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# Team Composition and Innovation Quality in High-tech Firms

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# Abstract

This paper examines the relationship between inventor team composition and innovation quality in the semiconductor industry. Especially, I aim to reconcile the mixed arguments regarding the effect of three aspects of team composition on team innovation quality: 1) prior technological experience diversity (functional diversity) of team members, 2) number of new team members, and 3) number of repeated collaborators.

Through an analysis of U.S. patent data filed by 3,802 inventor teams in 8 global semiconductor firms from 1988 through 1997, I find that 1) the diversity of team member's prior technological experience has an inverted-U shape relationship with innovation quality and 2) the number of repeated collaborators within a team has a negative effect on innovation quality.

**Keywords: Team Composition, Innovation Quality, U.S. Patent, Semiconductor Industry**

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## INTRODUCTION

Mixing and matching the right people in a team is a key factor determining a team's innovation performance (Reagans, Zuckerman, & McEvily, 2004). Teams incorporate individuals with diverse ideas, skills, and resources; this in turn, solves old problems and spurs the creativity needed for innovative outcomes (Guimera, Uzzi, Spiro, & Amaral, 2005; March, 1991). Accordingly, a plethora of research has been conducted to examine the relationship between certain team compositions and innovation performance. In specific, aspects of team composition such as *job-relevant diversity* (Milliken & Martins, 1996; Pelled, Eisenhardt, & Xin, 1999), *background diversity* (Milliken *et al.*, 1996; Pelled *et al.*, 1999; Webber & Donahue, 2001), *team size* (Singh & Fleming, 2010; Stewart, 2006), *team longevity* (Katz, 1982; West & Anderson, 1996), *inflow of newcomers* (Levine, Choi, & Moreland, 2003; March, 1991), and *existence of repeated collaborators* (Guimera *et al.*, 2005; Skilton & Dooley, 2010; Uzzi & Spiro, 2005) have been examined. In spite of the countless number of research done in this area, there still remains inconsistencies in the argument of whether such aspects are beneficial, harmful, or *even* unrelated to innovation performance (Williams & O'Reilly, 1998). Especially, the effects of three major aspects - prior technological experience diversity (functional diversity), number of newcomers, and number of repeated collaborators - still hold a great amount of ambiguity (Levine *et al.*, 2003; Skilton *et al.*, 2010; Williams *et al.*, 1998). Therefore, in this study, I aim to re-examine these three aspects using large longitudinal data, USPTO patent data, to find a relationship that can provide a better explanation of how these aspects of team composition affect innovation quality.

I analyzed USPTO (United States Patent and Trademark Office) patents filed by 3,802 inventor teams in 8 semiconductor firms during a ten-year period (1988-1997) to test my hypotheses. I hypothesize that 1) the prior technological experience diversity of members, 2) the number of newcomers (members who are new to the firm), and 3) the number of repeated collaborators (the dyads of members who have previously collaborated with each other in different patent projects) will all have an inverted-U shape relationship with innovation quality. Results show that 1) the diversity of team member's prior technological experience has an inverted-U shape relationship with innovation quality, 2) the number of repeated collaborators within a team has a negative effect on innovation quality, and 3) the number of newcomers within a team does not have a significant effect on innovation quality.

## LITERATURE REVIEW AND HYPOTHESES

### Diversity of Knowledge and Innovation Quality

Innovation is the outcome of a complex process which is generally composed of three phases: 1) problem identification and formulation, 2) exploration, formalization, and problem solving, and 3) decision dissemination and implementation (Bantel & Jackson, 1989; Daft & Weick, 1984; Zaltman, Duncan, & Holbek, 1973). Although the processes occurring in all three phases should be important to bring upon an innovation, particularly the processes occurring in the first two phases should affect the quality of an innovation; it is in these phases that participating members have the most opportunity and discretion to contribute new and valuable ideas that will affect the quality of the innovation (Bantel *et al.*, 1989). Especially, many prior works cite that the *diversity* of knowledge held within a team should affect the quality of the team's outcomes (Bantel *et al.*, 1989; Guimera *et al.*, 2005; March, 1991). This is because interaction with dissimilar team members promote learning and innovation by exposing members to new paradigms and perspectives and by enabling the cross-fertilization of ideas (Van Der Vegt & Bunderson, 2005).

