the change because of their past success. Companies with successful products are fixated on their success and ruin at the end. Although what we want to discuss is the dilemma of not companies, but teams of individuals, they share the same basis. There have not been quantitative analyses about the dilemma of creative projects.

Here, we provide extensive and quantitative analyses of the dilemma of creative projects by using patent data of Japan and the United States. The paper is organized as follows. First, we describe the data we use. Second we propose how we capture the dilemma in these data and quantitatively show inventors have the dilemma. Third, we propose strategies for prevention of abrasion and validate the strategies on data. Finally, we conclude the paper.
2 Data

If we want to tap into massive data on repetitive collaboration in creative projects, patent data is suitable. This is because patents show the occurrence of innovations over time [21]. We use the Institute of Intellectual Property (IIP) patent database as Japanese patent data [22] and the National Bureau of Economic Research (NBER) U.S. patent citations data and Patent Network Dataverse as United States patent data [3, 23]. Massive data enables us to acquire strong evidence of social activities. This is in line with ‘computational social science’ framework [24].

We can extract data based on a common data structure from the two datasets. Each patent has ID of inventors who applied for the patent, number of received citations, technological classification of patents, and year of application. We use International Patent Class for Japanese patent data and U.S. patent class for U.S. patent data as technological classification. To quantify the performance of patents, we define the impact \( I \) of a patent to be the number of citations [3]. Since old patents have more chance to be cited, impact is the number of citations normalized by the average number of citations of patents granted in the same year.

Teams are defined as assemblies of more than one individuals. Even if a team is a subset of another team, these are considered as different teams.

Table 1 summarizes the fundamental data from the datasets. The datasets have a lot of patents and citations between them. Figure 1 shows cumulative probability distributions of team size on datasets. Also, Figure 2 shows impact distributions for the datasets. It is interesting that we see no large deviations between datasets even they have different patent laws.
3 Quantitative proof of dilemma

One of the goals in this paper, again, is to provide extensive and quantitative analyses of the dilemma of creative activities. First, we propose how to capture the dilemma in patent data. Second, we show inventors have the dilemma.

A description of the dilemma is that a successful team tends to try reproducing the success and therefore lose their chance to achieve other success in different teams. In line with the description, we propose three conditions to capture the dilemma.

- Condition 1: The better impact of team patents is, the longer collaborations occur.
- Condition 2: Impact of consecutive patents decrease after hits a team makes.
- Condition 3: At some point of consecutive patents, expectation of impact by switching teams is better than one of a consecutive production.

Condition 1 means that team’s great patents (hits) tend to bind members long. That is, teams show to try reproducing patents if they success, and vice versa. Condition 2 has already been shown in previous studies [13, 14]. If there is no decrease or instead, increase in impact after hits, those situations are preferable and individuals never switch teams. Condition 3 means that teams lose their chances to produce better patents by switching teams. If all of these conditions are supported in datasets, we can say there is a dilemma in them.

Figure 3 shows the average number of consecutive patents after a patent with some impact. The horizontal axis means the impact of team patents. The vertical axis is the average number of consecutive patents by the same team. The better the impact of team patents is, the more consecutive patents the teams have. We can say datasets satisfy Condition 1.
If the slope in Figure 3 is located above, more consecutive patents are applied for. In addition, if the slope is steep, the number of consecutive patents is sensitive to the prior impact. Therefore, teams on Japanese patents tend to have more consecutive patents and the number is more sensitive to the prior impact than ones on United States patents.

Figure 4 shows average impact of consecutive patents after hits. Here, we define hits are patents with top 5% impact. The vertical axis is the average impact. The horizontal axis is the number of repetitions at hits and after hits (No switch. The red line is for Japan. The blue line is for the U.S.). Since we can see the descent of repetitions without switching teams, we can say datasets have fulfilled Condition 2.

There are other lines in Figure 4. They show the average impact of the first patents applied for by a new team including an individual of an original team (Switch to new team. The dark red line is for Japan. The dark blue line is for the U.S.). Therefore, the number of repetitions given by the horizontal axis is pseudo repetitions. The repetitions means when an individual switches their teams in those lines.

As we can see the results of switching, individuals belonging to teams with hits tend to create good patents because the impact is around two. The average impact of overall patents is one. This implies assortativity of inventors based on their ability of inventions.

Comparing lines between no switching and switching enables us to see when individuals should switch our teams statistically. Individuals should switch their teams after hits around the second patents in teams on Japanese patents and the number is around five on U.S. patents.

To clearly see the effect of switching and discuss Condition 3, we define a measure $\rho_r$. 
\[
\rho_r \equiv \frac{\text{Average impact of the first patents created in new teams after } (r-1)-\text{th patents}}{\text{Average impact at } r-\text{th patents}}.
\]
Here, all r-th patents are patents after hits by the same team. If \( \rho_r \) is greater than one, expectation of impact with new teams is larger than the r-th patents in current teams.

