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Monetary Incentives for Corporate Inventors: Intrinsic motivation, project selection and inventive performance*

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Abstract

Using novel panel data on Japanese inventors, we investigate how monetary incentives affect corporate inventors' behavior and performance, as well as how they interact with the strength of intrinsic motivation. In order to identify the effects, we exploit inventors' responses to a policy change in Japan in the early 2000s that forced firms to strengthen monetary incentives for inventors. Our major findings are as follows: (1) while introducing or increasing revenue-based payments is associated with a small improvement in patent quality, such schemes significantly decrease the use of science in research and development (R&D) projects; (2) the above positive effect of revenue-based payment on patent quality is smaller and the negative effect on scientific intensity is greater in research areas where risk heterogeneity among potential projects is greater; (3) the strength of intrinsic motivation is significantly associated with the inventor's patent productivity; and (4) strong intrinsic motivation weakens the marginal effect of monetary incentive on inventive productivity, and reinforces the negative effect of monetary incentive on scientific intensity in research areas where risk heterogeneity among potential projects is sufficiently large. The results are consistent with our model predictions and imply that strengthening monetary incentives changes project selection toward less risky and less exploratory ones.

Keywords: Monetary incentive, Employee-invention, Intrinsic motivation, Patent, Inventor
JEL classification: O31, M52, O34

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1. Introduction

Since innovation is the key to enhancing companies' competitive advantages, the design of the incentive system for innovation is a crucial issue for managing innovation. Offering monetary incentives could be one potential method to accomplish this purpose. Although the empirical literature has shown that appropriately designed monetary incentives promote employee effort and better performance (Lazear 2000), many prior studies have looked at jobs with simple routine work and/or clear goals and performance measures, such as production workers, salespersons, and professional athletes. Research on corporate researchers is scant. Unlike most other occupations, the tasks of corporate inventors are risky, unpredictable, complex, and difficult for employers to monitor. In particular, a valuable invention has to be novel and non-obvious from prior art, so contracting is bound to be significantly incomplete. Furthermore, intrinsic motivation, such as an interest in solving challenging problems and contributing to the advancement of science (we call this a "taste for science," following Stern 2004), seems to play an important role in motivating researchers' efforts. Because of these features, whether a simple pay-for-performance incentive for corporate researchers effectively enhances inventive productivity is an important and intriguing question that remains unanswered.

We investigate the effect of monetary incentives on corporate inventors' behavior and performance using a novel dataset of Japanese inventors. In Japan, many companies introduced revenue-based payments linked to the contributions to the company's sales, profits or licensing royalties generated by the patented technology, to employee-inventors after 2001 when a Tokyo High Court ruling presented a new interpretation for section 35 of Japanese patent law. Section 35 provides that employers should pay a "reasonable remuneration" to employee-inventors when their patent rights are transferred to the employer. Until the 2001 ruling, employers believed that the amount of payment that they decided based on internal company rules was "reasonable." However, the court newly interpreted the section to be a mandatory provision, under which an employee-inventor had the right to ask for additional compensation from the employer if the payment for the particular invention fell short of "reasonable" compensation. The Supreme Court endorsed the above judgment in 2003. As a result, many large Japanese companies were forced to introduce more generous invention remuneration policies with a stronger link to the actual commercial performance of the invention to prevent inventors from suing them. Consequently, Japanese companies involuntarily strengthened their monetary incentives for corporate inventors. This provides us with a chance to investigate how the exogenous changes in monetary incentives affect corporate inventors' performance and behavior.

Using this exogenous policy change, we first focused on the effect of monetary incentives on the individual productivity of corporate inventors. In theory, it remains ambiguous whether monetary incentives effectively motivate inventors' innovation. There are four salient features that typically characterize tasks in research and development (R&D) as discussed in Holmstrom (1989). First, there is substantial uncertainty in R&D activities where the path to success is hard to predict and the failure rate is much higher than that of non-R&D activities. Therefore, pay for performance might not only expose researchers to excessive risks but also might be ineffective as the optimal action and suitable performance measures are hard to know at the beginning. Second, many R&D projects take a long time and proceed in many steps that involve researcher turnovers. Hence, it is hard to evaluate the economic value of inventions within a given period of time and to precisely determine each researcher's contribution. Third, R&D activities are knowledge-intensive: they involve numerous decisions and selections from choice sets, each of which might affect the arrival of opportunities and the marginal return to efforts. Fourth, research projects all have unique specific features that prevent comparison with others, so it is not feasible to standardize the optimal incentive scheme.

From the contract design point of view, the fact that researchers put forth efforts to choose projects and methods as well as to implement the projects makes it extremely challenging to design optimal compensation for researchers. As Lambert (1986) shows, in contrast to standard agency theory, stronger monetary incentives could make employees choose well-known projects with low return and low risk over new projects with high return and high risk, resulting in lower performance. A similar implication is given by March (1991), who demonstrates the trade-off between the exploration of possibilities and the exploitation of certainties. In these views, as Manso (2011) shows, monetary incentives based on relatively short-term research output may be harmful because they might lead to a distortion of inventors' allocation of research efforts towards excessive exploitation.

Another consideration that needs to be given is the possibility that monetary incentives might affect inventors' intrinsic motivation. Intrinsic motivation seems to be one of the most important driving forces of successful inventions. In fact, recent surveys show that inventors are motivated more by intrinsic rewards than by extrinsic rewards (Giuri and Mariani et al. 2006; Sauermann and Cohen 2010; Nagaoka and Tsukada 2007). Moreover, many previous studies emphasize that extrinsic motivations, such as pay-for-performance, crowd out intrinsic motivation (Benabou and Tirole 2003; Deci 1975; Deci, Koestner and Ryan 1999: Kohn 1993; Frey 1997; Frey and Jegen 2001; Wiersma 1992). If this is true, introducing or increasing monetary rewards may discourage inventors with strong intrinsic motivation from taking a desirable course of action.

In this study, we investigate how stronger monetary incentives affect inventors' behavior. We first develop a simple theoretical model to disentangle the relationship between monetary incentives, inventors' intrinsic motivation, project selection and inventive performance. In this model, we confirm that while monetary incentives definitely induce inventors to exert greater effort (incentive effect), inventors who face stronger monetary incentives tend to choose lower risk projects (substitution effect). Whether an incentive induces higher inventive performance or not depends on the cost of effort, the strength of intrinsic motivation, risk aversion of the inventors, and output/risk distributions of expected projects. Further, our model predicts that monetary incentives are more likely to crowd out intrinsic motivation when the heterogeneities in uncertainty between projects are high.

In order to test the theoretical implications, we use novel datasets from two surveys. One is a survey of inventors conducted by the Research Institute of Economy, Trade, and Industry (REITI), which asked patent inventors about the detailed characteristics of projects and the inventors themselves, as well as their inventive processes. The other is an employee invention survey conducted by the Institute of Intellectual Property (IIP), which asked Japanese listed manufacturing companies about the detailed characteristics of their invention remuneration policies and their implementation histories in a retrospective format. We further supplement our dataset with the IIP patent database, which contains bibliographic information about patents applied for at the Japanese Patent Office as well as the citation counts of the non-patent literature within the main body of patent applications as identified by the Alife-Lab.

Combining these sources, we investigate how changes in revenue-based invention remuneration implemented at the company-level affect inventors' behavior and performance. We examine the impact on project choice using the number of non-patent literature citations that inventors reported in their patent applications. Non-patent literature citations are mostly composed of scientific literature (Tamada et al. 2006; Nagaoka and Yamauchi 2014). Since this number reflects the importance of scientific sources as the base of the R&D project generating the invention, we treat it as a proxy of the degree of exploration in the projects.

If introducing or increasing monetary payments for inventions induces an inventor to focus more on the exploitation of certainties, which is less risky, such policy changes will lead to less use of advanced scientific knowledge, as measured by the citation frequencies of non-patent literature. We also use the number of forward citations as our inventive performance indicator, and test whether stronger monetary incentives crowd out the effects of intrinsic motivation, which is measured by the inventors' assessments of the importance of intrinsic sources of motivation.

Our findings show that while introducing or increasing invention remuneration results in higher average patent quality, these schemes decrease the scientific intensity of the R&D projects as measured by the number of non-patent literature citations. In addition, our results suggest that a stronger "taste for science"—the most important measure of intrinsic motivation—is associated with higher quality of inventions, but this motivation not only reduces the marginal effect of monetary incentives on the quality of inventions, but also reinforces the negative effect of monetary incentives on the scientific intensity of the R&D projects. These results are consistent with the implication from our model that the substitution effect might be stronger for inventors who have strong intrinsic motivation.

This paper proceeds as follows. We review previous literature in Section 2, and present a simple model to help interpret our empirical findings in Section 3. Section 4 explains the legal treatment of employee inventions in Japan. We subsequently explain our data and estimation methodology in Section 5, and then present our results in Section 6. The final section discusses our findings and conclusions.

2. Prior Literature

2.1 Incentive and performance

A number of authors have pointed out that high risks involved in a typical innovation process may make high-powered incentive schemes for researchers too costly for the firm. Holmstrom (1989) suggests that other means, such as direct monitoring of activities and restricting workers' discretion to spend time on alternative activities, may be more efficient ways to enhance research productivity than providing researchers pay for performance, because exposing employees to high risks will require employers to pay large risk premiums. Using a model where agents collect costly information to choose between risky projects and safe ones, Lambert (1986) shows that offering high-powered incentives to agents could be counterproductive because such pay policies could induce them to choose safe projects with lower returns. His model reveals the tradeoffs between the incentives to induce efficient efforts and the incentives to select the right projects. In the equilibrium, project selections are often distorted.

Another important insight from the literature is that there are two distinct types of R&D activities—exploration and exploitation—and achieving balance between the two is a challenging task. Exploration of new knowledge and possibilities involves learning from outside the boundaries of the firm and experimenting with new approaches. Exploitation of existing knowledge and organizational capability requires integrating knowledge and information possessed by the members and coordinating activities to maximize the new value created. Manso (2011) uses a model based on the bandit problem where an agent chooses between an action with an outcome distribution that is well-known and an action with an output distribution that is unknown but can be learned by experiment. He shows that tolerance for early failure and rewards for long-term success encourage agents to learn from early experiments, which is desirable but often too risky for individuals to take under short-term incentive schemes.

