Pay and Networks in Organizations:
Incentive Redesign as a Driver of Network Change

Hitoshi Mitsuhashi *
Professor
Waseda University
ORCID: 0000-0003-4457-7357
Nishi Waseda 1-6-1, Shinfuku Tokyo 169-8050, Japan
hm18 @ waseda.jp

Azusa Nakamura
Ph.D. Fellow
Bocconi University
ORCID: 0000-0001-9102-0370
Via Roentgen 1, 20136, Milan MI, Italy
azusa.nakamura @ unibocconi.it

*corresponding author

Running head: Incentive-induced network adaptation

Keywords: Incentive redesign, performance-based incentive, social networks, innovation, inventors

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/smj.3335

Nakamura Azusa (Orcid ID: 0000-0001-9102-0370)

Research summary: We examine how corporate innovators adapt their intraorganizational networks when firms introduce performance-based incentive plans that center on the short-term achievement of individuals' measurable outputs. We postulate that such plans prompt individuals to revise goals and reconfigure their networks accordingly. Using the co-patenting data we analyzed cases of this incentive redesign by Japanese electronics firms in the 1990s. We found that the redesign engendered the emergence of more closed and smaller networks in organizations. Although inconsistent, we found some evidence that it promoted corporate innovators to build networks with others with similar expertise. These findings support the notion of incentive-induced network adaptation and suggest a new theme to study the effects of incentive redesign on network evolution. (117 / 125 words)

Managerial summary: Research suggests that innovators' networks assist with generating novel ideas, and that some structural characteristics encourage innovation. However, knowledge about how managers can create social conditions that promote the emergence of "ideal" networks in their firms is limited. We focus on the effects of incentive redesign and explore how corporate innovators can change their intraorganizational networks when firms introduce performance-based incentive plans. We found that the redesign engendered the emergence of more closed and smaller networks in organizations. We also obtained some evidence that suggests that the redesign prompts inventors to include those with similar expertise in their networks. Thus, it is possible that managers can use incentive plans to design innovation networks in organizations (115 / 125 words).

1 INTRODUCTION

Research on networks in organizations has focused on which network structures confer advantage and has expanded our understanding of how network structures promote knowledge transfer in organizations and create opportunities for individuals to re-synthesize knowledge (e.g., Wang *et al.*, 2014). Since "an understanding of network outcomes is incomplete and potentially flawed without an appreciation of the genesis and evolution of the underlying network structures" (Ahuja, Soda, and Zaheer, 2012: 434), scholars have also explored the drivers of network evolution and change. Previous studies have viewed network evolution as structurally embedded and path-dependent and found evidence of the effects of pre-existing ties and network structures on subsequent tie formations and terminations (Zhang and Guler, 2020). This research orientation comes at the expense of overlooking the role of management practices and policies as drivers of network change in organizations (Gulati and Srivastava, 2014).

Scholars have since begun focusing on this promising avenue. According to Biancani, McFarland, and Dahlander (2014), an implicit premise in studying such drivers is that managers cannot "engineer" (p. 334) social networks but do play a proactive role in creating the social conditions that engender the desired network structures in their organizations. Extant empirical research has yielded three important findings regarding these drivers. The first driver is spatial configuration: physical proximity among organizational members promotes interactions and generates dense, cohesive networks in organizations (e.g., Small and Adler, 2019). The second driver is the creation of social foci. Informal entities such as clubs and forums in organizations (Shipilov *et al.*, 2014) or formal ones such as cross-unit strategic committees (Gray *et al.*, 2019) create ties that span disconnected communities. The third driver is human resource (HR) practices such as job rotation programs (Kleinbaum, 2012), protégé-mentor assignments (Hasan and Bagde, 2015), and selection programs (Sasovova *et al.*, 2010). Some of these programs help individuals develop open networks, defined as sparse structures with many structural holes, and enable them to extract more benefits from their networks.

This study aims to enrich the literature of this third approach by exploring another potential HR driver of network change in organizations. While organizational scholars have long acknowledged incentive plans as a critical factor that influences a wide range of individuals' behaviors and performance (e.g., Ederer and Manso, 2013), the effect of incentive plans on network change in organizations has rarely been studied. Over a decade ago, Kaplan and Henderson (2005: 1047) pointed out that organizational scholars had left the detailed study of incentive plans in the hands of organizational economists and that research on incentives and the related behavioral consequences from an organizational perspective was scarce as compared to the economics literature. Despite their concerns, the progress in filling this gap has been slow.

The purposes of this study are to (1) examine how incentive redesign triggers network changes in organizations and (2) propose the notion of incentive-induced network adaptation i.e., individuals reformulate goals and proactively reconfigure their networks to achieve these revised goals as a response to incentive redesign in organizations. We focused on the change of incentive plans from those that weakly link short-term individualized contributions with remuneration (e.g., seniority-based pay) to those that tightly link them (i.e., performance-based incentive plans). The renewed plans evaluate individuals' short-term performance based on the achievement of quantifiable outputs relative to targets and recognize individuals' respective contributions (Lee and Meyer-Doyle, 2017; Lee and Puranam, 2017).

We also focused on effects of this form of incentive redesign on corporate innovators and argue that it predisposes them to seek two goals: to (1) deliver more measurable short-term outcomes and (2) receive a fair share of the credit from the supervisor who rates individual contributions to the outcomes that they jointly achieve with others in their networks. Credit here means supervisors' acknowledgement of each innovator's contributions to joint work (Graham and Cooper, 2013). We predict that to achieve the first goal, individuals would build closed networks with fewer structural holes and networks with others who possess similar expertise. We also postulate that to achieve the second goal, individuals would form smaller networks. Hence, the introduction of short-term and individualized incentive plans prompts corporate innovators to build easily manageable networks to quickly execute projects and get rewarded.

To test our predictions, we used Japanese electronics firms' patent application filing data, focused on co-innovator networks, and adopted a quasi-experimental research design. During the period between the two world wars in the 20th century, most Japanese manufacturing corporations relied on low-powered incentive plans based primarily on employee seniority and years of service. However, between 1993 and 1995, Fujitsu Limited and NEC Corporations introduced performance-based incentive plans. We considered the two firms as the treatment group and their incentive redesign as the treatment effects and conducted difference-in-differences (DID) analyses. The results supported our notion of incentive-induced network adaptation. We found that the incentive redesign gave rise to more closed and smaller networks in organizations. Furthermore, although inconsistent, we found some evidence that it promoted corporate innovators to build networks with others who have similar expertise.

2 THEORY AND HYPOTHESES

2.1 Effects of incentive redesign

In many settings, performance-based incentive plans operate on the principle of management by objective (Campbell, 2015). At the beginning of a term, a supervisor and a subordinate establish individualized measurable objectives. Since performance review cycles are relatively short (e.g., 6 or 12 months), the established objectives tend to be short-term. At the end of the term, the supervisor assesses the extent to which the subordinate has achieved those objectives and remunerates the subordinate accordingly.

When firms introduce performance-based incentive plans, individuals' behaviors change in three ways. First, the renewed incentive plans induce them to exert more effort in achieving high performance, which leads to increased productivity, as shown by a large amount of empirical research in the economic literature (e.g., Lazear, 2000). Vroom's (1964) expectancy theory argued that individuals have higher motivation when they believe that (1) more effort increases their work performance (i.e., expectancy), (2) higher work performance leads to the achievement of goals such as receiving remuneration (i.e., instrumentality), and (3) the achievement of goals is important (i.e., valence) (Miner, 2015). By tightly linking work performance with remuneration, firms with performance-based incentive plans can increase the instrumentality of work performance and motivate individuals to make more effort.

Second, the renewed incentive plans also change the goals that individuals pursue. Goals are "internal representations of desired states, where states are broadly construed as outcomes, events, or processes" (Austin and Vancouver, 1996: 338). Goal-setting theory (Locke, 2000) posits that goal setting has substantial effects on work performance and work processes particularly when the goals are clear and specific. This is due to the directive function that goals serve: individuals direct more attention and effort toward goal-relevant activities and divert them from goal-irrelevant activities. One characteristic of performance-based incentive plans is that they decrease the tolerance for failure in organizations and require individuals to accept risks for reduced remuneration if they fail to show visible short-term outcomes (Ederer and Manso, 2013). This reduced tolerance for failures discourages individuals from taking risks and engaging in experiments that present unclear associations between effort and outcome.

Instead, the introduction of performance-based incentive plans predisposes individuals to aim for increasing the number of measurable short-term outcomes of innovation activities. Individuals carefully select projects by avoiding those with uncertain long-term payoffs and favoring those that inevitably generate short-term returns. Therefore, they tend to focus on the generation of knowledge that does not require risk-taking and experimenting (Balachandran and Hernandez, 2018). Several empirical studies support this argument (Lee and Meyer-Doyle, 2017; Lerner and Wulf, 2007).

Lastly, the renewed incentive plans make it more cumbersome for supervisors to discern individual contributions to joint work and assign credit accordingly (Williamson, 1981). The introduction of performance-based incentive plans increases the chance that individuals face unfair assignments of credit wherein supervisors do not give them credit even when they are entitled to it but give credit to others who do not deserve it (Crant and Bateman, 1993). We followed Graham and Cooper (2013) and defined receiving credit as supervisors' acknowledgement of each individual's contributions to joint work. Since the introduction increases individualism (Collins and Smith, 2006) and strengthens the link between individualized remuneration and supervisors' credit assignment, it prompts individuals to ensure that they could receive a fair share of credit for their respective contributions to joint work with others.