Particularly, a major stream of research has sought to examine how the diversity of team members affects innovation performance at the top management team (TMT) level (Bantel *et al.*, 1989; Wiersema & Bantel, 1992). For example, team characteristics such as the heterogeneity of age, tenure, educational background, and functional background have been explored (Bantel *et al.*, 1989). Although these studies have provided much insight into how teams should be assembled at the upper level, I argue that TMT characteristics may not sufficiently explain firms' innovative outcomes in certain industries. Especially, this should be the case in high-tech industries such as the semiconductor industry, where innovative outcomes are mainly the products of lower level work groups, inventor teams (Almeida & Kogut, 1997; Edmondson, Bohmer, & Pisano, 2001; Giuri *et al.*, 2007).

Indeed, prior studies have also studied the relationship between team composition and innovation performance at the work group level as well (Agrell & Gustafson, 1994; Ancona & Caldwell, 1992; Kratzer, Leenders, & Engelen, 2004; Pelled *et al.*, 1999). Nevertheless, these studies still hold certain limitations. Especially, there have been inconsistent findings regarding the effect of diversity created by team composition on team innovation performance. On the one hand, diversity has been argued to have a positive effect. For example, Ancona and Caldwell (1992) found that new product teams whose members were from a more diverse set of functional areas produced more creative outcomes. However, on the other hand, researchers have found that the diversity of team members was associated with reduced cohesion and greater conflict, which in turn, led to less desirable outcomes (Moreland, Levine, & Wingert, 1996; Williams *et al.*, 1998). Taking these opposing views into account, I seek to re-examine the relationship between team diversity and innovation performance. Especially, in the paper, I test how the diversity of knowledge created by the prior technological experiences of members, the number of newcomers, and the number of repeated collaborators affects team innovation quality. I chose these three aspects because they are three major aspects that show inconsistent results, but also aspects that should be re-examined because of their importance in composing a team (Levine *et al.*, 2003; Skilton *et al.*, 2010; Williams *et al.*, 1998).

**Prior Technological Experience of Team Members**

According to Argote & Ingram (2000), a significant component of the knowledge that organizations acquire, especially tacit knowledge, is embedded in individual members. Therefore, the aggregate knowledge of individual organization members constructs a ‘reservoir’ of diverse knowledge that can be utilized in order to create new knowledge (Argote *et al.*, 2000; McGrath & Argote, 2001). The need for integrating these different ideas, skills, and resources embedded in individual members has brought upon the demand for teams (Guimera *et al.*, 2005). In an inventor team, individual inventors generally gather to create a new technology for patenting purposes (Giuri *et al.*, 2007). The inventors within a team could possess either homogeneous or heterogeneous prior technological experience. I argue that the extent to which team members are diverse in prior technological experience will affect the innovation’s (patent’s) quality. To some extent, technological experience diversity will enhance the quality of the innovation. When individuals who hold diverse knowledge begin to combine ideas, they have the potential to create new and impactful knowledge (Kimberly & Evanisko, 1981; Williams *et al.*, 1998). For example, Dewar & Dutton (1986) found that the number of different specialties within an organization had a positive effect on radical innovation adoption. Similarly, Smith, Collins, & Clark (2005) implied that hiring and training employees with diverse functional expertise will increase the likelihood that such employees will combine and exchange their ideas to form novel solutions. Finally, Cohen & Levinthal (1990) argued that the greater the unique knowledge held by members of a firm, the greater the chance for new knowledge to be generated through knowledge exchange.

Yet, above a certain threshold level of technological experience diversity, innovation quality may deteriorate. For instance, Souder (1988) found that functionally heterogeneous teams had difficulties reaching agreements on integrated programs of action. Also, specialized language and jargon used by certain team members may impede communication, and therefore make full exchange of knowledge difficult (Maznevski, 1994; Perretti & Negro, 2007). Furthermore, Lane & Lubatkin (1998) argued the need of relative absorptive capacity, the overlap of technological capabilities in order to improve interactive learning which may foster new ideas. The importance of relative absorptive capacity further suggests that excessive technological experience diversity should undermine innovation quality.