This implication from Manso has been supported by a number of empirical studies.[1] Azoulay, Zivin and Manso (2011) have shown that researchers at the Howard Hughes Medical Institute (HHMI), which tolerates early failure, rewards long-term success, and gives its appointees great freedom to experiment, produce high-impact articles at a much higher rate than a control group of NIH-funded scientists. Lerner and Wulf (2007) find that while long-term monetary incentives for R&D managers, such as stock options, increase research performance as measured by the number of highly cited patents, short-term incentives based on patent performance are not effective. Franzoni, Scellato and Stephan (2011) analyze the effects of three kinds of incentive (institutional incentives, cash bonus for academic researchers, career advancement for researchers) on performance indicators (number of submissions, publication and acceptance rate in *Science*) using country-level data. They find that in the countries that have implemented cash bonuses, the number of submissions to *Science* increased but their acceptance rate decreased. In contrast, greater reliance on career advancement as an incentive has increased the number of publications as well as submissions.

2.2 Monetary incentive and intrinsic motivation

Some existing studies have shown that inventive productivity is highly associated with strong intrinsic motivation rather than extrinsic motivation (Giuri and Mariani et al. 2006; Sauermann and Cohen 2010; Nagaoka and Tsukada 2007). Other studies indicate that monetary incentives may crowd out an inventor's intrinsic motivation, and this claim is empirically supported by laboratory experiments (Benabou and Tirole 2003; Deci 1975; Deci, Koestner and Ryan 1999; Kohn 1993; Frey 1997; Frey and Jegen 2001; Wiersma 1992).[2]

In an economic analysis, Owan and Nagaoka (2011) suggest that since inventors who find intrinsic benefits already work harder than others in the absence of monetary incentives, their introduction has a smaller effect on such inventors because their marginal cost of effort is already high. Their empirical findings are consistent with this interpretation.

Using a questionnaire survey for corporate researchers and engineers, Sauermann and Cohen (2010) find that inventors motivated by intellectual challenges worked longer, and not only produced more patents but also higher quality inventions. On the other hand, inventors who answered that they were motivated by monetary rewards worked shorter hours but invented more products, implying that those inventors invented more effectively. In contrast, Gambardella, Harhoff and Verspagen (2006), using Pat-val-EU survey, find that inventors more

[1] This prediction is also supported by his own experimental research (Ederer and Manso 2013).

[2] Deci's seminal paper finds that people who aren't offered monetary incentives continue to work on tasks longer than people who are offered monetary incentives in a laboratory experiment. According to his self-determination theory, when people perceive that they have determined their tasks on their own, they are highly motivated, but once monetary incentives are offered, the perception that they work on their tasks under external control weakens intrinsic motivation (Deci 1975, Deci, Koestner and Ryan 1999).

motivated by extrinsic factors such as monetary incentives or career promotion came up with significantly higher quality inventions than others.

3 Model

In this section, we present a simple model to capture the relationships between intrinsic motivation, monetary incentive, project selection and inventive effort. Employees who vary in the strength of intrinsic motivation search for and select different types of projects and choose varying levels of effort. We assume that there are two courses of action that employees can follow in order to find a project: (1) an exploratory search into scientific discoveries that might generate useful ideas for new inventions; and (2) a coordinated exploitation of existing knowledge whose outcome produces reasonable and predictable profits. We assume that the former course of action leads to project *H*, whose profit $y(e|H)$ is distributed as normal with mean $\mu_H + e$ and variance σ_H, while the latter course of action generates project *L*, whose profit $y(e|L)$ is also distributed as normal with mean $\mu_L + e$ and variance σ_L, where e is the level of implementation effort exerted by the researcher after the project is selected.

We assume that project *H* entails higher risk and higher return than project *L*, so $\mu_H > \mu_L$ and $\sigma_H > \sigma_L$. Researchers who choose project *H* additionally receive an intrinsic benefit *ue*, where $u \in [0, \bar{u}]$ is the strength of intrinsic motivation and varies across researchers. Let $F(u)$ and $f(u)$ be the probability distribution and density functions of *u*, respectively.

We assume that an inventor-employee with a level of intrinsic motivation *u* receives the following expected utility:

$$EU(w, e : k) = E[w] + kue - c(e) - RP(\sigma^2)$$

where *k* denotes the type of project such that *k* = 1 (= 0) indicates project *H* (project *L*) and $c(e)$ is the private cost of effort that is convex with $\lim_{e \to 0} c'(e) = 0$. $RP(\sigma^2)$ is the risk premium (in other words, $E[w]$ - $RP(\sigma^2)$ is the certainty equivalent).[3]

One key assumption is that the employer observes only the final profit $y(e|k)$, therefore, the worker's compensation can depend only on the final profit *y*, not on *e* and *k* directly.

When an employee works on project *k*, he/she chooses the level of effort solving the following optimization problem:

$$\max_e E[w] + kue - c(e) - RP(\sigma^2) \qquad (3.1)$$

[3] It is important that we do not assume liquidity or limited liability constraint. If we do so, it may become more likely that monetary incentives encourage inventors to choose project H because the former raises the option value of project H over project L.

Assuming that $E[w]$ is increasing, concave, and twice continuously differentiable in *e*, it is immediate that the optimal effort level $e_k^* = e_k^*(u)$ is increasing in *u*.

$$\frac{\boldsymbol{de_k^*}}{\boldsymbol{du}} = \frac{\mathbf{1}}{\boldsymbol{c}''(e_k^*) - \frac{\partial^2 E[w]}{\partial e^2}} > 0 \qquad (3.2)$$

In order to make our analysis simple and tractable, we restrict our analysis to a linear incentive scheme $\mathrm{w} = \alpha + \beta \mathrm{y}$, assume a quadratic cost function $c(e) = \frac{c}{2}e^2$, and represent the risk premium by $RP(\sigma^2) = \frac{1}{2}\gamma\beta^2\sigma^2$ where γ is the coefficient of absolute risk aversion. It is well known that the risk premium can be expressed in this form when we assume the exponential utility function as well as normal distribution for project output. Then, $e_1^* = \frac{\beta+u}{c}$ and $e_0^* = \frac{\beta}{c}$.

The worker will choose project *H* if

$$E[w|e_1^*] + ue_1^* - c(e_1^*) - RP(\sigma_H^2)$$
$$= \alpha + \beta\mu_H + \beta\frac{\beta+u}{c} + \mathrm{u}\frac{(\beta+u)}{c} - \frac{1}{2}\frac{(\beta+u)^2}{c} - \frac{1}{2}\gamma\beta^2\sigma_H^2$$
$$= \alpha + \beta\mu_H + \frac{1}{2}\frac{(\beta+u)^2}{c} - \frac{1}{2}\gamma\beta^2\sigma_H^2$$
$$> E[w|e_0^*] + ue_0^* - c(e_0^*) - RP(\sigma_L^2) = \alpha + \beta\mu_L + \frac{1}{2}\frac{\beta^2}{c} - \frac{1}{2}\gamma\beta^2\sigma_L^2$$

When β is sufficiently small, more precisely when $\beta < \underline{\beta} = \frac{2}{\gamma}\frac{\mu_H-\mu_L}{\sigma_H^2-\sigma_L^2}$, this inequality will always hold, even for a worker with $u = 0$. When $\beta \geq \underline{\beta}$, project *H* is chosen if

$$\Leftrightarrow\ u > \sqrt{-2c\beta(\mu_H - \mu_L) + \beta^2 + c\gamma\beta^2(\sigma_H^2 - \sigma_L^2)} - \beta$$

Let $\bar{u}(\beta)$ be the threshold for those who choose project *H*. Then,

$$\bar{u}(\beta) = \begin{cases} 0 \ \text{ if } \beta < \underline{\beta} \\ \sqrt{-2c\beta(\mu_H - \mu_L) + \beta^2 + c\gamma\beta^2(\sigma_H^2 - \sigma_L^2)} - \beta \ \text{ if } \beta \geq \underline{\beta} \end{cases} \qquad (3.3)$$

$\bar{u}(\beta)$ is non-decreasing in β and, strictly increasing when $\beta \geq \underline{\beta}$, implying that raising the incentive intensity results in more researchers choosing the safer project *L, due to higher risk imposed on the inventor*. Let us state this implication in the form of a proposition:

Proposition 1 Inventors with stronger intrinsic scientific motivations are more likely to choose project H. Furthermore, the share of those who choose project L is increasing in β. More precisely, for $\bar{u}(\beta)$ defined by Equation (3.3), researchers with $u \in [0, \bar{u}(\beta)]$ choose project L while those with $u \in [\bar{u}(\beta), \bar{u}]$ select project H. $\bar{u}(\beta)$ is increasing in β.

The next question is how the value of the invention changes as more performance pay is paid to the worker. On the one hand, all inventors work harder (i.e. $e_k^* = \frac{\beta + ku}{c}$) because the marginal return to effort increases (incentive effect). But, on the other hand, some inventors who previously selected project H will switch to project L, which has a lower value, in response to the increased risk because their income is more variable after the change (substitution effect).