2.2 Adapting networks

While research has long considered network evolution to be structural outcomes of pre-existing networks, recent research has complemented this "deterministic" view with the "agent" view (Ahuja *et al.*, 2012) and highlighted the role of individuals' "purposive actions" to "advance their own interest" in network evolution (Ibarra, Kilduff, and Tsai, 2005: 361). Empirical studies have demonstrated the role of individuals' motivations in creating (or terminating) network ties to exploit others' expertise and gain instrumental returns and personal rewards (e.g., Vissa, 2011).

Taking this "agent" view, Shea and Fitzsimons (2016: 53) pointed out that "little [is known] about the reverse causal direction—how goals may affect network structures." Drawing on goal-setting theory (Locke, 2000), they found that individuals change networks when they start pursuing revised goals because some networks are more suited to achieve specific goals. In this study, we argue that incentive redesign influences individuals to reformulate their goals, and thereby, encourages them to reconfigure their networks in organizations. It is notable that not all the individuals in firms have discretion over their network adaptation decisions: some co-work ties may be formally and hierarchically assigned. We resolved this problem in an empirical manner, whereby the following arguments presume such individuals' discretions over network adaptation.

2.3 Incentive-induced network adaptation

We argue that as a result of the introduction of performance-based incentive plans, individuals such as corporate innovators seek to deliver measurable short-term outcomes and ensure their fair share of credit for joint work from supervisors. To achieve the revised goals, they might adapt their co-work networks, which can be characterized by network structure, content, and size. The structure of networks refers to stable patterns of ego–alter and alter–alter relations. We focused on whether individuals build closed networks, dense structures with many common third-party ties, or open networks with more structural holes (Burt, 1992). The content of networks refers to the types of expertise that egos can obtain via network ties with alters (Reagans, Singh, and Krishnan, 2015). Specifically, we focused on whether individuals build networks consisting of alters having similar or dissimilar expertise. The size of networks refers to the number of alters in an ego's network (Paruchuri, 2010).

The revised goals will change the structure and content of networks because individuals prioritize the quantity of knowledge they deliver over its quality and attempt to generate knowledge that does not require risk-taking and experimenting. Moreover, the revised goal will change network size because individuals expect supervisors to be more likely to give a fair share of credit in smaller networks. Although smaller networks tend to have properties similar to closed networks, we developed separate hypotheses as they are based on different theoretical arguments.

2.3.1. Structure One of the central themes in the network literature is about the distinctive advantages that open and closed networks provide. In open networks, an ego has ties with sets of otherwise disconnected alters and spans structural holes among them, whereas in closed networks, an ego and alters have many common third-party ties. Knowledge residing in open networks is non-redundant and diversified (Sutton and Hargadon, 1996). When exposed to a set of unrelated and diversified ideas in an open network, an individual has a better chance of finding novel and atypical combinations to generate innovative ideas (Guimerà *et al.*, 2005).

However, this advantage of non-redundant information in open networks emerges at the expense of the benefits of knowledge transfer and coordination in closed networks (Singh *et al.*, 2016). Individuals in closed networks tend to develop shared meanings and common understandings and can exchange complex knowledge without incurring substantial transfer costs (Hansen, 1999). While those in open networks have limited means to interpret diverse information, the iterative interactions among those in closed networks generate timely access to detailed information and alleviate this interpretation problem (Ter Wal *et al.*, 2016). In addition, since those in closed networks have little incentive to exchange biased and inaccurate information that could cause negative reputation, they can preserve the resources required to confirm this information (Schilling and Fang, 2014). Moreover, while knowledge transfers in open networks should benefit recipients (but not sources), cohesion and reciprocity in closed networks reduce competitive tensions among network participants, increase their willingness to assist, and thereby, alleviate sources' perceived burdens (Reagans and McEvily, 2003).

Closed networks also present an implementation advantage. Generating novel ideas consists of the search and implementation stages (Carnabuci and Diószegi, 2015; Obstfeld, 2005). The latter stage requires collaboration and coordination, which can be generated by the mutual identification of collectivity among those in closed networks (Reagans and Zuckerman, 2001). Repeatedly developed collaborative relations among individuals in closed networks increase productivity by presenting more learning opportunities to understand how to help each other and work together (Sosa and Marle, 2013).

Therefore, both open and closed networks have advantages, suggesting the importance of adopting hybrid strategies to balance them (Kaplan and Vakili, 2015; Ter Wal *et al.*, 2016). Individuals can concurrently balance open and closed networks if their closed networks comprise alters with diversified knowledge or if they develop closed networks that comprise alters spanning more structural holes (McFadyen, Semadeni, and Cannella, 2009). Individuals can also sequentially balance the two by switching between them over time (Burt and Merluzzi, 2016).

However, when firms introduce performance-based incentive plans, individuals with the revised goals might trade off uncertain long-term innovation for measurable short-term outcomes and try to achieve immediate returns at the expense of unforeseeable future success. Individuals allocate more time and resources to activities that are less temporarily remote and deliver more certain outcomes. They also become more reluctant to take risks regarding experimenting with novel knowledge combinations and decrease their appreciation of the value that open networks present. In addition, the knowledge transfer and implementation advantages that closed networks offer speed up knowledge creation processes. For individuals incentivized by short-term outcomes, the limited variation in the combined knowledge in closed networks can also help them handle information quickly (Carnabuci and Bruggeman, 2009) and reduce the burden of tedious search (Hansen, 1999).

Hence, the introduction of performance-based incentive plans prevents individuals from reconciling the trade-off between open and closed networks and causes a one-sided focus on the latter that may enhance short-term returns even though it is likely to harm innovation in the long run. This form of incentive redesign therefore generates a biased preference for networks that offer such immediate returns, resulting in the development of closed networks. Hence, we hypothesized the following.

Hypothesis (H1). *An individual is more likely to develop closed networks with fewer structural holes after a firm introduces performance-based incentive plans.*

2.3.2 Content One way to characterize the content of networks is to focus on the types of expertise that egos can obtain via network ties with alters (Reagans *et al.*, 2015). Networks can be diversified (or homogeneous) if the expertise possessed by egos and alters are dissimilar (or similar). As in open and closed networks, diversified and homogeneous networks present different payoffs. Diversified networks allow individuals to experiment with novel and atypical combinations of distant knowledge and increase the chance of long-term innovation. Since novel and valuable ideas emerge when individuals combine more than two pre-existing ideas from seemingly unrelated knowledge fields (Leahey, Beckman, and Stanko, 2017; Rosenkopf and Nerkar, 2001), gaining access to diversified expertise via network ties is important for innovation.

However, research on networks has also shown that the experimental synthesis of distant knowledge for innovation requires individuals to search extensively and collaborate interactively with others who have dissimilar expertise. Carnabuci and Bruggeman (2009: 607) noted that "specializing in an increasingly homogeneous set of input ideas is both more efficient and less risky than brokering knowledge." Finding novel and atypical combinations through accessing diversified networks requires risk-taking as individuals' efforts might not yield an obvious short-term return (Kaplan and Vakili, 2015).

The introduction of performance-based incentive plans might encourage individuals to allocate more resources to the generation of knowledge that does not require risk-taking and experimenting. If this is the case, individuals who discount the value of access to diversified knowledge might prefer networks that consist of alters with similar expertise because of the following three advantages of homogeneous networks.

The first is a cognitive advantage, wherein common knowledge bases enhance absorptive capacity, resolve information overload problems, and enable information exchange in a timely manner (Reagans *et al.*, 2015). The second is a motivational advantage. Low costs of knowledge transfer motivate individuals to share and absorb more knowledge (Black, Carlile, and Repenning, 2004). The third is a relational advantage: while individuals often refrain from expressing ideas for fear of negative reactions from experts, this would not be a case if individuals share knowledge bases (Wang *et al.*, 2014). The absence of fear among those with similar expertise shortens the time required for knowledge creation.

Therefore, the introduction of performance-based incentive plans impels individuals to abandon the hybrid strategies and minimize any potential risks in delivering measurable short-term outcomes. Thus, they build networks consisting of others having similar expertise. This form of incentive redesign reduces individuals' ambitions to generate great ideas and instead prompts them to prioritize immediate reliability, resulting in the development of networks with those who have similar expertise. Therefore, we hypothesized the following.

Hypothesis (H2). *An individual is more likely to develop networks with others who have similar expertise after a firm introduces performance-based incentive plans.*

Size When firms introduce performance-based incentive plans, privately assigned credit can be exchanged for remuneration. For individuals to secure credits, their supervisors need to be clearly cognizant of the individual contributions and assign credit fairly. However, supervisors' fair credit assignment in multiparty effort settings is complicated by causal ambiguity: a certain individual's ideas may give greater impetus, but it is unclear which ideas matter the most in delivering the final outcomes (Graham and Cooper, 2013). If individuals select fewer colleagues to work with and build smaller networks, this reduces the cognitive burdens of their supervisors regarding credit assignment because of the fewer factors that have to be considered in the assignment process (Karau and Williams, 1993). The subsequent reduced ambiguity in credit assignment is favorable (Liden *et al.*, 2004). In addition, supervisors might respond to the complication by adopting the equality principle as a cognitive shortcut; in other words, they might split the credit evenly among those involved in joint work. If this is the case, individuals might avoid working with those who make marginal contributions, and this selective orientation might reduce the preferred number of collaborators.

Smaller networks are also advantageous in reducing the costs of coordinating and managing interdependence (Paruchuri, 2010). By reducing network size, individuals can avoid information overload by reducing the number of sources. Hence, we hypothesized the following:

Hypothesis (H3). *An individual is more likely to develop smaller networks after a firm introduces performance-based incentive plans.*

3 METHODS

3.1 Incentive redesign and treatment effects

3.1.1 Fujitsu and NEC In this study, we used a quasi-experimental design and DID method (Wing, Simon, and Bello-Gomez, 2018) to test how firms' introduction of performance-based incentive plans affects individuals' (i.e., corporate innovators) reconfiguration of intraorganizational networks. We estimated the treatment effects on the outcome variables by comparing individuals in treatment groups before and after the treatment with those in control groups before and after the treatment.

