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Academic Entrepreneurship and Disruption of Academic Cooperation

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Abstract
This study uses a sample of Japanese university scientists in life and materials sciences to examine how academic entrepreneurship has affected the norms and behaviors of academic scientists regarding sharing scientific resources. The results indicate that high levels of academic entrepreneurship in a scientific field are associated with less reliance on the gift-giving form of sharing (generalized exchange) traditionally recommended by scientific communities, and with a greater emphasis on direct benefits for givers (direct exchange), as well as a lower overall frequency of sharing. These shifts in sharing behavior are observed even among individual scientists who are not themselves entrepreneurially active, suggesting a general shift in scientific norms contingent on institutional contexts. These findings reflect the contradictions inherent in current science policies that simultaneously encourage open science and commercial application of research results, and suggest that the increasing emphasis on commercial activity may be fundamentally changing the normative structure of science.

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Academic Entrepreneurship and Disruption of Academic Cooperation: Math-analysis and Survey-based Empirical Analysis

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ABSTRACT

Based on math analysis and a survey of Japanese university scientists, this study examines how academic entrepreneurship affects scientific norms and forms of academic cooperation. The results indicate that high levels of academic entrepreneurship is associated with a greater emphasis on direct benefits in the exchange and less reliance on generalized (gratis and unconditional) exchange, even if the individual scientist is not herself entrepreneurially active. These finding suggest that scientific norms are contingent on the social context, and that the increasing emphasis on commercial activity in academic research may fundamentally jeopardize the cooperative relationship inside academia.
INTRODUCTION

Scientific research in the academic sector is considered the source of innovation and the engine of sustainable economic growth. The innovation process originating from academic science is facilitated by two types of cooperative relationships; one is among academic scientists and the other is between academia and industry. The latter, or technology transfer from academia to industry, has been emphasized in the science and technology (S&T) policies over the last decades so that it contributes to facilitating the economic growth. Consequently, universities and scientists worldwide have increasingly engaged in entrepreneurial activities (Etzkowitz 1998; Geuna and Rossi 2011; Nagaoka et al. 2009; OECD 2003; Slaughter and Leslie 1997; Slaughter and Rhoades 1996), but there is growing concern about the effects of this changing context on the other type of cooperation inside academia. Policy scholars (e.g., Dasgupta and David 1994; Nelson 2004) and scientific communities (Schofield et al. 2009; NAS 2003) have raised concerns that this trend could undermine the norms and practices of academic cooperation that underpins scientific progress. Empirical studies have shown that scientists engaging in commercial activities, collaborating with industry, and patenting are more likely to withhold research materials, avoid sharing information about their current research, and delay publication (Blumenthal et al. 1997; Blumenthal et al. 2006; Walsh, Cohen, and Cho 2007). Thus, the current S&T policy might be counterproductive in that university-industry relation (UIR) is strengthened at the sacrifice of the basis of academic science.

While prior literature focuses on the non-cooperative behaviors of entrepreneurially active scientists, this study is interested in the more fundamental question of how growing entrepreneurship affects scientific norms and behaviors in general. Because scientific norms can be contingent on context (Blume 1974; Hackett 1990), the entrepreneurial regime may have
transformed the norms (Etzkowitz 1998; Glenna et al. 2007; Nelson 2004; Owen-Smith 2003) and affected the majority of scientists not directly engaged in entrepreneurial activities. Drawing on social exchange theory (Ekeh 1974; Emerson 1981; Molm 1994; Takahashi 2000), I develop a set of hypotheses on the impact of entrepreneurship on sharing practices. These hypotheses are examined by mathematical models based on literature of the evolution of cooperation and evolutionary game theory (Axelrod and Hamilton 1981; Nowak and Sigmund 1998). Further, for empirical examination, I conducted a survey of Japanese university scientists in several fields of natural sciences, especially focusing on the practice of sharing of scientific resources. I find that a high level of academic entrepreneurship in a field discourages scientists from sharing resources, and that the forms of sharing shift from unconditional (generalized exchange) toward return-based (direct exchange).