The question of which effect dominates the other is ambiguous on the aggregated level. To illustrate the point, let us examine the expected value of invention, E[y] as a function of β:

$$\mathrm{E}[\mathrm{y}|\beta] = \int_0^{\bar{u}(\beta)} (\mu_L + \frac{\beta}{c}) f(u) du + \int_{\bar{u}(\beta)}^{\bar{u}} (\mu_H + \frac{\beta + u}{c}) f(u) du$$

$$= \frac{\beta}{c} + \mu_L \mathrm{F}\big(\bar{u}(\beta)\big) + \mu_H (1 - \mathrm{F}\big(\bar{u}(\beta)\big) + \int_{\bar{u}(\beta)}^{\bar{u}} \mathrm{u} f(u) du$$

By taking the derivative with respect to β,

$$\frac{\partial \mathrm{E}[\mathrm{y}\,|\,\beta]}{\partial \beta} = \begin{cases} \dfrac{1}{c} & \text{if } \beta \le \underline{\beta} \\ \underbrace{\dfrac{1}{c}}_{\text{Incentive effect}} \underbrace{- \left(\mu_H - \mu_L + \dfrac{\bar{u}(\beta)}{c} \right) f\big(\bar{u}(\beta)\big) \dfrac{\partial \bar{u}(\beta)}{\partial \beta}}_{\text{substitution effect}} & \text{if } \beta > \underline{\beta} \end{cases}$$

If we focus on the case where $\beta > \underline{\beta}$, some portion of researchers switch to a safer project L. In this case, the sign of the result is indefinite, because the substitution effect may or may not dominate the incentive effect. Comparative statics analyses with respect to key parameters are mostly indefinite. From the point of view of the optimal incentive design which maximizes the sum of the welfare of the firm and the researchers, the above incentive effect has to be large enough to compensate for the distortion of the optimal allocation of risk (i.e. the output linked payment forces the researchers to bear a greater share of the risk) in the equilibrium. This in turn implies that if the substitution effect is significant, the optimal incentive needs to be lowered so as to encourage all researchers to pursue H projects and to avoid the substitution effect.

To obtain the result for an individual worker with a particular level of intrinsic motivation, let us suppose that the pay for performance is raised from β_1 to β_2 for an exogenous reason. Then, all workers who do not change their project type work harder by raising their effort level from $e_k^* = \frac{\beta_1+ku}{c}$ to $e_k^* = \frac{\beta_2+ku}{c}$. But, those whose strength of intrinsic motivation is between $\bar{u}(\beta_1)$ and $\bar{u}(\beta_2)$ switch from Project H to Project L. Not all these switches lead to a decline in the value of the invention, though. If $\mu_H + \frac{\beta_1+u}{c} < \mu_\mathrm{L} + \frac{\beta_2}{c} \Leftrightarrow \mathrm{u} < \beta_2 - \beta_1 - c(\mu_H - \mu_L)$, the value of the invention is higher because the incentive effect more than offsets the substitution effect. Let $\tilde{u}(\beta_1, \beta_2) \equiv \beta_2 - \beta_1 - c(\mu_H - \mu_L)$. Then, the result can be stated more formally as follows:

Proposition 2 If $\tilde{u}(\beta_1, \beta_2) \leq \bar{u}(\beta_1)$, the inventive productivity falls for employees with $u \in [\bar{u}(\beta_1), \bar{u}(\beta_2)]$ whereas it rises for all others. If $\bar{u}(\beta_1) < \tilde{u}(\beta_1, \beta_2) < \bar{u}(\beta_2)$, the inventive productivity falls for employees with $u \in [\tilde{u}(\beta_1, \beta_2), \bar{u}(\beta_2)]$ whereas it rises for all others. If $\bar{u}(\beta_2) \leq \tilde{u}(\beta_1, \beta_2)$, then productivity rises for all employees.

The proof is straightforward, and thus omitted. Figure 1 illustrates the range of u and $\gamma(\sigma_H^2 - \sigma_L^2)$ where the increase in pay for performance from β_1 to β_2 results in a decline in the value of invention.[4] Suppose $\sigma_H^2 - \sigma_L^2$ is the measure of heterogeneity in project risk characteristics and differs across industries. As the figure shows, in an industry where $\sigma_H^2 - \sigma_L^2$ is high, the inventive productivity is more likely to decline (i.e. the range where the productivity is expected to decline is greater) after pay for performance is raised, assuming that u, the strength of intrinsic motivation of researchers, is relatively uniformly distributed in a sufficiently broad range above $\bar{u}(\beta_1)$.

Another implication from Figure 1 is that the substitution effect is more likely to dominate the incentive effect for inventors who are more intrinsically motivated when $\sigma_H^2 - \sigma_L^2$ is high. This is because: (1) the disutility of risk that the researcher additionally bears by choosing project *H* is more likely to dominate the additional intrinsic benefits he or she enjoys when $\sigma_H^2 - \sigma_L^2$ gets higher, thus leading to the choice of project L; and (2) the substitution effect is especially large for those with strong intrinsic motivation because their effort level changes from $e_1^* = \frac{\beta_1+u}{c}$ to $e_0^* = \frac{\beta_2}{c}$. The impact of monetary incentives should be much less dependent on the strength of intrinsic motivation when $\sigma_H^2 - \sigma_L^2$ is small. Note that this is also a new interpretation of the crowding-out effect of monetary incentives on intrinsic motivation. Monetary incentives are more likely to crowd out the intrinsic motivation when there is a

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[4] The figure illustrates comparative statics results with respect to u, γ and $\sigma_H^2 - \sigma_L^2$ keeping other parameters constant. However, it may be reasonable to assume that $\mu_H - \mu_L$ and $\sigma_H^2 - \sigma_L^2$ are correlated. As soon as $\frac{d(\mu_H - \mu_L)}{d(\sigma_H^2 - \sigma_L^2)}$ is low enough, the same implications are derived as those discussed here (i.e. Hypotheses 3 and 4).

distinct difference in uncertainty between exploring new possibilities and exploiting existing well-known research opportunities.

We summarize the above theoretical implications in the form of empirical predictions. Predictions 1 and 2 are directly derived from Proposition 1 whereas predictions 3 and 4 are implied by Proposition 2 under certain conditions.

Prediction 1: Intrinsically motivated inventors are more likely to choose exploratory/risky projects.

Prediction 2: A greater monetary incentive encourages inventers to choose exploitative/safe projects.

Prediction 3: When exploratory and exploitative projects are very different in terms of uncertainty, a greater monetary incentive is more likely to reduce the value of inventions. In contrast, when projects are not so different in their risk characteristics, a greater monetary incentive is more likely to raise the value of inventions.

Prediction 4: An increase in monetary incentives is more likely to have an adverse impact on the value of inventions for researchers with stronger intrinsic motivation than for those without it when exploratory and exploitative projects are very different in terms of uncertainty.

(Figure 1)

4. Legal Provision of Employee-Invention

Japanese Patent Law mandates that employers should pay “reasonable remuneration” to inventors when the exclusive right to use the invention is transferred from the employee-inventor to his/her employer. While this provision was enacted in 1885, employers had long deemed that it wasn't a mandatory provision for each invention transferred. Therefore, many companies which had introduced small fixed-amount compensation at the time of patent application or registration regarded their own remuneration policies as “reasonable.” In the *Olympus Optical vs. Tanaka* case,[5] the Tokyo High Court and The Supreme Court judged, in

[5] The *Olympus* case was not the first case for an employee-inventor to sue his/her employer demanding reasonable remuneration. However, it was the first case where the court ruled that the employer had to pay more despite the fact that they had already paid an amount according to their internally set payment rules. The Tokyo Direct Court judged that Olympus had to pay 2.3 million yen more as compensation because the original payment was short of “reasonable remuneration” in 1999, but the court didn’t mention whether this section was a mandatory provision or not. Subsequently, The Tokyo High Court ruled that Article 35 was a mandatory provision in 2001, and the employer had to pay the 2.3 million yen. The Supreme Court passed the same judgment in 2003.

2001 and 2003, respectively, that Section 35 was a mandatory provision, and that an employee-inventor can require additional compensation from his/her employer if the previous payments for a particular invention didn't match his/her actual contribution to the value created by the patent. Furthermore, there is no statute of limitations regarding this claim, unlike German patent law. As a result, many companies introduced or raised their revenue-based compensation payment—under which the payment is directly linked to sales, profit or licensing royalty arising from the commercial usage of the invention—over the past decade (IIP 2002) to avoid lawsuits from employee-inventors. This wide-spread policy change can be seen in Figure 2, which shows the number of companies that newly introduced revenue-based compensation policies during 1990-2005 (reproduced from Onishi 2013). Figure 3 presents how the upper limit set for each payment in such compensation plans changed over time. The companies that had revenue-based compensation plans dramatically increased their upper limit for the payment after 2000. This change in the legal environment, which is a totally exogenous factor for the firms and inventors, offers a chance to investigate how monetary incentive affects the performance of inventors.

Despite this upward trend of compensation for employee inventions, some companies were still legally challenged by their employee-inventors. Between 2001 and 2005, the average number of lawsuits was 5.4 cases per year, up from the average of 0.6 per year between 1990 and 2000 (Owan and Onishi 2010). In those cases, the courts often judged that the defendant-employer should pay more to the plaintiff-employee. For example, In *Nichia-Kagaku* case,[6] Tokyo District Court ordered the employer to pay 20 billion yen as "reasonable remuneration" in 2002, although this amount was significantly reduced in the subsequent High Court decision (the case was settled later).

(Figure 2 and 3)

5. Data and Empirical Method

5.1 Data

Our source of information about the characteristics of corporate inventors is the 2006 RIETI Inventor Survey, which targeted patents with application dates between 1995 and 2002 that were selected using stratified random sampling.[7] The data obtained in the survey include demographics of inventors as well as the inventive process of the focal patents.

We also examined all of the patents that the survey respondents had ever obtained, by matching their names and the applicant-employer names with the inventor/applicant name lists

[6] The *Nichia-Kagaku* case, started in 2001, had a strong impact on other companies' compensation policies. The plaintiff in this case was Shuji Nakamura, a 2014 Nobel Prize winner, who invented the blue light diode system while working for the company. In 2005 the plaintiff and defendant reached a settlement whereby the employer must pay 850 million yen.

[7] Details of this survey are explained by Nagaoka and Tsukada (2007).

of Japanese patents in the IIP Patent Database.[8] We additionally used the science literature citation database from Alife-Lab to obtain non-patent literature citations by inventor.[9] This database uniquely collects all patent and non-patent literature cited in all pages of patent application documents.