Hence, considering this tradeoff of prior technological experience diversity among members, I hypothesize an inverted U-shaped relationship between technological experience diversity among team members and the quality of innovation:

> ***Hypothesis 1.*** *The technological experience diversity among team members will have an inverted-U shape relationship with innovation quality.*

**Newcomers**

Another aspect of team composition that increases the diversity of available knowledge is the number of team members that are new to the firm. In this study, I term these members ‘newcomers’. While the previous section focuses on arguing how diversity created by members with different *within-firm* patenting experience affects innovation quality, this section sheds light on the effects of members that do *not* possess any within-firm patenting experience. These members may be individuals who are 1) currently firm members without any patenting experience, 2) from other firms, or 3) completely new to the industry. Regardless of the type, I argue that newcomers bring fresh and non-redundant ideas to the team because they are least likely to have been imbued with the focal firm’s specific patenting routines which may cause path dependent behaviors (Dosi, 1982; Nelson & Winter, 1982). Especially, March (1991) emphasizes the need for exploration activities through the recruitment of newcomers. In his seminal piece, he argues that novices know less on average, but what they know is less redundant, therefore are more likely to contribute to organizational knowledge. Similarly, Perretti & Negro (2007) implies that newcomers enhance innovation and the chances of finding more creative solutions to team problems.

Nonetheless, many studies also point out the negative aspects of newcomers as well. For example, diversity created by newcomers can be associated with less desirable outcomes such as reduced cohesion and greater conflict (Moreland *et al.*, 1996; Williams *et al.*, 1998).

Furthermore, newcomers possess relatively less amount of important know-how needed for adding to existing knowledge stocks and making further breakthroughs (Dierickx & Cool, 1989). Finally, an overemphasis on exploration will lead to spending high costs on experimentation without gaining many of its benefits (March, 1991). Therefore I hypothesize:

> ***Hypothesis 2.*** *The number of newcomers within a team will have an inverted U-shape relationship with innovation quality.*

**Repeated Collaborators**

Lastly, I argue that certain collaboration behaviors among team members will affect the diversity of available knowledge within a team and in turn innovation quality. Particularly, I argue that repeated collaboration among team members will affect the innovation quality of the team. To begin with, repeated collaboration should initially increase the sharing of valuable ideas. For example, Porac *et al.* (2004) argue that easier knowledge sharing and collaborations in learning-partnerships will be able when the partners involved have previous experience collaborating with each other and share disciplinary backgrounds and professional qualifications. In addition, repeated collaboration can reduce internal coordination costs (Rao & Drazin, 2002) and encourage the sharing of more valuable information (Granovetter, 1973).

However, if the degree of repeated collaboration should pass a certain level, it will make the team's knowledge pool redundant and have a detrimental effect on innovation quality. In specific, Uzzi & Spiro (2005) explain that cohesive cliques tend to overlook important information that is discrepant with their current thinking because members tend to exchange common rather than unique perspectives. Such loss of diverse knowledge may lead to premature convergence on a homogeneous set of ideas or routines and thwart long-run learning within groups (Fang, Lee, & Schilling, 2010; Levinthal & March, 1993; March, 1991). Also, when routines are created, path dependent behavior is likely to arise. This leads to resistance of searching for new solutions (Dosi, 1982; Nelson *et al.*, 1982). For example, members who have developed a certain routines among themselves tend to limit search process to those technologies which are conceptually close to the technologies with which they have previously worked on together (Stuart & Podolny, 1996). Similarly, path dependence may impede members' receptivity to external knowledge by reducing the motivation and ability to seek, recognize, and assimilate knowledge that may be distant from its current practice (Song, Almeida, & Wu, 2003). Overall, due to the aspect that repeated collaboration among team members hinders creativity and limits the efforts to find new possibilities, I hypothesize that the number of repeated collaborators within a team will have an inverted-U shape relationship with innovation quality:

> ***Hypothesis 3.*** *The number of repeated collaborators within a team will have an inverted U-shape relationship with innovation quality.*