We used the cases of incentive redesign by two similar major electronics manufacturers in Japan in the 1990s: Fujitsu and NEC. Both have long organizational histories (founded in 1935 and 1899, respectively). From 1990 to 1994, Fujitsu and NEC made comparable revenues and return on assets of 3.1 trillion yen and 3.6 trillion yen and 3.6% and 3.4%, respectively. Moreover, the two firms operate in three similar fields: communication, information processing and computers, and electronic devices.

We used the incentive redesign of Fujitsu and NEC as the treatment for two reasons. First, although performance-based incentive plans were diffused among Japanese manufacturing firms in the 1990s, these two firms were the earliest adopters, and hence, did not have any symbolic motivation for the adoptions (Tolbert and Zucker, 1983). Second, since we used patent application filing data to test the hypotheses, it was important to focus on technology firms that were highly active in the filings, such as Fujitsu and NEC.

To understand the incentive redesign at the two firms, we conducted fieldwork from the summer of 2017 to that of 2020 to interview 15 individuals who worked for one of the two companies as corporate innovators, human resources experts, or general managers at the time of the incentive redesign in the 1990s. The total interview time was about 22 hours. Online Appendix 1 presents the list of interviewees. In the following sections, we used the ID numbers in the appendix to refer to their comments.

3.1.2 Historical background Seniority-based pay started in Japanese firms before the Second World War (Yonekawa, 1984). Japanese manufacturing firms, including Fujitsu and NEC, applied their wage system for blue-collar workers in plants as well as office workers and corporate innovators. Before the 1990s, like most other Japanese firms, Fujitsu and NEC strongly linked base pay and bonuses, which were paid twice a year, with seniority and years of service. *The New York Times* reported that at Fujitsu, "older subordinates still get paid more than their younger boss, in line with the seniority system," and this is the case even when "younger people are in charge of older people" (Pollack, 1993). Employees could increase their remuneration either by working longer hours or by getting promoted. However, since the slow market growth in the 1980s made it difficult for these firms to create sufficient higher-level positions (Vanni, 2011), the only option for those interested in increasing remuneration was to work longer hours, thereby lowering productivity. A comment by HR1 described the situation prior to the incentive redesign[1].

> *At that time, corporate innovators' goal was very obscure, and they thought that spending more time at work indicated the size of the contributions that they could make to the company. We wanted them to become goal driven and focus on value creation. (HR1)*

After the Japanese government's 1988 legislative reform, which introduced a new system

[1] Additional comments on the situation from the interviewees are available in Section A of Online Appendix 2.

that allowed employers not to pay overtime compensations to employees with specialized skills (e.g., corporate innovators), Fujitsu and NEC started searching for alternative incentive plans. Apart from the underpayment problem for high performers, they recognized an overpayment problem regarding those who had been promoted to high-paying positions because of past achievements but no longer made significant contributions. The overpayment problem became serious after both firms started experiencing (or were forecasted to experience) slow organizational growth. Since employee dismissals and demotions were neither legally nor normatively allowed in the Japanese employment system, performance-based incentive plans were essential to resolve these two problems.

3.1.3 Incentive redesign Fujitsu started performance-based incentive plans for general and assistant managers in 1993 and 1994, respectively (Japan Institute for Labour Policy and Training, 2006). In 1994, Fujitsu expanded the coverage to those internally ranked as 6 *kyu* (級 / grade), the highest non-managerial positions (Labor Information Center, 1999). This included rank-and-file unionized corporate innovators, system engineers, or designers with expertise and skills in specific domains (Chingin Jitsumu, 1999; Rosei Jihou, 1996). According to our interviewees, those ranked 6 *kyu* had about seven years or more of tenure with the firm after being hired as new graduates and usually led small teams (RD6, RD7). With this program, Fujitsu terminated overtime pay and linked both base pay and annual bonuses with individual achievements.

NEC adopted performance-based incentive plans for unit leaders, managers, and assistant managers in 1993, 1994, and 1995, respectively (Japan Institute for Labour Policy and Training, 2006; Nikkei Newspaper, 1993a). NEC also expanded the plans to those internally ranked as *Kenkyu Shunin* (研究主任 / chief research expert), which refers to the top non-managerial positions (Labor Information Center, 1999; Nikkei Business, 1995; Rosei Jihou, 1995a). Those ranked as *Kenkyu Shunin* led the smallest unit of research groups in NEC and were aged 27 or older (Nikkei Newspaper, 1994). The Nikkei Weekly (1994) reported that “the company adopted a ‘free-time system’ and a merit pay system, under which engineers … are able to come to and leave their office any time they want and a major part of their salaries depends on their achievements.”

In both firms, the new incentive plans were based on short-term, achievement-based, and individualized performance measurements. The new incentive plans followed the management-by-objective method. One of the measures used at the two firms was the number of patent application filings (RD1, RD5)[2]. In Fujitsu, the cycle of performance review was every 12 months for general managers and six months for assistant managers (Nikkei Business, 1992; Nikkei Newspaper, 1993b; Rosei Jihou, 1995b). In NEC, the cycle was six months (Japan Institute for Labour Policy and Training, 2006; Nikkei Newspaper, 1993a).

The incentive redesign generated pay differences among those with the same job and length of service, which had been unrealistic under the seniority system (e.g., the maximum pay differences among those aged 45 years was five million yen (Nikkei Newspaper, 1993a)). Some interviewees recalled the shocks that they received or observed among colleagues when the firms made announcements of the incentive redesign[3]. HR5 commented that:

> This was a big change for our people. Society had long been built upon seniority. Before the adoption, we had many meetings with corporate innovators at the research centers to discuss and convince them of the value of doing this.

[2] Additional comments on performance measurements and challenges in quantitatively measuring innovators’ performance are available in Section B of Online Appendix 2.
[3] Additional comments on the shock are available in Section C of Online Appendix 2.

3.1.4 Impacts on corporate innovators The interviewees presented various views about how the incentive redesign changed corporate innovators' mindsets, values, and behaviors. We distilled three areas of change from their observations and experience[4]. First, many of the interviewees recognized that corporate innovators became more goal-oriented and focused more on achievement. HR1 commented that:

> I saw them focus on the goals and values that they delivered, not the number of hours they stayed at the office. As a result of the incentive redesign, they set written goals and received feedback from supervisors every six months. This must have been a big change for them.

Second, the short cycle of performance evaluation created a short-term orientation among individuals and increased their risk aversion. For example, RD3 recalled that: "many of my colleagues allocated their time only to work in which they could definitely demonstrate achievements to supervisors and tended not to spend time on nascent technology projects, whose success they were unsure about." RD7 echoed that: "We were in safe mode, we set goals that we could definitely achieve and avoided extreme or 'stretch' goals."

Finally, the incentive redesign made corporate innovators more individualistic. RD2 recognized that:

> After the incentive redesign, they (corporate innovators) became more sensitive about who made what contributions. Even in team settings, if they were confident that this specific achievement was theirs, they deterred others from claiming it.

These insights that we obtained through fieldwork were consistent with our view of the post-redesign behavioral changes. However, we also found that the interviewees' experience with regard to impacts on the reconfiguration of networks was inconclusive. RD2 made a comment

[4] Additional comments on the impacts are available in Section D of Online Appendix 2.

that supported our prediction:

> Before the incentive redesign, I invited those with inferior performance to work with me because they were my colleagues. After that, I lost the feeling of obligation and tried to be more selective.

By contrast, RD3 disagreed with an instrumental view of colleagues and recognized no change in the pattern of her network building: "I do not think that the incentive redesign changed my ways of selecting partners because this place is more social, collaborative, and supportive." Moreover, RD4 presented an alternative view: "I am not sure that the incentive redesign caused me to develop the instrumental view, but if there was any change, I tried to maximize the value that I could deliver by working with people with complementary expertise." In sum, the inconclusive support to our predictions from the fieldwork suggests the need for conducting further empirical investigations.

3.2 Samples

3.2.1 Data We studied co-innovator networks that we obtained from the patent application filings database (Fleming, Mingo, and Chen, 2007). For data collection, we used the IIP Patent Database[5] (Goto and Motohashi, 2007). We chose this dataset because it is longitudinal, fits with our research design, and captures how individuals adapt co-innovator networks (e.g., Wang *et al.*, 2014). Since there should be a time lag between project initiation (i.e., the timing of network formation) and patent application, we followed the method of two-year lag as in Ahuja *et al.* (2001). We used 1989–1993 and 1997–2001 as the pretreatment and posttreatment period, respectively. For the sake of brevity, we interchangeably used the term "project" instead of "patent application filing." Online Appendix 3 shows the co-innovator networks in Fujitsu and

---

[5] http://www.iip.or.jp/e/e_patentdb/

NEC before and after the incentive redesign[6].

DID analysis requires a control group. We used Hitachi and Mitsubishi, which (1) were also major Japanese electronics manufacturers, (2) had more business-to-business projects in International Patent Classification Sections G (physics) and H (electricity), and (3) did not adopt high-powered incentives until the end of 1999, as firms in the control group. We found, at least before the treatment effects, that changes in size (i.e., assets) and performance (i.e., return on assets) were relatively comparable between the two groups.

3.2.2 Identifying the treated We faced two cumbersome challenges in identifying individuals who received the treatment. First, since not all individuals in the two firms underwent the incentive redesign, we needed to make a reasonable assumption to identify those who were treated. The database contained information of both those who were treated and not treated. Second, we also needed to identify those who had discretions in reconfiguring their own networks. Network ties in organizations can either be built at network participants' discretion or assigned by authorities. Our samples needed to comprise only the former.