To avoid treating different persons with the same name as one unique inventor, we only used the records of inventors whose names appeared with the same applicant-employers, but not those with other firms. Within this restricted sample, we treat all inventors with the same name as the same inventor. This selection process is effective because same name persons are much rarer in Japan than in western countries and the probability of encountering inventors with the same name in a single company is almost negligible.[10]

Focusing on inventors who stayed in a single company eliminates concerns about the sorting effect, whereby an inventor may choose to work for a company which has recently introduced a monetary reward (Franzoni, Scellato and Stephan 2011; Lerner and Wulf 2007). While such selection would bias our estimation results, we can assume that for any inventor in our sample, a change in monetary incentives is exogenous to his/her unobservable characteristics, as a result of our sample restriction. If the intensity of monetary incentive schemes is positively correlated with an inventors' productivity, we can regard this as due to the incentive effect rather than the sorting effect.

Our third source of information is the IIP Employee Invention Survey, which asked listed Japanese manufacturing companies about their payment schemes for employee inventions in 1990-2005. Japanese companies typically have implemented two different monetary incentive schemes: (1) revenue-based payments linked to sales, profit or licensing royalties; (2) payments linked to patent application or patent registration. As the latter payments are typically small, e.g. less than 30,000 yen per patent application/registration, we mainly focus on the former.

We matched firm-level information from the IIP survey to the inventors in the sample of the 2006 RIETI Inventor Survey. Thus, our sample consists of 830 inventors in 155 large manufacturing companies. We restricted our analysis to the period from 2000 to 2005, during which most Japanese large companies changed their payment scheme in response to an exogenous change in the legal environment.

5.2 Estimation Methodology

8 This is the most comprehensive and sophisticated Japanese patent database. See Goto and Motohashi (2007).

9 This database is available at: http://www.alife-lab.co.jp/patdb/construction.html

10 The most common name in the Telephone Directory Database in 2001 was "Minoru Tanaka" (written using *Kanji*, Chinese characters). Still, only about 3,000 people out of 30,000,000 have that name, so even the probability of encountering the most frequent name is only 1/10,000.

Our theoretical model predicts that monetary incentives lead to choosing less exploratory projects for some inventors, but the overall effect on patent productivity is ambiguous in general (Proposition 1-2), as it partly depends on the strength of the inventors' intrinsic motivation and the distribution of risk characteristics of available projects.

To examine the effect of monetary incentive schemes on inventor output and research project choices, we first estimate the following equation:

$$FC_{it} = (\ NPL_{it} =)\beta_1 RBP_{it-1} + \beta_2 ARP_{it-1} + \beta_3 u_i + X_{1i}\beta_{k1} + X_{2it}\beta_{k2} + \sum_{t,j} \alpha_{t,j} year_t * technology\ dummies_j + c_i + \varepsilon_{it} \qquad (1)$$

where FC_{it} represents the logarithm of the number of forward citations per patent for inventor *i* in year *t*. Hence, the unit of observation is an individual inventor's yearly patent productivity. Forward citations cited by other patents are the most common patent quality indicator (Harhoff et al. 1999; Hall, Jaffe and Tratjenberg. 2005).

We count the number of forward citations—other patent documents' citations of the focal patent—cited by examiners who examined other patents.[11] As a measure of patent quality, we divide the number of forward citations by the number of patents each inventor applied for. This patent indicator is suitable for our analysis because highly cited patents are also likely to be commercially valuable.[12] Truncation is one of the big problems we face when using forward citations because the number of citations are restricted to those made by the patent applications observed before the last date of our available data. Furthermore, forward citations also depend on the amount of following patents in a similar technological area. To cope with these two problems, we employ the fixed effect approach proposed by Hall, Jaffe and Tratjenberg. (2001); the number of forward citations that a patent in year *t* in technological area *j* received is divided by the mean value of forward citations that every patent in year t in technological area j received.[13]

NPL_{it} indicates the logarithm of the number of backward citations of non-patent literature per patent cited by inventor *i* in year t. Non-patent literature cited by inventors is largely composed of scientific literature. This indicator, referred to as science linkage (Narin,

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[11] Citations by examiners in JPO are known to be correlated with the patents' economic value (Yamada 2010 and Wada 2010). They are also significantly correlated with the number of citations by inventors in the U.S. as well as by examiners in EPO for the same patent family (Goto and Motohashi 2007). Citations by inventors were not required before 2002 and not available in the IIP database.

[12] At the individual level, Toivanen and Väänänen (2012) find that inventor wage is strongly correlated with the number of highly cited patents in Finland, which has an employee invention law similar to that of Japan.

[13] We constructed various kinds of forward citation indicators such as the total number of citations or the number of citations received during the five years after application, and estimated the same models using those variables. We did not find any qualitatively different results.

Hamilton and Olivastro. 1997; Meyer 2000; Tamada, et al. 2006), is the best available proxy for inventors' project selection given the fact that economists (presumably even for research managers) cannot observe inventors' project choice sets and their final selections. We believe that this indicator reflects the inventor's propensity to choose exploration versus exploitation because science-based research, being typically far distanced from commercialization, should tend to be more challenging and risky for inventors. Although this indicator is not only noisy but also censored, that is, the vast majority have no citations (the mean number is 0.51), there is no good alternative. Another criticism of our approach is that the project may not be the choice of an individual researcher in large corporations. According to a MEXT (2002) survey, however, researchers have substantial discretion over project choice at almost fifty percent of companies surveyed.

Our methodology, which uses the citation intensity of non-patent literature as a project selection indicator, needs to satisfy the requirement of the assumption of our theoretical model. In our theoretical model, project H has higher returns but greater risk than project L. In the data, patents citing non-patent literature are, on average, more frequently cited than other patents (the mean of forward citations per patent of the former is 0.88, and that of the latter is 0.73). Moreover, the standard deviation of the former is larger than that of the latter (the former is 1.37, the latter is 1.09). This comparison indicates that projects which highly depend on scientific knowledge are more likely to generate inventions with higher value than other projects, while the former involve higher risk. This observation justifies our procedure.

The propensity to cite scientific literature is highly dependent on technological area, with a very high number of citations in life sciences and chemistry, and a very low number of citations in mechanical areas, while the actual use of science may not be so different. We control for these potential differences in citing propensities by including technology and firm fixed effects and by estimating with subsamples.

Our main independent variable is Revenue-based Payments (RBP_{it-1}). The IIP Employee Invention Survey asked the respondents to specify the ceiling levels of revenue-based payments in six intervals: "less than 100,000 yen," "100,000–1 million yen," "1–10 million yen," "10–100 million yen," "100 million yen or more" and "no upper limit."　We use a logarithm of the median of each interval as an indicator of the strength of incentive pay, and we introduce a one-year lag. Further, we combine the highest three intervals and use "100 million" as the expected maximum reward because many surveys have revealed that the actual payments based on these policies were at most 100 million yen.

Japanese companies often pay a small amount for patent application or registration, and the survey also asked companies about the level of these payments, grouping them into five intervals: "less than 5,000 yen," "5,000–10,000 yen," "10,000–30,000 yen," "30,000–100,000 yen," and "100,000 yen or more." We use the logarithm of the median of each interval as an independent variable (ARP_{it-1}) with a one-year lag. We expect that these payments are introduced not as an incentive for invention, but rather, as an incentive to encourage inventors to fill out patent application documents in a timely manner.

u_i is the strength of intrinsic motivation which is time-invariant. The RIETI survey asks the responding inventor to assess the importance of each of the following sources of motivation using a five-point Likert scale: Science (satisfaction with one's contribution to science), Challenge (satisfaction with solving challenging problems), Organization's performance (satisfaction with one's contribution to enhancing the organization's performance), Career (one's career advancement), Reputation (enhancing one's reputation), Research environment (improvement of research conditions) and Financial Reward (increasing inventor's monetary compensation). Among these motivations, Science and Challenge are highly correlated and well represent the strength of one's intrinsic motivation. We employ science motivation as the primary variable for intrinsic motivation. We construct the dummy (SM_i) indicating the strength of intrinsic motivation by assigning one to the responses "very important" and "important", and zero to "indifferent", "unimportant" and "quite unimportant".

Unfortunately, this variable is specific to a particular project $l(i)$ focused on in the RIETI survey rather than the overall nature of the inventor himself/herself. In other words, it measures the importance of science motivation in initiating project $l(i)$. Thus, the relationship between u_i and SM_i may be expressed as

$$SM_i = u_i + \eta_{l(i)}$$

where $\eta_{l(i)}$ is the random variable containing information on the project characteristics investigated in the RIETI survey with $\mathrm{E}\left[\eta_{l(i)}\right] = 0$. By substituting $u_i = SM_i - \eta_{l(i)}$ into Equation (1), we get

$$\begin{aligned} FC_{it} = (\,NPL_{it} =)\beta_1 RBP_{it-1} + \beta_2 ARP_{it-1} + \beta_3 SM_i + X_{1i}\beta_{k1} + X_{2it}\beta_{k2} \\ + \sum_{t,j} \alpha_{t,j} year_t * technology\ dummies_j + c_i + \varepsilon_{it} - \beta_3\,\eta_{l(i)} \qquad (2) \end{aligned}$$

X_{i1} is a set of time-invariant control variables that includes the gender and the latest education status of the inventors in order to control for their ability and roles in their companies. The gender dummy takes one if the inventor is a woman, zero otherwise. We construct four dummy variables: BA degree, MA degree, PhD degree and PhD-DO degree. The reference group is two-year college degree or less. PhD-DO is a unique PhD certification system in Japan, whereby DO is an abbreviation for "dissertation only". This PhD degree is given based solely on the examination of a submitted dissertation without completing any PhD coursework under the supervision of advisers.[14] X_{i1} also includes technology area dummies indicating chemicals, computers & communications, drugs & medical, electrical & electronic, mechanical, and other, based on technological areas identified by the RIETI inventor survey. We further add firm dummies to control for firm heterogeneity.