Figure 5 shows \( \rho_r \) for each dataset. The horizontal axis means r-th patents in teams. The vertical axis means \( \rho_r \). As the consecutive patents proceed, \( \rho_r \)-s increase in roughly monotonous manner. \( \rho_r \) surpasses one at the second patents after hits (the third patents of teams) in Japanese patents. The transit point in U.S. patents is five. Based on the above discussion, datasets satisfy Condition 3.

Since all conditions are satisfied, we could say we proved innovator’s dilemma quantitatively. The quantitative analyses of innovator’s dilemma has not been done before.

4 Prevention of abrasion

Section 3 showed that creativity of teams abrades on average and therefore the dilemma between to repeat and to switch teams exists for inventors. Since switching teams takes cost of communication to build new relationships and runs risk of success of projects, alleviation of abrasion when we repeat collaborations can help inventors. Here, we propose two strategies to alleviate abrasion.

The first strategy is developing technological diversity. Figure 6 shows results with patents separated into two groups: unexperienced and experienced technologies. If a patent at some repeat has a technology that has not been experienced by a team, it is categorized into an unexperienced technology and vice versa. Results show repeats with unexperienced technologies are better than ones with experienced technologies. Moreover, abrasion itself does not happen on Japanese patent data.
The second strategy is developing inventor diversity. To discuss the strategy, we need to redefine the repeat collaboration. The definition of the repeat collaboration so far is a consecutive patents that are published by the same team. Another definition proposed here is to repeat collaborations between two inventors. Regardless of other inventors on patents, repeats are counted if the two particular inventors are involved. Based on the definition, we can consider entrance and exit of other inventors in teams involving specific two inventors. Figure 7 shows results with patents separated into two groups: unexperienced and experienced team setups. If a patent that involves two inventors and team members other than the two inventors either enter or exit for the first time, the patent is categorized into an unexperienced team setup and vice versa. Results show repeats with unexperienced team setup are better than ones with experienced team setups. Moreover, abrasion itself is highly mitigated on Japanese patent data.

5 Conclusion

We focused on repeat collaboration in creative projects and how it affects the performance. Repeat collaboration has two contradictory aspects. One of them is a positive aspect: team development or experience. The other aspect is negative: team degeneration or abrasion. This dilemma has not been quantitatively analysed. We provided extensive and quantitative analyses of the dilemma of creative projects by using patent data of Japan and the United States. We proposed the three conditions to detect the dilemma. Condition 1: The better the impact of team patents is, the longer collaborations occur. Condition 2: The impact of consecutive patents decrease after hits a team makes. Condition 3: At some point of consecutive patents, expectation of the impact by switching teams is better than one of a consecutive
production. We found these conditions arise in patents of Japan and the United States. Next, we proposed preventive strategies for abrasion. One is developing technological diversity and the other is developing inventor diversity. We found the two strategies are both effective through the validation on data.

**Acknowledgement**

This work was supported by KAKENHI 22730321.
References

[1] M.E. Porter. On Competition. Harvard Business School Press, 1998.

[2] R. M. Grant. Toward a knowledge-based theory of the firm. Strategic management journal, 17:109–122, 1996.

[3] B. H. Hall, A. B. Jaffe, and M. Trajtenberg. The nber patent citations data file: Lessons, insights and methodological tools. National Bureau of Economic Research Working Paper 8498, 2001.

[4] S. K. McEvily and B. Chakravarthy. The persistence of knowledge-based advantage: an empirical test for product performance and technological knowledge. Strategic Management Journal, 23(4):285–305, 2002.

[5] P. Drucker. The Age of Discontinuity: Guidelines to Our Changing Society. Transaction Publishers, 1992.

[6] P.J. Bowler and I.R. Morus. Making Modern Science: A Historical Survey. University of Chicago Press, 2005.

[7] S. Wuchty, B. F. Jones, and B. Uzzi. The increasing dominance of teams in production of knowledge. Science, 316(5827):1036–1039, 2007.

[8] R.K. Merton. The Sociology of Science: Theoretical and Empirical Investigations. University of Chicago Press, 1979.

[9] B.F. Jones. The burden of knowledge and the ‘death of the renaissance man’: Is innovation getting harder? NBER Working Paper Series, 2005.
[10] S.W.J. Kozlowski and B.S. Bell. Work groups and teams in organizations. In W.C. Borman, D.R. Ilgen, and R.J. Klimoski, editors, Handbook of Psychology, volume 12, pages 333–375. John Wiley and Sons, Inc., 2003.