For constructing the datasets for hypothesis testing, we established three sampling rules: we focused on (1) those who made at least one filing in each of the periods, (2) those who collaboratively worked with others in both periods, and (3) those who had seven or more years of tenure and the longest tenure among project members. We set the first two rules to analyze the data with DID tests.

We set the third rule for two reasons. First, we used a seven-year tenure as the threshold because individuals who received the treatment must be internally ranked above 6 *kyu* at Fujitsu or *Kenkyu Shunin* at NEC. The two firms are large, traditional Japanese firms with internal labor

[6] In these diagrams, we removed isolated nodes and disconnected small cliques for the sake of clarity.

markets, wherein firms hire new graduates at entry level, internally train them, and promote them automatically to the top of non-managerial positions based on seniority (Graen *et al.*, 2006). To be promoted to these ranks, the new hires must have seven or more years of tenure. These ranks are non-managerial, for which automatic promotions apply. In the interviews with RD5, RD6, and RD7, we found that new hires at the two firms are initially trained to file patent applications. This training practice, together with that of hiring new graduates, enabled us to precisely measure the tenure clock from the filing database.

Second, through our fieldwork we found that those ranked above assistant managers have full discretion over network adaptation, and those in non-managerial positions (i.e., 6 *kyu* at Fujitsu or *Kenkyu Shunin* at NEC) had clout if they were above the top non-managerial positions and the most senior in a project. RD7 commented that "it is incorrect that we [those in non-managerial positions] had no clout in deciding whom we work with because our supervisors listen to the most senior among us." Looking over his own filing records, RD6 noted that: "In this case, I remember that my supervisor consulted Mr. X when launching this project because he was the oldest among us." Their experience suggests that even non-managerial innovators could exercise their discretion over network adaptation via consultation by supervisors if they were the most senior in projects.

In our empirical context, such a supervisor-subordinate relation is not surprising for three reasons. First, even after the social and economic changes involved in industrialization, the value of seniority as part of the cultural systems did not fade away at least until the beginning of the 1990s (Keifer, 1990). Second, those in the Japanese firms tend to have high interpersonal sensitivity and consider management participation and social harmony in workplaces to be important (Dollinger, 1988). Hence, consultations by supervisors are not rare. Lastly, this context has the characteristics of the separation of authority (i.e., an entitlement to command) from power (i.e., the capacity to coerce others to do something that they would not otherwise do) (Haley, 1991: 13). Since centralized HR groups at headquarters, rather than line managers, make most of the important personnel decisions (e.g., hiring) (Jacoby, 2007), supervisors who have authority without power allow individuals to use their clout over some decisions (e.g., co-working partner selection if they were above the top non-managerial positions and the most senior in projects).

With the sampling rules, we identified those who were treated from the filing database and constructed adjacency network matrixes. For each of the treated, we created an ego-centric adjacency matrix that included ties surmised to be built under the treated individual's discretion[7]. We identified 4,765 corporate innovators as our sample and transformed the project-level data into innovator–year data. Regression analyses has 11,525 and 10,573 innovator–year observations for the pretreatment and posttreatment periods, respectively. The two numbers are different because corporate innovators do not make filings every year (i.e., unbalanced panel).

3.3 Variables

3.3.1 Outcome variables We used three dependent variables in the DID analysis: (1) network constraints, (2) alters' expertise dissimilarity, and (3) network size. First, to test Hypothesis 1, we used the adjacency matrixes and computed Burt's measures of network constraints in R-3.6, which is an inverse measure of structural holes (Burt, 1992). Network constraints capture the extent to which the focal individual *i* concentrates resources within an interconnected group.

Second, to test Hypothesis 2, we created a variable that represented the expertise dissimilarity between the focal individual and the individual's alters in the ego-centric networks. Japanese patent systems use the International Patent Classification with five hierarchical levels (Goto and Motohashi, 2007). With some exceptions (e.g., Giarratana, Mariani, and Weller, 2018),

[7] Additional notes on adjacency networks are available in Online Appendix 4.

most previous studies have viewed subclasses as representing a fine-grained classification of a technology (e.g., Arts and Veugelers, 2015). Hence, we regarded individuals who filed patent applications for a subclass between *t-3* and *t-1* as having expertise in the subclass at time *t* (Fleming *et al.*, 2007). Our dataset had 122 subclasses in Sections G and H.

We created a vector of expertise for the focal individual *i* and for the individual's respective alters, *j*, in the ego-centric network and used Sampson's (2007) measure of alter dissimilarity:

$$D_{ij.t} = 1 - \frac{V_{i.t-3\ to\ t-1} \cdot V'_{j.t-3\ to\ t-1}}{\sqrt{(V_{i.t-3\ to\ t-1} \cdot V'_{i.t-3\ to\ t-1}) \cdot (V_{j.t-3\ to\ t-1} \cdot V'_{j.t-3\ to\ t-1})}},$$

where $D_{i.j.t}$ is the focal individual *i*'s knowledge dissimilarity with the alters at time *t*; and $V_{i.t\text{-}3\ to\ t\text{-}1}$ is a multidimensional vector that contains information about the number of patent applications made by *i* in each of the 122 patent subclasses; $V_{j.t\text{-}3\ to\ t\text{-}1}$ represents the alters' expertise. Since Sampson's measure assesses dyad-level knowledge dissimilarity, it does not capture differences in network size. Due to the upper bound of 122 in $V_{i.t\text{-}3\ to\ t\text{-}1}$ and $V_{j.t\text{-}3\ to\ t\text{-}1}$, it is more difficult for an ego with larger networks to find alters with expertise that other alters do not possess. Hence, we made size-adjustments by multiplying $D_{i.j.t}$ with the log of the number of alters.

Third, to test the effects of incentive redesign on the development of small networks (Hypothesis 3), we measured the degree of centrality of or the number of unique alters in the ego centric networks at time *t* (Morrison, 2002; Paruchuri, 2010).

3.3.2 Control variables We used the following firm- and individual-level variables to control for alternative explanations. We controlled for the focal firm's absorptive capacity. Since Japanese corporations in the early 1990s did not disclose research and development expenditure, we could not use an expenditure-based measure of absorptive capacity. Instead, we followed Narasimhan *et al*. (2006) and used the focal firm's number of forward citations for all its patents granted in a given year with the time-decay function. We rescaled this by multiplying it by 1/10,000 for readability. Furthermore, we followed Greve (2003) and included two control variables that captured the focal firm's slack resources, namely, absorbed slack resources and unabsorbed slack resources. We also used firms' return on sales as a control for firm performance. These variables were lagged one year.

We measured the focal individual *i*'s knowledge diversity using data on *i*'s number of projects in the 114 patent subclasses between *t-3* and *t-1* and computing Blau's diversity measures (Blau, 1977). We measured the focal individual *i*'s rates of successful applications as a proxy for *i*'s performance by dividing the number of patents that *i* was granted between *t-3* and *t-1* by the total number of the filings in the same period (Rothaermel and Hess, 2007). We included the log-transformed tenure of the focal individual *i*. As a transitory measure, the two firms set the post-redesign base pay to be partially correlated with the pre-redesign compensations (Japan Institute for Labour Policy and Training, 2006); therefore, this variable represents a coarse proxy for pay levels. Since some individuals had both collaborative and independent projects, we measured the focal individual's tendency to work independently by dividing the number of filings solely made by the individual between *t-3* and *t-1* by the total number of the individual's filings between *t-3* and *t-1*. We also included a variable that measured the focal individual's tendency to make filings in Section H (electricity) by dividing the number of the individual's filings in Section H between *t-3* and *t-1* by the total number of the filings between *t-3* and *t-1*.

3.4 Estimations

We tested the treatment effects using the interaction of two dummy variables. *Treatment* was coded one for observations of a firm's individuals who experienced the treatment and zero otherwise. *Post* was coded one for observations in the posttreatment period and 0 for those in the pretreatment period. An advantage of this method is that it allowed us to remove time-invariant observed or unobserved differences between the two groups as it captured the differences within the groups over time and subtracted the differences between the groups.

4 RESULTS

4.1 Hypothesis testing

Table 1 shows the descriptive statistics and correlations of the variables. Corporate innovators were granted patents for about one-third of their applications from time t-3 to t-1. Although some of the correlation coefficients are relatively high, we found that the mean and highest VIF scores were 1.98 and 4.39 (firm's unabsorbed slack resources), respectively.

Table 2 displays the DID results. The values not in parentheses are results of using the *diff* command in Stata, whereas those in parentheses are adjusted predicted values obtained by using the *margins* command in Stata. The former provides the DID with standard errors by setting the other variables to zero (Villa, 2016), whereas the latter reports the predicted values when the other variables are adjusted to take the values of the means (Williams, 2012). Each individual has at least one observation for the pretreatment and posttreatment period, and thus, the residuals might not be independent. To avoid biased estimates of the coefficients and standard errors, we clustered robust standard errors by individual using the *cluster* option available in Stata 15. The models in Table 2 contain all the control variables.

Model 1 tested Hypothesis 1 regarding effects on network constraints, in which the DID was 0.085 (p = 0.000). Relative to counterfactuals in the control group, individuals in the treatment group had 0.085 higher points of network constraints after the treatment, suggesting that the incentive redesign caused the development of closed networks. The average changes over time for the control and treatment groups were 0.046 (= 0.809 – 0.762) and 0.131 (= 0.789 – 0.658), respectively. Thus, the treatment effect was 0.085 (= 0.131 – 0.046). This corresponds to a 12.92% increase from the treatment group's baseline or an increase of 11.04 % of the sample mean.