X_{2it} is a vector of time-varying covariates including inventor's age. As the previous literature shows, we typically observe an inverted U-shaped relationship between age and productivity (Levin and Stephan 1991, Hoisl 2007, Onishi and Nagaoka 2012). Thus, we use a quadratic form of age as an independent variable. We expect that age variables partially control for inventors' promotion, and that the maturity of their research is associated with age.

Finally, equation (2) also includes cross terms between year effects and six technology area dummies to control for technological opportunities and demand conditions. c_i is the fixed inventor effect to control for unobserved inventor heterogeneity.

If $E\left[c_i + \varepsilon_{it} - \beta_3 \eta_{l(i)} \middle| RBP_{it-1}, ARP_{it-1}, SM_i, X_{1i}, X_{2it}\right] \neq 0$, then our OLS estimates for $\beta_1 - \beta_3$, β_{k1}, and β_{k2} are potentially biased. In order to correct for these potential biases, we take two approaches. First, we estimate the equations using fixed-effect models, which exploits only the variations within inventor, in response to exogenous policy changes. Although this allows us to identify unbiased estimators of β_1 and β_2, β_3 cannot be identified because all time-invariant terms are washed away. Therefore, we also take a second approach. In order to obtain the unbiased estimator of β_3, we estimate Hausman-Taylor models under the assumption:

$$E\left[c_i + \varepsilon_{it} - \beta_3 \eta_{l(i)} \middle| RBP_{it-1}, ARP_{it-1}\right] = 0$$

and

$$E\left[c_i + \varepsilon_{it} - \beta_3 \eta_{l(i)} \middle| SM_i, X_{1i}, X_{2it}\right] \neq 0.$$

We further estimate the equations using the Tobit models to correct for the biases due to the fact that our dependent variables, FC_{it} and NPL_{it}, are censored at zero.

One last issue that might be a major source of concern is the endogeneity of revenue-based payment. If firms introduce revenue-based pay when they anticipate an increase in opportunities in the development stage, fewer patents might cite non-patent literature, and revenue-based payment generally induces more valuable inventions. The introduction of a

[14] While the education variables seem to be good indicators of inventor ability (Angrist and Pischke 2009), the PhD-DO degree is often granted for a dissertation based on the inventor's research in his/her company, so some inventors in our sample earned advanced degrees after entering their companies. Therefore, these education variables may not be good control variables for innate ability.

revenue-based remuneration policy and the hike of its upper limit, however, are most likely driven by the firm’s precaution to avoid legal risk for three reasons (Onishi and Owan 2010, Onishi 2013). First, new introduction of revenue-based remuneration policies are parallel to a rise in lawsuits on employee inventions. Second, new introduction of revenue-based remuneration policies is more common in larger firms with greater patent stock, which most likely face legal risks. Third, such relationship is more distinct in industries which observe more lawsuits related to invention remuneration. Using a dummy for the new legal environment (i.e. the years after the Tokyo High Court ruling in 2001 and its endorsement by the Supreme Court in 2003) as an instrumental variable does not work, however, because firms’ responses are gradual and very heterogeneous among industries.

Tables 1 and 2 present summary statistics and correlation matrixes.

(Table 1 and 2)

6. Results

6.1 Project choice

Table 3 presents the results for the number of non-patent literature citations by inventor as a dependent variable. We show the OLS results using only three key explanatory variables, including revenue-based payments, in column [1], and then we employ all control variables in column [2]. We then show the estimation results for our Hausman-Taylor model in column [3], and for the Tobit model in column [4]. Finally, we estimate the equation using an inventor fixed effects model in column [5].

Revenue-based payments are significantly negative for the number of non-patent literature in all estimations. These results show that inventors who face higher monetary incentives cite less non-patent literature in both within-inventor variations as well as in the pooled variations. One may argue that revenue-based payments may be more likely to be introduced in firms where the researchers engage in more downstream research which requires less scientific knowledge. However, this is unlikely because: (1) firm dummies account for unobservable firm characteristics; and (2) the same result holds even in the model with inventor fixed effects in column [5] where the impact of revenue-based payments is identified only using variations within inventor. Therefore, this relationship is likely to be causal rather than spurious—supporting Prediction 2.

Science motivation is statistically significant and positive for non-patent literature in all model specifications but only weakly in columns [2] and [3]. Very large coefficients of science motivation in the Hausman-Taylor and Tobit models, however, seem to suggest that its

OLS estimate, which is prone to biases caused by the endogeneity of the independent variable and the censoring of dependent variables, is not upward biased. The Tobit model estimation that corrects for the bias due to censoring in particular shows a statistically significant effect of the “taste for science” at the 1% level. These results indicate that the inventors who want to contribute to science choose projects that rely more on scientific discoveries—supporting Prediction 1.

(Table 3)

6.2 Patent output

Next, we present the average effect of monetary incentives on patent performance. In theory, whether monetary incentives enhance inventive productivity is ambiguous because it depends on: (1) the strength of intrinsic motivation of the inventor; (2) his/her degree of risk aversion; and (3) risk characteristics of the projects available to the inventors

Table 4 shows the results for using the number of forward citations per patent as the output indicator. Estimation specification is the same as in Table 3. In all model specifications, revenue-based payments are positively associated with patent quality but the coefficients are only weakly significant in columns [1]-[4] and insignificant in column [5] where the coefficient is estimated using only within-inventor variation. The magnitude of the effect of revenue-based payment is economically small as well. A 10% increase in the ceiling of revenue-based payments results in about a 0.05% increase in forward citations per patent according to columns [1]-[4].

In our theoretical model, the impact of monetary incentives on inventive performance depends on two counteracting effects: the incentive effect and the substitution effect. The latter decreases inventive output by distorting inventors’ project selection. In the next subsection, we evaluate whether the effect is small because the incentive effect is partially offset by the substantial substitution effect or mainly because the incentive effect itself is small.

Fixed payments at the time of application or registration are not significant and negative in all model specifications, implying that these payments have no impact on patent quality, which is consistent with the results of Lerner and Wulf (2007).

The coefficient of science motivation is positive and significant in all specifications except for the fixed effects model which cannot identify the coefficient of time-invariant independent variables. Inventors who are strongly motivated by a pursuit of scientific contribution tend to make, on average, higher quality inventions, which is again consistent with Prediction 1.

(Table 4)

6.3 Incentive effect and substitute effect

In this subsection, we attempt to decompose the overall impact of monetary incentives into incentive and substitutions effects by inserting the number of non-patent literature citations as an independent variable in equation (2). If this backward citation measure captures the actual change in the inventors' project selection, the coefficient of revenue-based payment should mostly reflect the incentive effect.

Table 5 shows the results. Our model specifications are the same as in Table 4 except that the number of non-patent literature citations is included as an independent variable. The coefficient of the non-patent literature citations is significant and positive, implying that the patents which cited more non-patent literature receive more forward citations. Since Table 3 indicates that an increase in revenue-based payments lower the non-patent literature citation, the effect of monetary incentives through this channel is negative as predicted by our theoretical model. The coefficients of revenue-based payments have increased as expected, but only slightly, and are no more significant than those in Table 4. This seems to suggest that the substitution effect is much smaller than the incentive effect on average, although the latter is not very economically significant either.

To compare the magnitude of the two effects, let us use the estimated coefficients of the HT model in column [3]. The coefficient of revenue-based payments is 0.0044, which reflects the incentive effect. The comparable size of the substitution effect is -0.0062×0.0423 = -0.00026 (the coefficient of revenue-based payments in Table 3 times that of non-patent literature in Table 5), much smaller than the incentive effect. The sum of those estimates is 0.0041, which is exactly the coefficient of revenue-based payments in Table 4.

We believe that the above estimated substitution effect is understated because the number of non-patent literature citations is a very noisy and imperfect measure of science linkage. Nonetheless, the above derivation supports the validity of our theoretical model.

(Table 5)

6.4 Upstream in the research stage

As described in Prediction 3, Proposition 2 implies that the larger the uncertainty for exploratory projects relative to conventional projects (i.e. $\sigma_H^2 - \sigma_L^2$ is large), the more frequently the inventive productivity declines in response to a rise in monetary incentives. In other words, the incentive effect is less likely to dominate the substitution effect when the risk characteristics are very heterogeneous among potential projects. This is very likely in basic research where the degree of reliance on scientific discoveries varies more substantially than in development. In order to assess this prediction, we restricted our analyses to the subsample of inventors who engaged in basic or applied research by excluding those engaging in development and technical services when they invented the focal patent.

The results are in Table 6. Columns [1] and [2] show estimates for the number of non-patent literature citations per patent by Hausman-Taylor and fixed effects models, respectively, whereas columns [3] and [4] display the results for the number of forward citations per patent. In this sample, the negative effect of revenue-based payments on the science intensity is roughly doubled compared to that in Table 3. The 10% increase in payment ceiling results in about a 0.13-0.14% decline in backward citations of non-patent literature per patent. This shows that the substitution effect is much more notable for this subsample. Consistently, the coefficients of revenue-based payments become insignificant for the estimation of patent quality in columns [3] and [4], and decrease to about one quarter of the coefficients in Table 3. These results show that the substitution effect almost offsets the incentive effect, leading to a more neutral impact on patent quality for this subsample.

(Table 6)

6.5 Technology area

Prediction 3 can be further examined by repeating the same analyses separately by technology area because the risk characteristics of available projects must vary across technology areas. As we have shown in the theory section, monetary incentives are less likely to raise the inventive productivity when $\sigma_H^2 - \sigma_L^2$ is greater. For this purpose, we split our sample into two technology groups: (1) chemicals, and drugs & medicals, where science intensity is high and the difference between exploring frontiers and exploiting the status quo is expected to be more distinct (hereafter, we refer to this as the CD area); and (2) computers & communications, electrical & electronic, mechanical and others where technological development in the future is more predictable, thus the heterogeneity in available projects is relatively small (hereafter, we call this the CEM area). Our assumption is that $\sigma_H^2 - \sigma_L^2$ is greater in the former than in the latter. In our sample, the difference in standard deviation between a patent group citing non-patent literature and the other group in the CD area is 61% bigger than those in the CEM area. Therefore, our theory predicts that stronger monetary incentives lead to a greater substitution effect and thus lower impact on inventive productivity in the CD area than in the CEM area.