[11] A. Schwab and A.S. Miner. Learning in hybrid-project systems: The effects of project performance on repeated collaboration. Academy of Management Journal, 51:1117–1149, 2008.

[12] J.F. Porac, J.B. Wade, H.M. Fischer, J. Brown, A. Kanfer, and G. Bowker. Human capital heterogeneity, collaborative relationships, and publication patterns in a multidisciplinary scientific alliance: a comparative case study of two scientific teams. Research Policy, 33(4):661–678, 2004.

[13] R. Guimera, B. Uzzi, J. Spiro, and L. A. N. Amaral. Team assembly mechanisms determine collaboration network structure and team performance. Science, 308(5722):697–702, 2005.

[14] H. Inoue and Y. Liu. Revealing the intricate effect of collaboration on innovation. arXiv:1309.2797, 2013.

[15] R. Reagans, E. Zuckerman, and B. McEvily. How to make the team: Social networks vs. demography as criteria for designing effective teams. Administrative Science Quarterly, 49(1):101–133, 2004.

[16] G. Delmestri, F. Montanari, and A. Usai. Reputation and strength of ties in predicting commercial success and artistic merit of independents in the italian feature film industry*. Journal of Management Studies, 42(5):975–1002, 2005.

[17] B. Uzzi and J. Spiro. Collaboration and creativity: The small world problem1. American journal of sociology, 111(2):447–504, 2005.
[18] F. Perretti and G. Negro. Mixing genres and matching people: a study in innovation and team composition in hollywood. *Journal of Organizational Behavior*, 28(5):563–586, 2007.

[19] P.F. Skilton and K.J. Dooley. The effects of repeat collaboration on creative abrasion. *Academy of Management Review*, 35(1):118–134, 2010.

[20] C. Christensen. *The innovator’s dilemma: when new technologies cause great firms to fail*. Harvard Business Press, 1997.

[21] Z. Griliches. *R&D and Productivity-The Economic Evidence*. The University of Chicago Press, Chicago, 1998.

[22] A. Goto and K. Motohashi. Construction of a japanese patent database and a first look at japanese patenting activities. *Research Policy*, 36(9):1431–1442, 2007.

[23] R. Lai, A.D. Amour, D.M. Doolin, G Li, S. Ye, V. Torvik, A. Yu, and L. Fleming. Disambiguation and Co-authorship Networks of the U. S. Patent Inventor Database (1975-2010). Technical report, the Harvard Dataverse Network, 2012.

[24] D. Lazer, A. Pentland, L. Adamic, S. Aral, A.L. Barabási, D. Brewer, N. Christakis, N. Contractor, J. Fowler, M. Gutmann, T. Jebara, G. King, M. Macy, D. Roy, and M.V. Alstyne. Computational social science. *Science*, 323:721–723, 2009.
Table 1: Overview of datasets: datasets are Japan patent data (JPP) and United States patent data (USP). The range of the year in which patents were applied is labeled “Duration”. In addition, the table lists the numbers of patents, inventors, teams, and citations.

| Datasets      | JPP         | USP         |
|---------------|-------------|-------------|
| Duration (year) | 1964-2012   | 1975-2010   |
| Number of patents | 4,349,161   | 3,984,771   |
| Number of inventors | 1,538,525   | 2,665,7091  |
| Number of teams | 967,159     | 1,325,869   |
| Number of citations | 18,410,996 | 48,911,485  |
Figure 1: Cumulative probability distribution of team size
Figure 2: Cumulative probability distribution of impact
Figure 3: Average number of consecutive patents after some impact of patent: Horizontal axis is impact of a team patent. Vertical axis is average number of consecutive patents by the same team. Condition 1 is satisfied in datasets. The horizontal axis is cut so that the number of samples is greater than 100.
Figure 4: Average impact of consecutive patents after hits: We define hits are patents with top 5% impact. Horizontal axis is consecutive patents in the same teams. Vertical axis is average impact. Condition 2 is satisfied in datasets. The horizontal axis is cut so that the number of samples is greater than 100.
Figure 5: $\rho_T$: Horizontal axis is repetitions of team patents. Vertical axis is $\rho_T$. The hit in this figure is top 5% patents in impact. The horizontal axis is cut so that the number of samples is greater than 100.
Figure 6: Average impact of repeat collaboration separated by technological development: Horizontal axis is repetitions of team patents. Vertical axis is average impact. Unexperienced technology means patents at a repeat have technologies that teams have not experienced. Experienced technology means the opposite. The horizontal axis is cut so that the number of samples is greater than 100.
Figure 7: Average impact of repeat collaboration separated by team-member development: Horizontal axis is repetitions of team patents. Vertical axis is average impact. Unexperienced team setup means some member of a team enter or exit. Experienced means the opposite. The horizontal axis is cut so that the number of samples is greater than 100.