Model 2 tested Hypothesis 2, positing effects on knowledge similarity between the focal individual and the individual's alters. We found that the DID was –0.050 (p = 0.009). Since we used a measure of knowledge dissimilarity, the negative sign we obtained is consistent with our prediction. Relative to counterfactuals in the control group, individuals in the treatment group had 0.050 lower points of expertise dissimilarity with their alters after the treatment, suggesting that the incentive redesign promoted the formation of homogeneous networks. Average changes over time were –0.035 (= 0.316 – 0.351) for the control group and –0.085 (= 0.278 − 0.364) for the treatment group. The treatment effect is thus −0.050 or a 13.74% decrease from the treatment group's baseline. This equals a decrease by 15.15% of the sample means.

We tested Hypothesis 3 regarding the effects on network size in Model 3, in which we found that the DID was –0.592 (p = 0.000). This is equal to an 11.63% decrease from the treatment group's baseline or a decrease by 14.84% of the sample means. These results indicate that the incentive redesign caused individuals in the treatment group to develop smaller networks.

In Table 3, we tested our hypotheses using firm- and individual-level fixed effects to further enhance the comparability of the treatment and control groups by controlling for time-invariant firm and individual-level characteristics. The results in Table 3 present two unique findings. First, the coefficient size of Treatment x Post was smaller in Models 5, 7, and 9. This interaction variable might be correlated with unobserved individual characteristics included in error terms in Models 4, 6, and 8. Indeed, the adjusted R^2 in Models 5, 7, and 9 indicate a better fit. Second, although the results of hypothesis testing were mostly similar with those shown in Table 2 above, the support for Hypothesis 2 is weaker in Model 7 (p = 0.080). Since our analyses below also present inconsistent support for Hypothesis 2, the supportive results reported in Table 2 should not be overemphasized.

===== Tables 1 to 3 about here =====

4.2 Ex Post Analysis

We conducted several ex post analyses to ensure the findings above by (1) checking the parallel path assumption, (2) testing the hypotheses using matching techniques, (3) using an alternative cut-off point of tenure, (4) conducting firm-by-firm analyses, and (5) assessing sample representativeness.

4.2.1 Parallel path assumption DID methods are based on the parallel path assumption. Specifically, in the absence of treatment, the average change in the dependent variable for the treatment and control groups remains similar, whereby the two groups' pretreatment patterns of the dependent variables show parallel paths (Angrist and Pischke, 2008). We followed previous studies (e.g., Rowley, Shipilov, and Greve, 2017) and conducted parallel trends tests with Mora and Reggio's *didq* command in Stata (Mora and Reggio, 2015). In this test, the null hypothesis is that the dependent variables of the two groups have pretreatment parallel paths, which would be rejected in case the parallel path assumption was violated. In testing this null hypothesis, we included all the control variables and clustered robust standard errors by individual. We found that p-values in a model of network constraint, alter dissimilarity, and network size were 0.715, 0.2591, and 0.1715, respectively. Hence, we cannot reject the null hypothesis, suggesting common pretreatment dynamics for the two groups.

4.2.2 Using matching methods Since the treatment was not randomly assigned in our analysis, it is important to ensure further comparability of treatment and control groups. We followed Teodoridis et al. (2019) and re-tested our hypotheses using matched samples. Of the several matching techniques, we followed Shipilov et al. (2019) and used coarsened exact matching (see also Koo and Eesley (2021) and Nagle and Teodoridis (2020)). We matched treatment and control groups based on the level and trend of their dependent variables in the pretreatment period[8]. Online Appendix 5 presents the results of using the matched samples in Models A1 to A3. It is noteworthy that the sample size in these analyses was smaller because we created the trend variables by using the data of individuals with multiple filings in the pretreatment periods and dropped unmatched samples. Models A1 to A3 included both firm and individual fixed effects. Results in these models are comparable with those reported in Table 2. All the coefficients of Treatment x Post were larger when we used the matched samples rather than those in Table 3. In Model A3, we found support for Hypothesis 2.

Using the matched samples, we assessed the treatment effects over time. Since the data of patent application filings were unbalanced, we followed previous research (e.g., Chen, Kim, and Miceli, 2021), used the two- or three-year window, and ran regression models. We entered interactions between the treatment variable and the time-window variables together with other variables from Table 3. In Online Appendix 6, we used the year of 1989 as the baseline and plotted the estimated coefficients with error bars that indicate 95% confidence intervals (Autor, 2003).

The graphs present two insights. First, the graphs demonstrate that a significant difference between the treatment and control groups appeared only after the treatment. The observed patterns enhanced our confidence in the findings above, that is, the incentive redesign triggered significant changes in the dependent variables among individuals in the treatment group.

Second, the graphs helped us alleviate concerns regarding the effects of subsequent changes that Fujitsu and NEC made in the late 1990s. In 1998, Fujitsu expanded performance-based

---

[8] Results for the hypothesis testing remained unchanged when we matched the two groups on the level of the dependent variables and on three individual-level control variables, including past success ratios, knowledge diversity, and log of tenure.

incentive to all of the unionized researchers, specialists, employees, and workers (Nikkei Newspaper, 1998). In the same year, NEC also removed overtime pay and linked a part of annual bonuses with performance for all individuals in research and development (Japan Institute for Labour Policy and Training, 2006). Although these subsequent changes might generate confounding effects and could account for the differences in the 2000-2001 window, the observed significant differences in the 1997-1999 window are attributable to effects of the preceding incentive redesign we focused on.

4.2.3 Alternative cut-off point We established the sampling rules and focused on those who had seven or more years of tenure and the longest tenure among project members. In our sample, the mean of individuals' tenure was 15.33 years with a standard deviation of 1.40 years. 15.65% of our sample had a tenure shorter than 10 years. These statistics suggest that our results are conservative since many of our sample individuals had a tenure longer than the cut-off point. To check the robustness of our above findings further, we additionally tested the hypotheses by using an alternative cut-off point of 11 years, which is about the 75th percentile of the full sample. In Models A4 to A6 in Online Appendix 5, we found that results for Hypotheses 1 and 3 were consistent with those reported above, whereas we found no support for Hypothesis 2.

4.2.4 Firm-differences We also conducted firm-by-firm analyses, which are shown in Online Appendix 7. When we used only Fujitsu as the treatment group, we found significant support for Hypotheses 1 and 3 in Models A7 and A9 (p = 0.000) but no support for Hypothesis 2 in Model A8. However, when we used only NEC as the treatment group, we found support for Hypothesis 2 in Model A11 (p = 0.023), but the p-values decreased in Models A10 and A12 relative to Models A7 and A9 in testing the effects on network constraints and network size, respectively. Moreover, the effect of network constraints in Model A10 and network size in Model A12 was smaller. We provide our interpretations of these findings in the discussion section.

4.2.5 Sample representativeness The three sampling rules allowed us to focus on samples of individuals in Fujitsu and NEC who received the treatment and could exercise some clout over network adaptation decisions. However, the rules limited the representativeness of our samples, which we assessed in this subsection.

In Online Appendix 8, we assessed how each of the sampling rules caused drops in the number of samples. In the filing databases, we identified 91,543 individuals working for one of these firms during the observation periods. When we applied the active rule (i.e., those making at least one filing in each of the pretreatment and posttreatment periods), the number of individuals decreased to 24,123 (26.35%). This number further dropped to 21,227 (23.19%) when we additionally applied the team rule (i.e., those working in team settings), and to 4,765 (5.21%) when we additionally adopted the tenure rule (i.e., those who have seven or more years of tenure and longest tenure among project members). It is apparent that the sample representativeness is highly limited, which reduces the generalizability of our findings.

Our further analysis presented two more insights. First, in the case of the NEC data, the number of samples dropped more when we solely applied the team rule. Accordingly, we found that 55.29% of the NEC innovators in the filing database worked independently, which is much higher than Fujitsu (18.34%), Hitachi (5.46%), and Mitsubishi (23.72%). Second, the decrease caused by the active rule was greater in Fujitsu (73.65%) than in Hitachi (69.77%) and Mitsubishi (69.15%), suggesting that those active in Fujitsu in the pretreatment period had lower rates of survival in the posttreatment period.

Although the sampling rules helped us resolve challenges in identifying those who got treated and reacted with discretion, the limited representativeness might invalidate generalizability. However, we view our work as illustrative or illuminative rather than definitive or decisive (Sutton and Staw, 1995) and believe that the fruitfulness of our work does not exclusively depend on whether the samples were fully representative.

5 DISCUSSION

5.1 Interpretations

Our results provide overall support to the notion of incentive-induced network adaptation, that is, individuals rebuild their networks in organizations to pursue renewed goals as a response to the introduction of performance-based incentive plans. We found consistent support for our predictions that incentive redesign causes the development of more closed and smaller networks (Hypotheses 1 and 3). However, our findings regarding the effects on knowledge homogeneous networks (Hypothesis 2) were inconsistent across various models.

A potential reason for this lack of consistent support might be that our arguments did not account for temporal variations in the treatment effects on different outcomes. For example, it might be that relative to effects on network structures and size, effects on network contents (e.g., knowledge similarity) appear slowly. This delay might result from cognitive costs in assessing others' expertise and knowing who knows what (Lewis and Herndon, 2011). In a situation in which individuals need to achieve short-term outcomes to get rewarded quickly, such unfavorable costs might cause the development of homogeneous networks to appear slowly.