The CD sample results are shown in Table 7 while the CEM sample results are shown in Table 8. In Table 7, revenue-based payments have negative and significant coefficients for the number of non-patent literature citations, and their magnitude is greater than that for the whole sample in Table 3. Furthermore, they no longer have a significant impact on the number of forward citations. This result shows that the substitution effect mostly offsets the incentive effect in these areas. In contrast, the coefficients of revenue-based payments are almost zero and insignificant in the estimation of non-patent literature citations, while they are positive and significant (although weak) in the fixed effect models in the estimation of patent quality in Table 8. Thus, in the CEM area, monetary incentives remain effective—we do not observe any substitution effect on average. Taken together, these results support Prediction 3. In technology areas where the risk characteristics are very different among projects, the substitute effect tends to overwhelm the incentive effect, thus monetary incentives tend to be inefficient.

(Table 7 and 8)

6.6 Monetary incentive and intrinsic motivation

We next examine Prediction 4: an increase in monetary incentives is more likely to have an adverse impact on the value of inventions for researchers with stronger intrinsic motivation than for those without it when exploratory and exploitative projects are very different in terms of uncertainty. More precisely, in order to investigate the relationship between intrinsic motivation and monetary compensation, we expand equation (2) by including the interaction between RBP_{it} and SM_i as an additional independent variable as follows:

$$\begin{aligned} FC_{it} = (\ NPL_{it} =) \\ \beta_1 RBP_{it-1} + \beta_2 ARP_{it-1} + \beta_3 RBP_{it-1} * SM_i + \beta_4 SM_i + X_{1i}\beta_{k1} + X_{2it}\beta_{k2} \\ + \sum_{t,j} \alpha_{t,j} year_t * technology\ dummies_j + d_i + \varepsilon_{it} \end{aligned} \quad (3)$$

where d_i is the inventor effect.

We estimate equation (3) separately for the areas of chemicals and drugs & medical (CD area), and computers & communications, electrical & electronic, mechanical and others (CEM area) as we did in the previous section because risk characteristics is more likely to be heterogeneous in the CD area. Table 9 shows the results for the CD area and Table 10 for the CEM area. Our primary interest is the coefficient of the interaction term between revenue-based payments and science motivation. The first two columns show the results for forward citations per patent and the next two columns show those for non-patent literature citations. They are estimated using Hausman-Taylor and fixed effects models.

As we predict, the coefficients of the interaction terms are negative for the CD area (Table 9) where $\sigma_H^2 - \sigma_L^2$ is expected to be relatively large, while they are positive and insignificant for the CEM area (Table 10) where $\sigma_H^2 - \sigma_L^2$ is expected to be small—supporting Prediction 4.[15] Our evidence is very weak because the positive coefficient in Table 9 is only weakly significant for forward citations when using the Hausman-Taylor model. Nonetheless, the magnitudes of the coefficients are substantially large—greater than the coefficient for revenue-based payment. The finding that monetary incentives weaken the relationship between intrinsic motivation and inventive productivity only in the CD area, although weakly significant, is consistent with our theory (Figure 1). In other words, monetary incentives may crowd out intrinsic motivation only in areas where exploratory projects are very different in risk characteristics from existing exploitative projects. However, it is also possible that the weakly significant result in the Hausman-Taylor model or the insignificant result in the fixed effect model may simply reflect the substantial heterogeneity in risk characteristics of available projects and the distribution of inventors with strong intrinsic motivation across firms. Further investigation of this line of research is necessary.

(Table 9 and 10)

7. Conclusions and discussions

There have been a limited number of empirical studies that investigate the effect of monetary incentives on innovative activities. Using novel panel data of Japanese inventors, we investigated how monetary incentives affect corporate inventors' behavior and performance and how they interact with the strength of intrinsic motivation. We exploited the inventors' responses to the policy change in Japan in the early 2000s that forced firms to strengthen monetary incentives for inventors in order to identify its effect. Our major findings are the following: (1) while introducing or increasing revenue-based payments is associated with a relatively small improvement in patent quality, such schemes decreased the scientific intensity of R&D projects as measured by the number of the inventor's backward citations of the non-patent literature; (2) the above positive effect of revenue-based payment on patent quality is smaller and the negative effect on scientific intensity is greater in research areas where differences in the risk characteristics (uncertainty) of potential projects are greater; (3) the strength of intrinsic motivation as measured by the inventor's interest in contributing to the advancement of science is significantly associated with the inventor's patent productivity and (4) the strength of intrinsic motivation significantly weakens the marginal effect of monetary incentive on inventive productivity while tending to reinforce the negative effect of monetary incentive on the use of science in research areas where differences in the risk characteristics of potential projects are sufficiently great.

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[15] The same analysis using the whole sample produces negative but insignificant coefficients.

Inventive activities are inherently risky, unpredictable, and complex, but our results indicate that monetary incentives for employee inventors are effective, especially in research in the developmental stages or in the electric, electronics, computer, communication or machinery industries, where the commercial value of individual inventions are often interdependent. Those industries are producing a lot of patents in their inventive process to develop a broader patent portfolio, which, as a set, will be used and embodied in a product or provided to other firms through cross-licensing. As a result, it is hard to imagine that a single invention or a single project will cause a disruptive change in the firm's profitability or its competitive landscape. Since the risk characteristics are unlikely to differ substantially across projects, an increase in monetary incentive is less likely to affect project selection while encouraging implementation efforts, thus increasing the value of inventions.

In contrast, in basic research (or in the relatively upstream stages of research), or in the chemical, drugs & medical-related industries, the inventive process depends more on scientific discovery and the choice of approach, and a target could significantly affect the applicability and success rate. A stronger monetary incentive offered to researchers in such areas could affect the choice of projects, encouraging them to choose safer projects with more predictable outcomes. A stronger monetary incentive is also found to weaken the relationship between intrinsic motivation and inventive productivity by making the choice of exploratory project especially costly for those with strong intrinsic motivation. In other words, monetary incentives are likely to crowd out intrinsic motivation in such areas. Overall, monetary incentives could be counterproductive, and thus their use may well be limited in these areas.

Our analyses certainly suffer from data limitation. First, using the number of non-patent references that each patent cites as a scientific intensity indicator may be problematic because of its noise and incompleteness, and furthermore, it only captures one aspect of intrinsic motivation. Second, our measure of intrinsic motivation is the inventor's response to the question regarding the importance of scientific motivation to a particular invention, and thus depends on the project and workplace characteristics at the time of the RIETI survey. Although we selected an estimation method that minimizes potential bias, our estimation may still not be perfect. Despite these limitations, however, our estimations consistently indicate clear evidence that monetary incentives distort inventors' behavior and thus have a limited impact on research performance. We believe that our novel dataset has allowed us to identify the incentive effect and the substitution effect separately and successfully clarify the relationships among monetary incentives, intrinsic motivation, inventors' behavior, and their performance.

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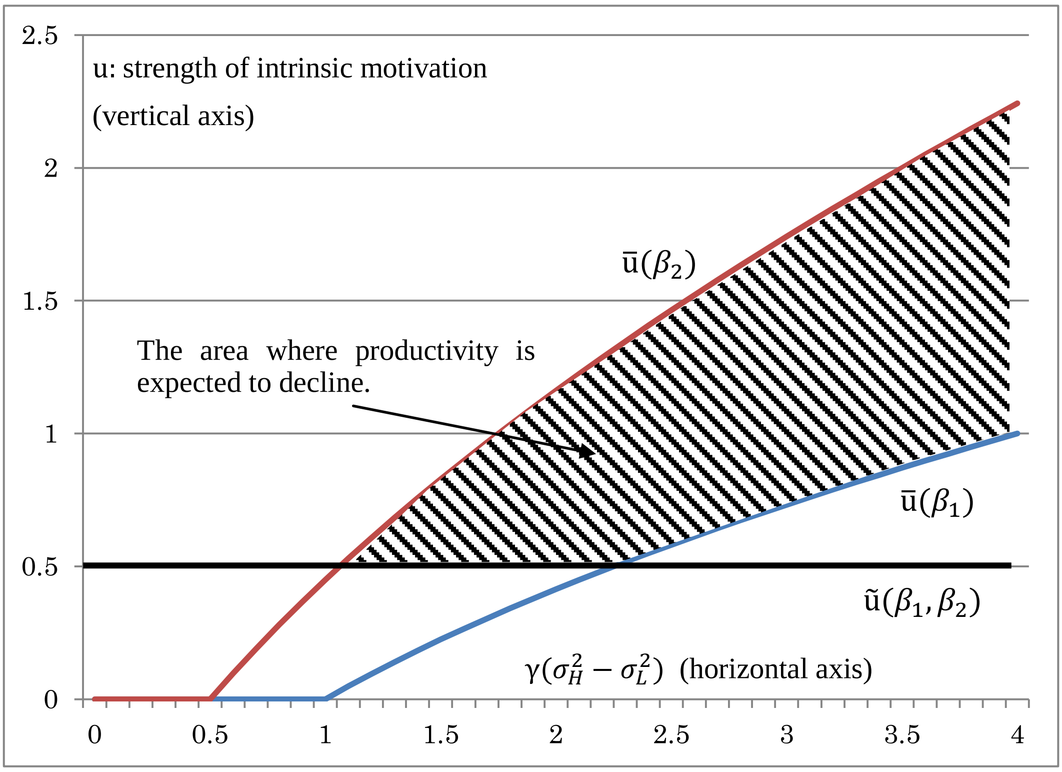
Figure 1. When will inventive productivity decline due to stronger incentive?



Note: This graph is drawn using a numerical example with $\mu_H - \mu_L = \frac{1}{2}$, $c = 1$, $\beta_1 = 1$ and $\beta_2 = 2$.