## DATA AND METHODOLOGY

I examine the relationship between team composition and innovation quality using United States Patent and Trademark Office (USPTO) data. The reason for using such data is to avoid the limitations caused by data or methodology in prior studies. For example, in previous studies, 1) sample sizes were usually limited (Ancona *et al.*, 1992; Lovelace, Shapiro, & Weingart, 2001), 2) cross-sectional data were used (Bharadwaj & Menon, 2000; Lee, 2008), and 3) the measurement of innovation performance relied on the use of self-reporting methods. While the first two limitations regarding data and methodology prevented researchers from drawing general conclusions and making causal inferences (Johnson & Hall, 1988), the last one may cause measurement errors due to the subjectivity of the reporting individual (Donaldson & Grant-Vallone, 2002). Although various tools have been developed to minimize biases created by self-reporting methods, these methods still create measurement errors that may threaten the validity of a research (Donaldson *et al.*, 2002). In this sense, USPTO's patent data are very attractive for several reasons. First, they include detailed information such as inventor name, inventor country and city, and patent technological class, making it possible to identify a patent team's composition and current technology area. Second, the longitudinal nature of the data allows for tracing past experiences of inventors in terms of their prior patenting experience and collaboration activities with other inventors and also makes possible causal inferences (Singh *et al.*, 2010). Third, future citations received by patents provide a systematic method of measuring innovation quality in a way that is comparable across outcomes (Fleming, 2001; Kim, Song, & Nerkar, forthcoming; Singh *et al.*, 2010; Trajtenberg, 1990). Finally, being able to draw a large sample across a wide range of firms increases the power of statistical tests and makes findings more general (Singh *et al.*, 2010).

Inventor teams of global semiconductor firms are used for analysis because high quality innovation is critical for the survival of firms in the semiconductor industry (Almeida *et al.*, 1997). A total of 7,645 inventor teams in 8 semiconductor firms are identified from patents filed from 1988 through 1997[1]. Teams are initially defined as patent teams in which two or more inventors collaborated to file a patent. However, since I am conducting a study examining the effect of diversity created by team compositions, I use a final sample of 3,802 inventor teams with 3 or more inventors to better capture such effects[2].

**Dependent Variable: Innovation Quality**

I define innovation quality as the number of future citations that each patent receives (Fleming, 2001; Kim *et al.*, forthcoming; Lahiri, 2010; Singh *et al.*, 2010). Each patent builds on prior art, that is, previous inventions documented in patents (Song *et al.*, 2003). Thus, a patent cited by a larger number of future inventors has greater impact, hence a better quality, than a patent cited by fewer inventors (Lahiri, 2010). Since

1) I draw my sample from the 8 largest semiconductor firms in terms of sales figures in 1998.
2) I run my analysis with 4 inventors or more to check for robustness.

citations to patents typically peak 4 - 5 years after the date of issue of the cited patent (Mowery & Ziedonis, 2002), I allow for at least a 5 year term for patents to receive citations. Therefore, citations of the sample patents are measures at the end of 2003.

**Independent Variables**

***Technological Experience Diversity.*** I measure the diversity of team members' prior technological experience ($D$) using the Blau index of diversity (Blau, 1977):

$$D = 1 - \sum_{i=1}^{N} p_i^2$$

where $p_i$ is the portion of the team members' prior patenting experience in a certain technological subclass $i$ and $N$ is the number of discrete technological subclasses that members had prior patenting experience in. For example, US patent '5225904', filed in 1991 by Intel, was the work of 4 inventors, Stuart J. Golin, Allen H. Simon, Brian Astle, and John M. Keith. The technological subclass to which their patent was filed was '375/240.12', a subclass representing a specific technology in the 'Pulse or Digital Communications' patent class (classified by the USPTO). Prior to their collaboration efforts to file patent '5225904', the four inventors had a total of 14 prior patenting experiences in 5 discrete technological subclasses. Among these, 4 experiences were in subclass '348/396', 3 in '341/067', 4 in '348/399', 2 in '348/390', and 1 in '348/415'. Therefore, $D$

would be calculated as 0.77. It should be noted that although my sample is limited to patent teams that have filed a patent from 1988 through 1997, the history of a patenting experience is traced back to the first patent filed by the firm. Also, I applied inventor-matching algorithm similar to that of Fleming *et al.* (2007) to create a reliable patent-inventor mapping (Singh *et al.*, 2010). These conditions apply identically to all of the remaining independent variables.

***Number of Newcomers.*** As aforementioned, 'newcomers' are defined as inventors who may be 1) current firm members without any patenting experience, 2) from other firms, or 3) completely new to the industry. Any types of these newcomers within a team are counted in this variable. Information of inventor names in patent data is used to identify newcomers.

***Number of Repeated Collaborators.*** Repeated collaborators are those members within a firm that have previously collaborated with each other in other patent projects (Guimera *et al.*, 2005). In this variable, the number of repeated collaborator *pairs* within a team is counted. These pairs can be also traced by comparing the names of inventors within a focal patent team with those of previous patents.

**Control Variables**

***Team Size.*** The larger the team size, the higher the chance that members will be able to draw from a more diverse reservoir of knowledge (Perretti *et al.*, 2007). This in turn, will affect innovation quality. Therefore, I control team size using the number of inventors within a focal patent project team.