Another intriguing finding from our analysis concerns firm-differences: excluding the support for Hypothesis 2, the NEC data presented weaker support for Hypotheses 1 and 3 as compared to the Fujitsu data. Interestingly, despite the two firms' common background in introducing performance-based incentive plans, our fieldwork suggested several important differences. First, while Fujitsu linked performance evaluation with base pay and annual bonuses, NEC linked it only with the latter (Chingin Jitsumu, 1997). HR5 commented that "performance evaluation in NEC was refreshed every term and not linked with base pay such that it had no long-lasting effects on corporate innovators' lifetime income levels." Second, in the late 1980s and early 1990s, Fujitsu experienced more modest economic growth because of fierce competition with IBM (Japan Institute for Labour Policy and Training, 2006). This competitive threat might have increased Fujitsu's sense of the importance of redesigning its incentive to improve productivity. Third, according to HR3 and RD3, the incentive redesign should have had greater impacts at Fujitsu than at NEC because the former was founded as a spin-off company of Fuji Electric and had imprinted individualism as an important value among its employees, which fit well with ideas underlying high-powered incentive plans. Lastly, empirically, the number of NEC observations was too small to produce meaningful parameter estimates.

These interpretations are tentative and need to be validated theoretically and empirically. In addition to the sample representativeness issue, our work highlights some unanswered questions for future research.

5.2 Contributions

Our work makes several contributions to the literature. First, this study highlights a novel intersection of two hitherto separate research paths, namely, pay and networks in organizations, and suggests a new research theme to study the role of incentive redesign as a driver of network change in organizations. Since research has long viewed network change as path-dependent and structurally embedded, one enduring criticism has been its failure to adequately address the role of managerial policies in creating the conditions that facilitate the development of ideal network structures in organizations (Biancani *et al.*, 2014). By developing an array of drivers of network change, recent studies have started responding to such criticism (e.g., Kleinbaum, 2012). Our research extends these recent efforts by advancing our knowledge of how organizational policies such as incentive plans create social conditions that influence the patterns of network evolution and change in organizations.

Second, since both open networks with structural holes and closed networks that increase cohesion among network participants confer distinct benefits, balancing them is crucial (e.g., Ter Wal *et al.*, 2016). However, not enough is known about why it is difficult to balance them and what organizational policies impede or enable this quest. Our work shows that performance-based incentive plans predispose individuals to trade off long-term innovation for short-term outcomes and compel them to favor closed networks. Some organizational policies that aim to resolve problems such as overpayment and underpayment can negate the benefit of achieving such a balance and prevent individuals from properly extracting the benefits from networks.

Third, this study advances the literature on individuals' strategic and discretional building of networks with motives to instrumentally mobilize resources and the knowledge of other members to achieve their goals (Engel, Kaandorp, and Elfring, 2017; Shea and Fitzsimons, 2016). The instrumental view complements the path-dependent view of network evolution. We substantiate Vissa's (2011) claims that individuals engage in instrumental networking only when incentivized to do so. Moreover, our findings not only reinforce the argument that networks help individuals achieve goals (Dobrev and Merluzzi, 2018) but also propose that individuals can proactively reconfigure networks to achieve such goals.

Finally, this study also advances the incentive literature. Our findings capture an interesting portrait of organizational life, that is, as a result of the reconfiguration of networks, individuals might create knowledge that does not require risk-taking and experimenting to seek measurable short-term outcomes. This implication concurs with the incentive literature regarding the harmful effects of performance-based incentive plans on innovation, as they hamper the intrinsic motivation critical for creativity and impair risk-taking, inductive thinking, and trial-and-error learning necessary for long-term innovation (e.g., Ederer and Manso, 2013). Thus, this study extends previous research by suggesting an alternative explanation for the harmful effects. Performance-based incentive plans promote the building of closed, homogeneous, and small networks in organizations, and thereby, inhibit the adoption of hybrid strategies for building networks effective for innovations.

5.3 Limitations and Future Research Directions

There are several notable limitations of this study, which also suggest the directions for future research. First, our claims need to be tested in different contexts for achieving generalizability. We only used data from four Japanese firms and focused only on the two cases of incentive redesign from more than two decades ago. The representativeness of our samples is highly limited. Our results would be different if the control group comprised individuals sampled from other firms. Moreover, it is still questionable whether the results can be applied to other types of ties (e.g., cross-unit ties) as opposed to co-innovator networks. To develop an overarching framework, these lines of inquiry appear to be a promising extension of our work.

Second, future research could explicate individual differences in terms of how individuals differently adapt their networks as a response to incentive redesign. For example, individuals might be better able to reconstruct networks for maximizing the pay-offs if their personal traits help them correctly understand network structures.

Third, since we focused on the case of strengthening performance-based incentives, future research needs to symmetrically investigate how individuals react to firms' weakening performance-based incentives. Our theoretical argument can be extended to predict that as a response, individuals develop open, diversified, and large networks. However, such prediction requires careful empirical analyses. In addition, since we focused on a type of performance-based incentive plans that operates on the principle of management-by-objectives, future research can explore effects of other types of plans.

Finally, a more direct examination of the effects of incentive redesign on goal reformulation could enhance the understanding of such a mechanism. The effects of incentive redesign on those in charge of the early phases of innovation might differ from the effects on those responsible for the later phases because the former's goal is extensive search, whereas the latter strives for implementation and commercialization. Relatedly, in addition to goal reformulation, the introduction of performance-based incentive plans causes pay dispersion and stratification in organizations (Yanadori and Cui, 2013). Due to the principle of homophily (McPherson, Smith-Lovin, and Cook, 2001), the generated dispersion might increase the formation of within-strata ties and decrease between-strata ties in organizations. This might be an alternative causal path between incentive redesign and network change, which future research can theorize and test.

5.4 Conclusions

This study examined how individuals in organizations proactively reconfigure their networks in response to incentive redesign. We introduced the notion of incentive-induced network adaptation. An analysis with a quasi-experimental research design supported our arguments, validating the role of incentive redesign as a driver of network change in organizations. Our work suggests a new theme to study intersection of two research paths, pay and networks in organizations, which have not fully merged into one. For those researching organization theory, our findings should be intriguing in themselves; further, from a practitioners' standpoint, our findings highlight the role of managerial policies in shaping networks in organizations. Thus, the findings of this study and their implications open exciting new avenues to advance knowledge on drivers of network change in organizations.

Acknowledgements The authors sincerely appreciate the guidance and efforts of editor, Andrew Shipilov, and the two anonymous reviewers. This research was supported by JSPS KAKENHI Grant Number 16H03658 and 19H01527. The authors are thankful to the fieldwork interviewees, Christina Ahmadjian, Mario Daniele Amore, Yuta Kikuchi, Myriam Mariani, Ryo Nakajima, Marco Tortoriello, Steven Vogel, and Yoshio Yanadori, and participants in both the Waseda OT and COORS Tokyo Workshops for their helpful insights and comments.

REFERENCES

Ahuja G, Morris Lampert C. 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal* **22**(6–7): 521–543.

Ahuja G, Soda G, Zaheer A. 2012. The genesis and dynamics of organizational networks. *Organization Science* **23**(2): 434–448.

Angrist JD, Pischke J-S. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Arts S, Veugelers R. 2015. Technology familiarity, recombinant novelty, and breakthrough invention. *Industrial and Corporate Change* **24**(6): 1215–1246.

Austin JT, Vancouver JB. 1996. Goal constructs in psychology: Structure, process, and content. *Psychological Bulletin* **120**(3): 338–375.

Autor DH. 2003. Outsourcing at will: The Contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*. The University of Chicago Press **21**(1): 1–42.

Balachandran S, Hernandez E. 2018. Networks and innovation: Accounting for structural and institutional sources of recombination in brokerage triads. *Organization Science* **29**(1): 80–99.

Biancani S, McFarland DA, Dahlander L. 2014. The semiformal organization. *Organization Science* **25**(5): 1306–1324.

Black LJ, Carlile PR, Repenning NP. 2004. A dynamic theory of expertise and occupational boundaries in new technology implementation: Building on barley's study of CT scanning. *Administrative Science Quarterly* **49**(4): 572–607.

Blau PM. 1977. *Inequality and Heterogeneity.* Free Press: New York.

Burt RS. 1992. *Structural Holes: The Social Structure of Competition.* Harvard University Press: Cambridge, MA.

Burt RS, Merluzzi J. 2016. Network oscillation. *Academy of Management Discoveries* **2**(4): 368–391.

Campbell DJ. 2015. Management by objectives. In *Wiley Encyclopedia of Management*, Cooper CL, Guest DE, Needle DJ (eds).

Carnabuci G, Bruggeman J. 2009. Knowledge specialization, knowledge brokerage and the uneven growth of technology domains. *Social Forces* **88**(2): 607–641.

Carnabuci G, Diószegi B. 2015. Social networks, cognitive style, and innovative performance: A contingency perspective. *Academy of Management Journal* **58**(3): 881–905.

Chen T, Kim C, Miceli KA. 2021. The emergence of new knowledge: The case of zero-reference patents. *Strategic Entrepreneurship Journal* **15**(1): 49–72.

Chingin Jitsumu. 1997. NEC's new compensation systems for managers. (in Japanese, 賃金実務『NECの管理職新報酬管理制度』5/1).

Chingin Jitsumu. 1999. Fujitsu's job systems and incentive pay. (in Japanese, 賃金実務『富士通の職責に基づく等級制度と成果主義賃金 3/1).

Collins CI, Smith KG. 2006. Knowledge exchange and combination: The role of human resource practices in the performance of high-technology firms. *Academy of Management Journal* **49**(3): 544–560.

Crant JM, Bateman TS. 1993. Assignment of credit and blame for performance outcomes. *Academy of Management Journal* **36**(1): 7–27.

Dobrev SD, Merluzzi J. 2018. Stayers versus movers: Social capital and early career imprinting among young professionals. *Journal of Organizational Behavior* **39**(1): 67–81.

Dollinger MJ. 1988. Confucian ethics and Japanese management practices. *Journal of Business Ethics* **7**(8): 575–584.