Figure 2. Number of new implementations of revenue-based payments (based on Onishi 2013)

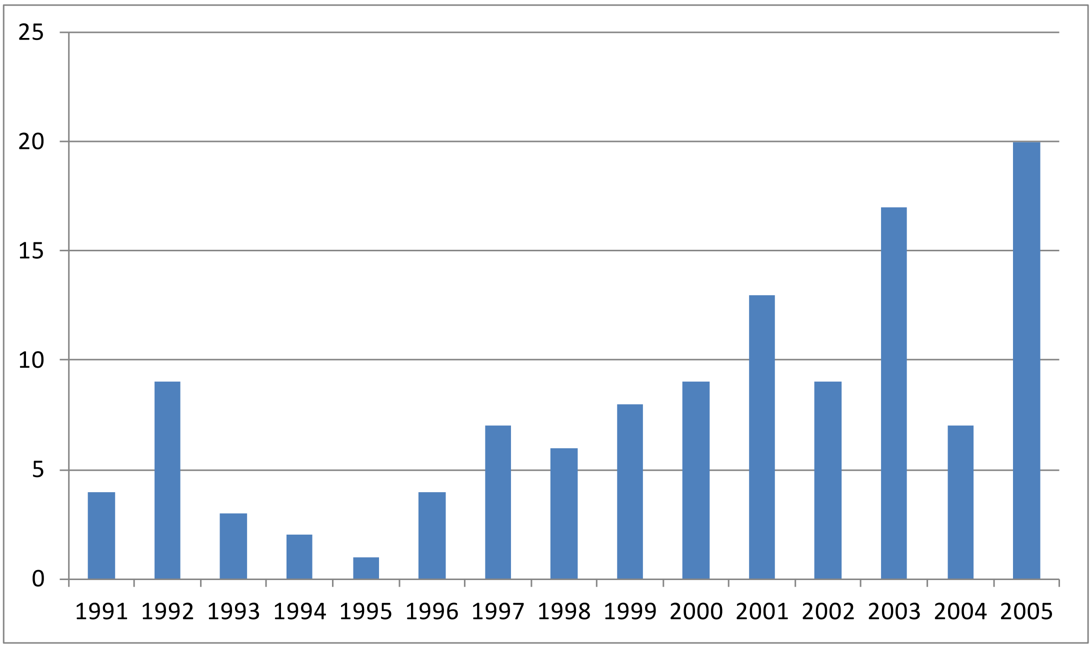


Figure 3. Trends in the payment ceilings of revenue-based payments made from (based on Onishi 2013)

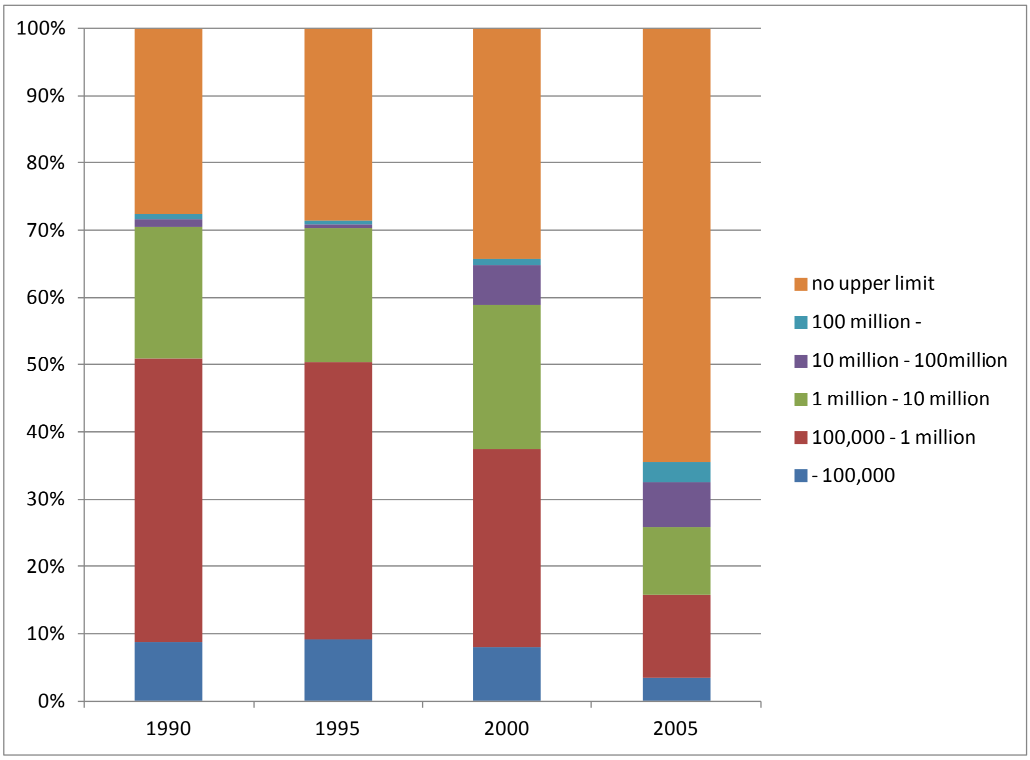


Table 1. Summary statistics

Variables	Mean	Std. Dev.	Min	Max
Log of the number of forward citations per patent	0.46	0.38	0	2.32
Log of the number of non-patent literature citations per patent	0.21	0.48	0	3.71
Revenue-based payments	13.84	6.17	0	17.62
Application/registration payments	10.05	0.72	0	12.04
Science Motivation	0.64	0.48	0	1
Age	40.65	6.62	25	57
Male	0.98	0.13	0	1
BA degree	0.38	0.49	0	1
MA degree	0.42	0.49	0	1
PhD degree	0.05	0.23	0	1
PhD-DO degree	0.04	0.19	0	1

Table 2. Correlation matrix

	Variables	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)
(a)	Log of the number of forward citations per patent	1.00										
(b)	Log of the number of non-patent literature citations per patent	0.03	1.00									
(c)	Revenue-based payments	0.05	0.01	1.00								
(d)	Application/registration payments	-0.02	0.01	0.11	1.00							
(e)	Science motivation	0.05	0.08	-0.01	-0.03	1.00						
(f)	Age	-0.12	0.01	0.04	0.05	0.03	1.00					
(g)	Male	-0.05	-0.02	-0.06	0.00	-0.03	0.09	1.00				
(h)	BA degree	-0.06	-0.20	-0.04	-0.05	0.01	-0.01	-0.03	1.00			
(i)	MA degree	0.06	0.12	0.04	-0.01	-0.05	-0.13	0.04	-0.68	1.00		
(j)	PhD degree	0.05	0.12	-0.03	-0.03	0.09	0.02	-0.04	-0.19	-0.21	1.00	
(k)	PhD-DO degree	0.03	0.15	0.00	0.07	0.04	0.17	-0.03	-0.16	-0.17	-0.05	1.00

Table 3. Estimation results: non-patent literature citations per patent

	[1]	[2]	[3]	[4]	[5]
	full sample				
	OLS	OLS	HT	Tobit	FE
Revenue-based payments	-0.0072**	-0.0069**	-0.0062***	-0.0209**	-0.0062**
	(0.003)	(0.003)	(0.002)	(0.010)	(0.003)
Science motivation	0.0632**	0.0545*	0.3481*	0.2279***	
	(0.029)	(0.030)	(0.196)	(0.085)	
Application/registration payments	-0.0016	0.0015	-0.002	0.0728	-0.0019
	(0.024)	(0.024)	(0.016)	(0.101)	(0.022)
Age	0.0305*	0.0284	0.0248	0.0971*	0.1575***
	(0.018)	(0.018)	(0.016)	(0.058)	(0.036)
Age^2	-0.0382*	-0.0364*	-0.0330*	-0.1221*	-0.0371
	(0.021)	(0.022)	(0.019)	(0.069)	(0.024)
Male	-0.0777	-0.0549	-0.0236	-0.2608	
	(0.099)	(0.111)	(0.166)	(0.282)	
BA degree		0.0138	-0.0387	0.205	
		(0.045)	(0.084)	(0.181)	
MA degree		0.0677	0.0492	0.4944***	
		(0.050)	(0.079)	(0.175)	
PhD degree		0.2226**	0.1322	0.9680***	
		(0.095)	(0.141)	(0.221)	
PhD-DO degree		0.2319**	0.2005	0.8827***	
		(0.094)	(0.147)	(0.206)	
Constant	0.1914	0.1284	0.5929	-2.5105	-5.5696***
	(0.580)	(0.589)	(0.779)	(1.653)	(1.315)
Adj. R square	0.2902	0.3017			0.0361
Observation	3610	3610	3610	3610	3610

Dependent variable is the number of backward citations of non-patent literature per patent.
All specifications include firm dummy and technology dummy*year dummy.
Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 4. Estimation results: forward citations per patent

	[1]	[2]	[3]	[4]	[5]
	OLS	OLS	HT	Tobit	FE
Revenue-based payments	0.0047*	0.0049*	0.0041*	0.0057*	0.0041
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Science motivation	0.0410**	0.0362**	0.3554**	0.0448**	
	(0.018)	(0.018)	(0.166)	(0.021)	
Application/registration payments	-0.035	-0.0325	-0.0268	-0.03	-0.0257
	(0.023)	(0.023)	(0.018)	(0.030)	(0.023)
Age	-0.0066	-0.0071	-0.0261	-0.0049	-0.0691**
	(0.013)	(0.013)	(0.017)	(0.014)	(0.034)
Age^2	0.0029	0.0036	0.0252	-0.0001	0.0417
	(0.015)	(0.015)	(0.019)	(0.017)	(0.026)
Male	-0.0627	-0.0532	-0.0118	-0.0628	
	(0.064)	(0.060)	(0.139)	(0.062)	
BA degree		0.0035	-0.0282	0.0009	
		(0.032)	(0.070)	(0.039)	
MA degree		0.0513	0.0394	0.0588	
		(0.032)	(0.066)	(0.038)	
PhD degree		0.1663***	0.0864	0.1933***	
		(0.048)	(0.117)	(0.055)	
PhD-DO degree		0.0958**	0.0513	0.1156**	
		(0.048)	(0.122)	(0.056)	
Constant	1.5509***	1.4734***	1.018	0.5617	2.7144**
	(0.403)	(0.397)	(0.702)	(0.450)	(1.199)
Adj. R square	0.131	0.139			0.115
Observation	3610	3610	3610	3610	3610