***Time Passed.*** Although citations to patents typically peak 4 - 5 years after the date of issue of the cited patent (Mowery *et al.*, 2002), older patents are exposed to citation opportunities longer. Therefore, I control the time passed since the issue of a patent by using the number of days since the issue date.

***Firm Dummy.*** Firms may differ in their capabilities to create high quality patents. I analyze teams from 8 firms in this study. Therefore I use dummy variables for each firm.

**Methodology**

I employ the Negative Binomial Regression model for hypothesis testing. Since my dependent variable is a count variable which takes only discrete, non-negative integer values, Poisson or Negative Binomial models may be appropriate. However, since over-dispersion exists in the distribution of citation counts ($\mu$ = 12.72, $\sigma$ = 15.45), the negative binomial model should be a better model (Kim *et al.*, forthcoming; Lahiri, 2010; Singh *et al.*, 2010; Song *et al.*, 2003).

## RESULTS

A Pearson correlation analysis between variables was first performed as a preliminary test.

The correlation matrix in Table 1 indicates a potential multicollinearity problem. Thus, I checked Variance Inflation Factors (VIF) for the full model in Table 2. Values were all less than 10, the threshold level. Therefore, all of the variables were included in the regression model.

Table 2 presents two models from the negative binomial regression. As a baseline, Model 1 includes only control variables. The estimated coefficients for all of the control variables are statistically significant. Among the variables, the coefficient of the team size variable is positive. This implies that larger teams produce higher quality patents. This is probably because the larger the team, the more diverse the knowledge pool will be, contributing to the overall quality of a patent. Another interesting finding is that all the coefficients of the firm dummy are positive. Taking into account the fact that the baseline firm is a firm that has almost the greatest amount of patents among the 8 firms, it would be important to acknowledge that 'innovation performance' may reveal paradoxical results when examined separately in terms of quantity and quality.

**<Table 1> Descriptive Statistics and Correlation Matrix**

| | Mean | S.D. | Min. | Max. | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) Innovation Quality | 12.72 | 15.45 | 0 | 159 | 1.00 | | | | | |
| (2) Tech. Exp. Diversity | 0.69 | 0.29 | 0 | 0.98 | 0.0345* | 1.00 | | | | |
| (3) Num. of Newcomers | 1.18 | 1.42 | 0 | 13 | 0.0580* | -0.2527* | 1.00 | | | |
| (4) Num. of Repeated Collaborators | 4.73 | 16.41 | 0 | 351 | -0.0055 | 0.1152* | -0.1491* | 1.00 | | |
| (5) Team Size | 4.60 | 2.33 | 3 | 28 | 0.0869* | 0.1385* | 0.3638* | 0.6427* | 1.00 | |
| (6) Time Passed | 5904.78 | 933.28 | 4689 | 8439 | 0.1441* | -0.0570* | 0.1177* | -0.0349* | 0.1156* | 1.00 |
| (7) - (13) Firm Dummy | . | . | . | . | . | . | . | . | . | . |

* Correlation is significant at the 0.05 level (two-tailed)
(*Note*: Statistics for the firm dummy variables are omitted due to the limit of page space. None of them show any signs of multicollinearity.)

<Table 2> **Negative Binomial Models for Innovation Quality**

| | Model 1 | Model 2 |
|---|---|---|
| **Explanatory Variables** | | |
| Technological Experience Diversity | | 0.60*** |
| | | (0.22) |
| Tech. Exp. Diversity Squared | | -0.46** |
| | | (0.22) |
| Number of Newcomers | | -0.02 |
| | | (0.03) |
| Number of Newcomers Squared | | 0.00 |
| | | (0.00) |
| Number of Repeated Collaborators | | -0.01*** |
| | | (0.00) |
| Number of Repeated Collaborators Squared | | 0.00 |
| | | (0.00) |
| **Control Variables** | | |
| Team Size | 0.05*** | 0.10*** |
| | (0.01) | (0.02) |
| Time Passed | 0.00*** | 0.00*** |
| | (0.00) | (0.00) |
| Firm 2 Dummy | 0.45*** | 0.47*** |
| | (0.12) | (0.12) |
| Firm 3 Dummy | 0.49*** | 0.49*** |
| | (0.09) | (0.09) |
| Firm 4 Dummy | 0.55*** | 0.55*** |
| | (0.08) | (0.08) |
| Firm 5 Dummy | 0.22*** | 0.20** |
| | (0.08) | (0.08) |
| Firm 6 Dummy | 0.30** | 0.31** |
| | (0.13) | (0.13) |
| Firm 7 Dummy | 1.05*** | 1.05*** |
| | (0.12) | (0.12) |
| Firm 8 Dummy | 0.48*** | 0.47*** |
| | (0.09) | (0.09) |
| **Constant** | 0.54*** | 0.34** |
| | (0.14) | (0.15) |
| N | 3802 | 3802 |
| Log Likelihood | -13482.688 | -13467.944 |
| LR Chi2 | 259.65*** | 289.14*** |

** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Explanatory variables were added to Model 2 for hypothesis testing. The improvement of the log-likelihood function, from -13482.688 ($\chi^2$ = 259.65, $p$ < 0.001) in Model 1 to -13467.944 ($\chi^2$ = 289.14, $p$ < 0.001) in Model 2, suggests that a better fitting model emerges as the explanatory variables are introduced. Hypothesis 1 predicts that the diversity of team members' prior technological experience will have an inverted-U shape relationship with innovation quality. Since the coefficient of the linear term of technological experience diversity is positive ($\beta$ = 0.60, $p$ < 0.05) and the quadratic term of it is negative ($\beta$ = -0.46, $p$ < 0.05), the curvilinear relationship is supported. In Hypothesis 2, it was suggested that the number of newcomers within the team will also have a curvilinear relation with innovation quality. Results do not support this hypothesis. Both coefficients of the linear term and the quadratic term show negative signs and are not statistically significant at the 0.05 level. Finally, Hypothesis 3 predicts that the number of repeated incumbents as well will have a curvilinear relation with innovation quality. Contrary to what I predicted, results reveal only a negative relationship between the number of repeated incumbents and innovation quality ($\beta$ = -0.01, $p$ < 0.001). The hypothesized inverted-U relationship is not found.

## DISCUSSION

While my hypotheses predicted that team composition in terms of prior technological experience diversity, number of newcomers, and number of repeated collaborators should have an inverted-U shape relationship with innovation quality, results showed that they all had different effects on such quality. First, prior technological experience diversity was found to have a curvilinear relationship with innovation quality. I argue that this finding is the most important theoretical breakthrough of this paper, for no previous study (to my knowledge) has yet to empirically show this curvilinear relationship. While prior studies have found either a positive or negative relationship (or in fact, have failed to find any relationship), I suggest that both relationships exist. To begin with, I argue that technological diversity to a certain degree is conducive to a team's innovation outcome. This is because the diverse experiences of individual members can be shared to create a more novel and useful innovation outcomes (Kimberly *et al.*, 1981; Williams *et al.*, 1998). However, over a certain threshold, the diversity of the team members may create communication problems (Maznevski, 1994) or hinder integrated actions (Souder, 1988), leading to worse innovation outcomes. Second, I found that the number of newcomers within a team did not have a statistically significant effect on innovation quality. I believe that this may be due to the confounding characteristics of newcomers within a team. On the one hand, many previous studies imply that newcomers will be conducive to innovative outcomes of the team because they possess knowledge and skills that are less redundant and not subject to firm's existing routines (March, 1991; Perretti *et al.*, 2007). On the other hand, newcomers may hinder innovative outcomes of the team because they lack the knowhow needed for adding to existing knowledge stocks and make further breakthroughs (Dierickx *et al.*, 1989). This should be especially a critical problem in the high-tech industry where important knowledge is usually embedded in tacit knowledge (Almeida *et al.*, 1997). Also, newcomers bring upon reduced cohesion and greater conflict within the team (Moreland *et al.*, 1996; Williams *et al.*, 1998). Furthermore, newcomers are often submissive and susceptible to incumbent member's influence attempts (Moreland *et al.*, 1996). This implies that although newcomers bring with them a wealth of knowledge, this knowledge will not be useful unless it is successfully incorporated into the social context of the organization (Perretti *et al.*, 2007). Last, my results show that the number of repeated collaboration of team members had only a negative effect on innovation quality. I argue that this is because repeated collaborators tend to possess common knowledge and rely on routines that they have constructed in the past (Guimera *et al.*, 2005; March, 1991). In this case, search processes become limited to those technologies which are conceptually close to the technologies with which repeated collaborators have previous worked on together (Song *et al.*, 2003; Stuart *et al.*, 1996). Especially, since we are focusing on the effect of repeated collaboration on innovation *quality*, not quantity, repeated collaboration seems to have only a negative effect.