Ederer F, Manso G. 2013. Is pay for performance detrimental to innovation? *Management Science* **59**(7): 1496–1513.
Engel Y, Kaandorp M, Elfring T. 2017. Toward a dynamic process model of entrepreneurial networking under uncertainty. *Journal of Business Venturing* **32**(1): 35–51.
Fleming L, Mingo S, Chen D. 2007. Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly* **52**(3): 443–475.
Giarratana MS, Mariani M, Weller I. 2018. Rewards for patents and inventor behaviors in industrial research and development. *Academy of Management Journal* **61**(1): 264–292.
Goto A, Motohashi K. 2007. Construction of a Japanese patent database and a first look at Japanese patenting activities. *Research Policy* **36**(9): 1431–1442.
Graen G, Dharwadkar R, Grewal R, Wakabayashi M. 2006. Japanese career progress: an empirical examination. *Journal of International Business Studies* **37**(1): 148–161.
Graham WJ, Cooper WH. 2013. Taking credit. *Journal of Business Ethics* **115**(2): 403–425.
Gray SM, Bunderson JS, Boumgarden P, Bechara JP. 2019. Engineering interaction: Structural change, locus of identification, and the formation and maintenance of cross-unit ties. *Personnel Psychology* **72**(4): 599–622.
Greve HR. 2003. A behavioral theory of R&D expenditures and innovations: Evidence from shipbuilding. *Academy of Management Journal* **46**(6): 685–702.
Guimerà R, Uzzi B, Spiro J, Amaral LAN. 2005. Team assembly mechanisms determine collaboration network structure and team performance. *Science* **308**(5722): 697–702.
Gulati R, Srivastava SB. 2014. Bringing agency back into network research: Constrained agency and network action. In *Contemporary Perspectives on Organizational Social Networks*, Research in the Sociology of Organizations, 40: 73–93.
Haley JO. 1991. *Authority without Power: Law and the Japanese Paradox*. Oxford University Press: New York.
Hansen MT. 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly* **44**(1): 82–111.
Hasan S, Bagde S. 2015. Peers and network growth: Evidence from a natural experiment. *Management Science* **61**(10): 2536–2547.
Ibarra H, Kilduff M, Tsai W. 2005. Zooming in and out: Connecting individuals and collectivities at the frontiers of organizational network research. *Organization Science* **16**(4): 359–371.
Jacoby SM. 2007. *The Embedded Corporation*. Princeton University Press: Princeton.
Japan Institute for Labour Policy and Training. 2006. *A Survey on Incentive Redesign by Large Corporations after the 1990s*. Tokyo, Japan. (in Japanese, 日本労働研究機構: 主要企業における賃金制度改革の変遷に関する調査:大手電機メーカーにみる 1990 年代以降の賃金制度改定).
Kaplan S, Henderson R. 2005. Inertia and incentives: Bridging organizational economics and organizational theory. *Organization Science* **16**(5): 509–521.
Kaplan S, Vakili K. 2015. The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal* **36**(10): 1435–1457.
Karau SJ, Williams KD. 1993. Social loafing: A meta-analytic review and theoretical integration. *Journal of Personality and Social Psychology* **65**(4): 681–706.
Keifer CW. 1990. The elderly in modern Japan: Elite, victims or plural players? In *The Cultural Context of Aging: Worldwide Perspectives*, Sokolovsky J (ed). Bergin and Garvey: New York: 181–196.
Kleinbaum AM. 2012. Organizational misfits and the origins of brokerage in intrafirm networks.

Administrative Science Quarterly **57**(3): 407–452.

Koo WW, Eesley CE. 2021. Platform governance and the rural–urban divide: Sellers' responses to design change. *Strategic Management Journal* **42**(5): 941–967.

Labor Information Center. 1999. Performance-driven Human Resource Systems and Incentives (III). Tokyo (in Japanese, 生産性労働情報センター『成果主義人事・賃金 III』).

Lazear EP. 2000. The power of incentives. *American Economic Review* **90**(2): 410–414.

Leahey E, Beckman CM, Stanko TL. 2017. Prominent but less productive: The impact of interdisciplinarity on scientists' research. *Administrative Science Quarterly* **62**(1): 105–139.

Lee S, Meyer-Doyle P. 2017. How performance incentives shape individual exploration and exploitation: Evidence from microdata. *Organization Science* **28**(1): 19–38.

Lee S, Puranam P. 2017. Incentive redesign and collaboration in organizations: Evidence from a natural experiment. *Strategic Management Journal* **38**(12): 2333–2352.

Lerner J, Wulf J. 2007. Innovation and incentives: Evidence from corporate R&D. *The Review of Economics and Statistics* **89**(4): 634–644.

Lewis K, Herndon B. 2011. Transactive memory systems: Current issues and future research directions. *Organization Science* **22**(5): 1254–1265.

Liden RC, Wayne SJ, Jaworski RA, Bennett N. 2004. Social loafing: A field investigation: *Journal of Management* **30**(2): 285–304.

Locke EA. 2000. Motivation by goal setting. In *Handbook of Organizational Behavior, Revised and Expanded*, Golembiewski RT (ed). Marcel Dekker: New York: 43–56.

McFadyen MA, Semadeni M, Cannella AA. 2009. Value of strong ties to disconnected others: Examining knowledge creation in biomedicine. *Organization Science* **20**(3): 552–564.

McPherson M, Smith-Lovin L, Cook JM. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology* **27**(1): 415–444.

Miner JB. 2015. *Essential Theories of Motivation and Leadership*. M. E. Sharpe: Armonk, NY.

Mora R, Reggio I. 2015. didq: A command for treatment-effect estimation under alternative assumptions. *The Stata Journal* **15**(3): 796–808.

Morrison EW. 2002. Newcomers' relationships: The role of social network ties during socialization. *Academy of Management Journal* **45**(6): 1149–1160.

Nagle F, Teodoridis F. 2020. Jack of all trades and master of knowledge: The role of diversification in new distant knowledge integration. *Strategic Management Journal* **41**(1): 55–85.

Narasimhan O, Rajiv S, Dutta S. 2006. Absorptive capacity in high-technology markets: The competitive advantage of the haves. *Marketing Science* **25**(5): 510–524.

Nikkei Business. 1992. Incentive redesign and employee motivation. (in Japanese, 日経ビジネス『相次ぐ年俸制導入、士気の維持が課題』8/3).

Nikkei Business. 1995. Exemption systems for promoting research activities. (in Japanese, 日経ビジネス『裁量労働で研究所活性化』12/4).

Nikkei Newspaper. 1993a. Management by objectives for division managers. (in Japanese, 日本経済新聞『事業部長も目標管理』10/13).

Nikkei Newspaper. 1993b. Performance-based pay for managers. (in Japanese, 日本経済新聞『富士通 管理職に年俸制』2/9).

Nikkei Newspaper. 1994. R&D strategy. (in Japanese, 日本経済新聞『R&D 活性化戦略』9/23).

Nikkei Newspaper. 1998. Fujitsu will cease seniority-based pay. (in Japanese, 日本経済新聞『富士通 年功賃金を全廃』3/25).

Obstfeld D. 2005. Social networks, the tertius iungens orientation, and involvement in innovation.

Administrative Science Quarterly **50**(1): 100–130.
Paruchuri S. 2010. Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. *Organization Science* **21**(1): 63–80.
Pollack A. 1993. Japanese starting to link pay to performance, not tenure. *New York Times (October 2)*.
Reagans R, McEvily B. 2003. Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly* **48**(2): 240.
Reagans R, Singh PV, Krishnan R. 2015. Forgotten third parties: Analyzing the contingent association between unshared third parties, knowledge overlap, and knowledge transfer relationships with outsiders. *Organization Science* **26**(5): 1400–1414.
Reagans R, Zuckerman EW. 2001. Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organization Science* **12**(4): 502–517.
Rosei Jihou. 1995a. NEC Research Center. (in Japanese, 労政時報『NEC 中央研究所』4/21).
Rosei Jihou. 1995b. New incentive systems for 7000 managers. (in Japanese, 労政時報『管理職 7000 人を対象に目標管理に基づく年俸制を導入』9/29).
Rosei Jihou. 1996. Fujitsu's SPIRIT. (in Japanese, 労政時報『富士通 SPIRIT』6/21).
Rosenkopf L, Nerkar A. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal* **22**(4): 287–306.
Rothaermel FT, Hess AM. 2007. Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effects. *Organization Science* **18**(6): 898–921.
Rowley TJ, Shipilov AV, Greve HR. 2017. Board reform versus profits: The impact of ratings on the adoption of governance practices. *Strategic Management Journal* **38**(4): 815–833.
Sampson RC. 2007. R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. *Academy of Management Journal* **50**(2): 364–386.
Sasovova Z, Mehra A, Borgatti SP, Schippers MC. 2010. Network churn: The effects of self-monitoring personality on brokerage dynamics. *Administrative Science Quarterly* **55**(4): 639–670.
Schilling MA, Fang C. 2014. When hubs forget, lie, and play favorites: Interpersonal network structure, information distortion, and organizational learning. *Strategic Management Journal* **35**(7): 974–994.
Shea CT, Fitzsimons GM. 2016. Personal goal pursuit as an antecedent to social network structure. *Organizational Behavior and Human Decision Processes* **137**: 45–57.
Shipilov A, Labianca G, Kalnysh V, Kalnysh Y. 2014. Network-building behavioral tendencies, range, and promotion speed. *Social Networks* **39**: 71–83.
Shipilov AV, Greve HR, Rowley TJ. 2019. Is all publicity good publicity? The impact of direct and indirect media pressure on the adoption of governance practices. *Strategic Management Journal* **40**(9): 1368–1393.
Singh H, Kryscynski D, Li X, Gopal R. 2016. Pipes, pools, and filters: How collaboration networks affect innovative performance. *Strategic Management Journal* **37**(8): 1649–1666.
Small ML, Adler L. 2019. The role of space in the formation of social ties. *Annual Review of Sociology* **45**(1): 111–132.
Sosa ME, Marle F. 2013. Assembling creative teams in new product development using creative team familiarity. *Journal of Mechanical Design* **135**(8): 081009.
Sutton RI, Hargadon A. 1996. Brainstorming groups in context: Effectiveness in a product design firm. *Administrative Science Quarterly* **41**(4): 685.