Dependent variable is the number of forward citations per patent.
All specifications include firm dummy and technology dummy*year dummy.
Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 5. Estimation results: incentive effect and substitution effect

	[1]	[2]	[3]	[4]	[5]
	OLS	OLS	HT	Tobit	FE
Non-patent literature citations	0.0613***	0.0512**	0.0423**	0.0648***	0.0426*
	(0.021)	(0.021)	(0.019)	(0.024)	(0.024)
Revenue-based payments	0.0051*	0.0053*	0.0044*	0.0062*	0.0043
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Science motivation	0.0371**	0.0334*	0.3293	0.0414**	
	(0.018)	(0.018)	(0.237)	(0.021)	
Application/registration payments	-0.0349	-0.0326	-0.0261	-0.0302	-0.0256
	(0.023)	(0.023)	(0.017)	(0.030)	(0.022)
Age	-0.0084	-0.0086	-0.0337*	-0.0068	-0.0758**
	(0.013)	(0.013)	(0.018)	(0.014)	(0.034)
Age^2	0.0052	0.0055	0.0344*	0.0024	0.0433*
	(0.015)	(0.015)	(0.020)	(0.017)	(0.026)
Male	-0.0579	-0.0504	-0.0042	-0.0591	
	(0.064)	(0.059)	(0.206)	(0.061)	
BA degree		0.0028	-0.0217	-0.0003	
		(0.032)	(0.104)	(0.039)	
MA degree		0.0478	0.0404	0.0541	
		(0.032)	(0.098)	(0.038)	
PhD degree		0.1549***	0.087	0.1783***	
		(0.048)	(0.174)	(0.056)	
PhD-DO degree		0.0839*	0.0481	0.1009*	
		(0.049)	(0.183)	(0.057)	
Constant	1.5392***	1.4668***	1.6629*	0.558	2.9517**
	(0.404)	(0.399)	(0.965)	(0.450)	(1.240)
Adj. R square	0.135	0.142			0.116
Observation	3610	3610	3610	3610	3610

Dependent variable is the number of forward citations per patent.
All specifications include firm dummy and technology dummy*year dummy.
Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 6. Estimation results: basic and applied research

	[1]	[2]	[3]	[4]
	Non patent literature		Forward citation	
	HT	FE	HT	FE
Revenue-based payments	-0.0133***	-0.0138***	0.001	0.0015
	(0.004)	(0.005)	(0.004)	(0.004)
Science motivation	-0.0022		0.2331**	
	(0.192)		(0.092)	
Application/registration payments	-0.002	-0.0056	-0.0369	-0.033
	(0.032)	(0.046)	(0.031)	(0.028)
Age	0.033	0.2202***	-0.0324	-0.0965**
	(0.029)	(0.060)	(0.021)	(0.047)
Age^2	-0.0441	-0.061	0.0261	0.0999**
	(0.034)	(0.045)	(0.025)	(0.043)
Male	0.0055		0.0871	
	(0.228)		(0.101)	
BA degree	-0.0836		-0.0091	
	(0.140)		(0.064)	
MA degree	-0.0418		0.1002*	
	(0.127)		(0.057)	
PhD degree	0.2082		0.1870**	
	(0.171)		(0.077)	
PhD-DO degree	0.1042		0.1241	
	(0.187)		(0.084)	
Constant	0.6793	-7.6131***	1.2849**	2.9097*
	(0.968)	(2.130)	(0.654)	(1.566)
Adj. R square		0.056		0.108
Observation	1742	1742	1742	1742

All columns are estimated using inventors who engaged in basic or applied research.
All specifications include firm dummy and technology dummy*year dummy.
Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 7. Estimation results: Chemicals & Drug areas.

	[1]	[2]	[3]	[4]
	Non patent literature		Forward citation	
	HT	FE	HT	FE
Revenue-based payments	-0.0157***	-0.0154**	0.0006	0.0009
	(0.006)	(0.006)	(0.005)	(0.005)
Science motivation	0.5575		0.2531	
	(0.546)		(0.156)	
Application/registration payments	-0.1049*	-0.1058	-0.0498	-0.0421
	(0.061)	(0.101)	(0.048)	(0.037)
Age	0.071	0.1143	-0.0687*	-0.1714***
	(0.061)	(0.075)	(0.037)	(0.056)
Age^2	-0.1034	-0.1126	0.0724*	0.1622**
	(0.069)	(0.075)	(0.044)	(0.063)
Male	0.3558		-0.095	
	(1.555)		(0.446)	
BA degree	-0.4392		0.0547	
	(0.416)		(0.118)	
MA degree	-0.2942		0.0803	
	(0.369)		(0.107)	
PhD degree	-0.2996		0.2657**	
	(0.452)		(0.126)	
PhD-DO degree	-0.0254		-0.0442	
	(0.573)		(0.159)	
Constant	0.5723	-0.9275	2.1901**	5.0300***
	(1.838)	(2.191)	(0.921)	(1.377)
Adj. R square		0.081		0.075
Observation	731	731	731	731

All columns are estimated using inventors who invented in Chemicals or Drug and Medical areas.
All specifications include firm dummy and technology dummy*year dummy.
Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 8. Estimation results: Electronics and Mechanical areas.

	[1]	[2]	[3]	[4]
	Non patent literature		Forward citation	
	HT	FE	HT	FE
Revenue-based payments	0.0005	-0.0001	0.0059*	0.0058*
	(0.002)	(0.002)	(0.003)	(0.003)
Science motivation	0.1767*		0.3744	
	(0.103)		(0.384)	
Application/registration payments	0.0168	0.0168	-0.023	-0.0228
	(0.016)	(0.017)	(0.019)	(0.026)
Age	0.0169	0.025	-0.0144	-0.0590**
	(0.013)	(0.022)	(0.021)	(0.029)
Age^2	-0.0187	-0.0194	0.0123	0.0151
	(0.015)	(0.023)	(0.023)	(0.029)
Male	-0.0755		0.0195	
	(0.072)		(0.290)	
BA degree	0.049		-0.0433	
	(0.039)		(0.160)	
MA degree	0.1036***		0.0222	
	(0.037)		(0.154)	
PhD degree	0.3845***		0.0706	
	(0.074)		(0.306)	
PhD-DO degree	0.2191***		0.0991	
	(0.071)		(0.301)	
Constant	-0.5256	-0.7048	1.1098	2.7547***
	(0.427)	(0.647)	(1.213)	(0.862)
Adj. R square		0.005		0.127
Observation	2879	2879	2879	2879

All columns are estimated using inventors who invented in Electronics or Mechanical areas.
All specifications include firm dummy and technology dummy*year dummy.
Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 9. Estimation results: the interaction effects between monetary incentives and intrinsic motivation in Chemicals & Drug areas.

	[1]	[2]	[3]	[4]
	Forward citation		Non patent literature	
	HT	FE	HT	FE
Revenue-based payments	0.0160*	0.0094	-0.0127	-0.0177
	(0.009)	(0.006)	(0.013)	(0.013)
RBP*Science motivation	-0.0186*	-0.0103	-0.0037	0.0028
	(0.010)	(0.008)	(0.014)	(0.014)
Science motivation	0.3151**		0.177	
	(0.157)		(0.248)	
Application/registration payments	-0.0486	-0.0418	-0.1041	-0.1059
	(0.047)	(0.037)	(0.064)	(0.101)
Age	-0.0770**	-0.1696***	0.0621	0.1139
	(0.037)	(0.057)	(0.057)	(0.075)
Age^2	0.0836*	0.1591**	-0.0902	-0.1118
	(0.044)	(0.063)	(0.067)	(0.076)
Male	-0.2618		0.1976	
	(0.445)		(0.924)	
BA degree	0.0953		-0.4043	
	(0.117)		(0.246)	
MA degree	0.1343		-0.2084	
	(0.103)		(0.214)	
PhD degree	0.2612**		-0.2745	
	(0.126)		(0.266)	
PhD-DO degree	0.0299		0.0616	
	(0.157)		(0.333)	
Constant	2.3591***	4.9918***	1.1373	-0.9171
	(0.907)	(1.382)	(1.457)	(2.204)
Adj. R square		0.075		0.080
Observation	731	731	731	731

All specifications include firm dummy and technology dummy*year dummy.
Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 10. Estimation results: the interaction effects between monetary incentives and intrinsic motivation in Electronics and Mechanical areas.

	[1]	[2]	[3]	[4]
	Forward citation		Non patent literature	
	HT	FE	HT	FE
Revenue-based payments	0.0045	0.0039	-0.0011	-0.0016
	(0.004)	(0.004)	(0.003)	(0.003)
RBP*Science motivation	0.0028	0.0035	0.0028	0.0028
	(0.006)	(0.006)	(0.005)	(0.004)
Science motivation	0.0048		-0.0177	
	(0.102)		(0.078)	
Application/registration payments	-0.0233	-0.0225	0.0171	0.017
	(0.019)	(0.026)	(0.016)	(0.017)
Age	-0.006	-0.0590**	0.0175	0.025
	(0.017)	(0.029)	(0.012)	(0.022)
Age^2	0.0034	0.0149	-0.0189	-0.0196
	(0.021)	(0.029)	(0.015)	(0.023)
Male	0.0045		-0.0798	
	(0.122)		(0.071)	
BA degree	0.0003		0.0694*	
	(0.063)		(0.036)	
MA degree	0.0418		0.1115***	
	(0.063)		(0.036)	
PhD degree	0.17		0.4318***	
	(0.116)		(0.066)	
PhD-DO degree	0.161		0.2496***	
	(0.119)		(0.068)	
Constant	0.8394	2.7507***	-0.5831	-0.7079
	(0.631)	(0.862)	(0.420)	(0.647)
Adj. R square		0.127		0.005
Observation	2879	2879	2879	2879

All specifications include firm dummy and technology dummy*year dummy.
Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01