Other than the aforementioned theoretical contributions, this study also advances prior literature on team composition and innovation performance by methodologically contributing to it in three major aspects. First, by examining innovation performance at the work group level, this study provides a more relevant view of team composition and innovation performance. This should be especially important in high-tech industries where innovative outcomes are mainly the products of lower level work groups (Almeida *et al.*, 1997; Edmondson *et al.*, 2001; Giuri *et al.*, 2007). Second, this study overcomes the limitations of existing work group level innovation studies by using a unique data set. Work group level innovation studies have mostly relied on small (Ancona *et al.*, 1992; Lovelace *et al.*, 2001), cross-sectional (Bharadwaj *et al.*, 2000; Lee, 2008), and survey-based data (Agrell *et al.*, 1994; Kratzer *et al.*, 2004). This made it difficult to draw general conclusions, make causal inferences (Johnson *et al.*, 1988), and avoid measurement errors (Donaldson *et al.*, 2002). Patent data have advantages over these data in that they 1) can be collected in huge amounts across a wide range of firms, 2) are longitudinal in nature, and 3) provide information on future citations that can provide measurements exempt from self reporting biases (Singh *et al.*, 2010). Last, my study examines innovation performance in terms of the ex post quality of the innovation. This is an important aspect to firms competing in high-tech industries because the quality of an innovation, measured by the number of future citations a patent receives, is found to be correlated with the consumer surplus generated (Trajtenberg, 1990), patent renewal rates (Harhoff, Narin, Scherer, & Vopel, 1999), and contribution to an organization's market value (Hall, Jaffe, & Trajtenberg, 2000).

My research is not without limitations. First, I have only included inventor teams of semiconductor firms in my sample. In order to draw a more general conclusion on the effect of certain team compositions on innovation quality in high-tech firms, data of inventor teams in firms such as the biotechnology, telecommunications, or aerospace industry must be included. Next, in this study, I only focused on team level factors that may affect innovation outcomes. However, as Gupta, Tesluk, & Taylor (2007) suggest, a multilevel analysis comprised of a mixture of individual, team, organizational, and industry level factors should provide a much more clearer insight into the processes and mechanisms that improve innovation quality. Lastly, I assume that newcomers are conducive to high quality innovations regardless of their possible previous activities in other organizations because they should possess knowledge or skills that are non-redundant to the focal firm. However, the effects of newcomers may differ according to their type because of the different levels of prior patenting experience they hold. For example, an newcomer from a different firm may be ‘new’ to the focal firm, but their skill sets or the amount of knowledge that they can contribute to the team would be incomparable to those of an inventor who is completely new to the world of patenting. Therefore, I suggest that further research be done in this area to clarify such ambiguity.

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# 국문초록

## 하이텍 기업의 팀 구성이 혁신의 질에 미치는 영향

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본 논문은 반도체 산업에서의 과학자(발명자) 팀 구성이 혁신의 질에 미치는 영향에 대하여 연구하고 있다. 특히, 팀 구성과 혁신의 질 간의 관계를 연구한 기존 문헌에서 일관된 결과를 제시하지 못하고 있는 세 가지 팀 구성 요소의 영향에 대하여 보다 명확한 관계를 밝히는 데에 그 목적이 있다. 그 세 가지 요소는 팀 구성원 간의 기존 기술적 경험 다양성, 새로운 팀원의 수, 그리고 반복된 협업을 하고 있는 팀원의 수이다.

1988년부터 1997년까지 8개의 글로벌 반도체 기업에서 3,802개의 과학자(발명자) 팀이 출원한 미국 특허의 데이터를 바탕으로 본 논문은 두 가지 결과를 제시한다. 첫째, 팀 구성원 간의 기존 기술적 경

험 다양성은 혁신의 질과 역-U자 관계를 가지고 있다. 둘째, 팀 내에서 반복된 협업을 하고 있는 팀원의 수가 늘어날수록 혁신의 질은 낮아진다. 본 연구의 결과는 향후 하이텍 기업에서의 팀 구성 방법에 대한 통찰력을 제시해줄 것으로 기대한다.

**주요어: 팀 구성, 혁신의 질, 미국 특허, 반도체 산업**

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