Sutton RI, Staw BM. 1995. What theory is not. *Administrative Science Quarterly* **40**(3): 371–384.

Teodoridis F, Bikard M, Vakili K. 2019. Creativity at the knowledge frontier: The impact of specialization in fast- and slow-paced domains. *Administrative Science Quarterly* **64**(4): 894–927.

Ter Wal ALJ, Alexy O, Block J, Sandner PG. 2016. The best of both worlds: The benefits of open-specialized and closed-diverse syndication networks for new ventures' success. *Administrative Science Quarterly* **61**(3): 393–432.

The Nikkei Weekly. 1994. Redundant workers falling through cracks in lifetime-employment system, January 24.

Tolbert PS, Zucker LG. 1983. Institutional sources of change in the formal structure of organizations: The diffusion of Civil Service Reform, 1880-1935. *Administrative Science Quarterly* **28**(1): 22–39.

Vanni L. 2011. Overview of NEC EMEA operations. In *Proceedings of HRC Telepresence Meeting*.

Villa JM. 2016. diff: Simplifying the estimation of difference-in-differences treatment effects. *The Stata Journal* **16**(1): 52–71.

Vissa B. 2011. A matching theory of entrepreneurs' tie formation intentions and initiation of economic exchange. *Academy of Management Journal* **54**(1): 137–158.

Vroom V. 1964. *Work and Motivation*. Jossey-Bass: San Francisco, CA.

Wang C, Rodan S, Fruin M, Xu X. 2014. Knowledge networks, collaboration networks, and exploratory innovation. *Academy of Management Journal* **57**(2): 484–514.

Williams R. 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. *The Stata Journal* **12**(2): 308–331.

Williamson OE. 1981. The economics of organization: The transaction cost approach. *American Journal of Sociology* **87**(3): 548–577.

Wing C, Simon K, Bello-Gomez RA. 2018. Designing difference in difference studies: Best practices for public health policy research. *Annual Review of Public Health* **39**(1): 453–469.

Yanadori Y, Cui V. 2013. Creating incentives for innovation? The relationship between pay dispersion in R&D groups and firm innovation performance. *Strategic Management Journal* **34**(12): 1502–1511.

Yonekawa S. 1984. University graduates in Japanese enterprises before the Second World War. *Business History* **26**(2): 193–218.

Zhang L, Guler I. 2020. How to join the club: Patterns of embeddedness and the addition of new members to interorganizational collaborations. *Administrative Science Quarterly* **65**(1): 112–150.

Table 1: Descriptive Statistics and Correlations

		Mean	S.D.	1	2	3	4	5	6	7	8
1	Network constraint	0.77	0.29	1							
2	Alter dissimilarity	0.33	0.48	-0.11	1						
3	Network size	3.99	3.68	-0.79	0.12	1					
4	Firm's absorptive capacity	7.77	1.80	-0.12	0.04	0.20	1				
5	Absorbed slack resources	0.24	0.03	0.06	-0.04	-0.09	-0.31	1			
6	Unabsorbed slack resources	0.90	0.12	-0.12	-0.04	0.16	0.65	-0.41	1		
7	ROS	0.04	0.02	0.01	-0.12	-0.05	-0.19	0.03	0.40	1	
8	Past success ratios	0.68	0.38	-0.16	-0.21	0.13	0.06	0.00	0.10	0.08	1
9	Knowledge diversity	0.31	0.28	-0.13	0.05	0.09	-0.03	0.02	0.05	0.10	0.24
10	Log of tenure	2.73	0.34	-0.18	0.20	0.27	0.34	-0.12	-0.13	-0.55	0.11

11	Lone	0.14	0.26	0.16	-0.07	-0.22	-0.29	0.14	-0.20	0.13	0.10
12	Section H	0.48	0.43	-0.02	-0.11	0.00	-0.09	-0.01	-0.06	0.03	0.18
13	Post	0.48	0.50	0.00	0.13	0.05	0.21	-0.04	-0.40	-0.75	-0.08
14	Treatment	0.26	0.44	0.09	-0.05	-0.13	-0.58	0.80	-0.56	0.13	-0.02

	9	10	11	12	13	14
9	1					
10	-0.05	1				
11	0.00	-0.26	1			
12	0.14	-0.03	0.11	1		
13	-0.13	0.65	-0.17	-0.05	1	
14	0.00	-0.17	0.22	0.01	-0.02	1

Table 2: Results of the DID Analyses

			Pre-treatment		Post-treatment		Difference	Robust s.e.	
1	Network constraint	Control	1.402	(0.762)	1.448	(0.809)	0.046	0.008	[0.000]
		Treatment	1.297	(0.658)	1.428	(0.789)	0.131	0.013	[0.000]
		Difference	-0.105		-0.020		0.085	0.013	[0.000]
		Robust s.e.	0.015	[0.000]	0.011	[0.065]			
2	Alter dissimilarity	Control	-0.324	(0.351)	-0.359	(0.316)	-0.035	0.013	[0.009]
		Treatment	-0.311	(0.364)	-0.396	(0.278)	-0.085	0.020	[0.000]
		Difference	0.013		-0.038		-0.050	0.019	[0.009]
		Robust s.e.	0.023	[0.577]	0.018	[0.037]			
3	Network size	Control	-7.790	(4.243)	-8.619	(3.413)	-0.829	0.108	[0.000]
		Treatment	-6.942	(5.091)	-8.363	(3.669)	-1.422	0.148	[0.000]
		Difference	0.848		0.256		-0.592	0.141	[0.000]
		Robust s.e.	0.157	[0.000]	0.139	[0.065]			

N = 22098 All the control variables are included. We present individual-level clustered robust standard errors (s.e.). Predicted values using the Stata *margins* command are in parentheses. P-values are in square brackets.

Table 3: Results of the Regression Analyses

	4	5	6	7	8	9
	Network constraint		Alter dissimilarity		Network size	
Firm fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed-effects	No	Yes	No	Yes	No	Yes
Firm's absorptive capacity	0.016	0.015	-0.032	-0.030	-0.171	-0.144
	(0.007)	(0.008)	(0.012)	(0.012)	(0.086)	(0.090)
	[0.028]	[0.051]	[0.006]	[0.015]	[0.047]	[0.110]
Absorbed slack resources	0.776	0.587	-0.336	0.218	-7.719	-3.917
	(0.182)	(0.195)	(0.316)	(0.332)	(2.179)	(2.325)
	[0.000]	[0.003]	[0.288]	[0.513]	[0.000]	[0.092]
Unabsorbed slack resources	-0.219	-0.138	-0.171	-0.191	1.622	-0.083
	(0.063)	(0.065)	(0.105)	(0.112)	(0.757)	(0.773)
	[0.000]	[0.035]	[0.105]	[0.087]	[0.032]	[0.914]
ROS	0.254	0.113	0.379	0.388	-1.597	-1.222
	(0.156)	(0.163)	(0.271)	(0.270)	(1.766)	(1.840)
	[0.105]	[0.488]	[0.162]	[0.151]	[0.366]	[0.507]
Past success ratios	-0.082	-0.039	-0.329	-0.247	0.745	0.367
	(0.005)	(0.006)	(0.010)	(0.012)	(0.059)	(0.061)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Knowledge diversity	-0.094	-0.052	0.218	-0.014	0.920	0.491
	(0.009)	(0.011)	(0.013)	(0.020)	(0.126)	(0.131)
	[0.000]	[0.000]	[0.000]	[0.503]	[0.000]	[0.000]
Log of tenure	-0.205	-0.113	0.397	0.240	3.442	1.517
	(0.010)	(0.025)	(0.016)	(0.042)	(0.156)	(0.310)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Lone	0.137	0.055	0.046	0.062	-2.072	-0.856
	(0.008)	(0.011)	(0.014)	(0.019)	(0.085)	(0.098)
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]
Section H	-0.003	-0.014	-0.093	-0.241	0.010	0.069
	(0.006)	(0.009)	(0.009)	(0.020)	(0.086)	(0.093)
	[0.679]	[0.111]	[0.000]	[0.000]	[0.907]	[0.462]
Post	0.042	0.007	-0.023	0.032	-0.790	-0.094
	(0.009)	(0.012)	(0.015)	(0.020)	(0.109)	(0.146)
	[0.000]	[0.550]	[0.126]	[0.103]	[0.000]	[0.517]
Treatment x Post	0.096	0.078	-0.068	-0.042	-0.910	-0.541
	(0.014)	(0.015)	(0.021)	(0.024)	(0.153)	(0.169)
	[0.000]	[0.000]	[0.001]	[0.080]	[0.000]	[0.001]
Constant	1.231	0.964	-0.073	0.280	-3.612	1.841
	(0.095)	(0.108)	(0.153)	(0.180)	(1.128)	(1.268)
	[0.000]	[0.000]	[0.632]	[0.119]	[0.001]	[0.147]
R^2	0.100	0.423	0.118	0.433	0.149	0.499
Adjusted R^2	0.099	0.264	0.117	0.277	0.149	0.360
Log likelihood	-2998.188	1917.806	-13862.285	-8970.326	-58365.435	-52522.940
F-values	117.053	15.607	178.337	89.376	109.153	37.742
N of cases	22098	22098	22098	22098	22098	22098

Individual-level clustered robust standard errors are in parentheses. P-values are in square brackets.