THEORETICAL BACKGROUND

Academic Cooperation and academic entrepreneurship

Among various types of academic cooperation, this study focuses on the sharing of scientific resources such as cell lines, model organisms, proteins, reagents, software, and data. In the case of US life scientists, about 80% of scientists have made a recent request for other’s research material or data, averaging 3-5 requests per year, with 80-95% of the requests fulfilled (Blumenthal et al. 1997; Campbell et al. 2002; Walsh et al. 2007). This exchange allows scientists to avoid redundant effort, reproduce previous findings, standardize research methods, and accelerate the accumulation of scientific discoveries. Put differently, inability to access others’ research material can impede the progress of science (Campbell et al. 2002; Murray and Stern 2007; Walsh et al. 2007; Zuckerman 1988). For this importance, scientific communities
have a norm that requested materials should be provided gratis and unconditionally (NAS 2003). This is consistent with the communism norm described by Merton and others; scientific findings are possessions of the community and the individual’s ownership right is limited to recognition and esteem (Barber 1952; Merton 1973). However, since modern science is highly dependent on the social context, the extent of compliance depends on circumstances (Blume 1974; Frickel and Moore 2005; Hackett 1990; Merton 1973; Mitroff 1974).

The trend of academic entrepreneurship has occurred globally over the last 30 years, as S&T policies have emphasized UIRs and universities and scientists have been encouraged to claim their private rights and apply their research for commercial purposes (Etzkowitz 1998; Glenna et al. 2007; Slaughter and Leslie 1997; Slaughter and Rhoades 1996). One high profile change was the US Bayh-Dole Act and similar policies in other countries that encouraged university patenting and licensing (Grimaldi et al. 2011; Kenney and Patton 2009; Mowery and Sampat 2005). A substantial number of scientists are now engaging in entrepreneurial activities such as university start-ups, patent applications by universities, and technology transfer to industry (e.g., Grimaldi et al. 2011; AUTM 2007; Nagaoka et al. 2009; OECD 2003). However, the rise in academic entrepreneurship raises concerns about adverse effects on science (Dasgupta and David 1994; Nelson 2004). In fact, empirical analyses suggest that compliance with sharing requests has been decreasing (Walsh et al. 2007). Grounded in these findings, prior literature argues that universities and scientists are adopting a new set of norms (Glenna et al. 2007). Owen-Smith (2003) and Murray (2010) argue that contemporary academic science is increasingly operating in a hybrid space that integrates the norms and practices of industry with those of open science.
To investigate how the norm of unconditional sharing in academia has been sustained and can be undermined in the entrepreneurial regime, I draw on social exchange theory (Ekeh 1974; Emerson 1981; Molm 1994, 2010; Takahashi 2000). Social exchange theory, in examining resource exchange undertaken by actors within a social structure, generally distinguishes two forms of exchange: *generalized* exchange and *direct* exchange. Generalized exchange consists of three or more actors who can give to or receive from one another, where givers do not expect a direct return from their recipients but expect a return from a third party in the future;^2^ direct exchange consists of two actors, both of whom directly contribute to each other, where one’s giving is based on the expectation or agreement of reciprocation from the other (e.g., Befu 1977; Blau 1964; Ekeh 1974; Sahlins 1972). In generalized exchange, acts of giving may appear to occur independently and may not look like “exchange.” Nevertheless, every actor has a certain probability of becoming a recipient of goods or services at some point, which collectively lends the system a quality of exchange (Ekeh 1974; Yamagishi and Cook 1993; Bearman 1997). Since givers are likely to be eventually reciprocated, the expectation for future benefit leads actors to provide their resources without demanding immediate return. This characteristic is also observed in the unconditional sharing in academia. Scientists are supposed to provide their material to anyone who needs it without expecting a return from the recipient (consumer of the material). In the long term, most scientists have a high probability of needing someone’s material and benefiting from unconditional sharing (Blumenthal et al. 1997; Campbell et al. 2000; Walsh et al. 2007).

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^2^ Among several forms of generalized exchange described in the literature (Ekeh 1974; Yamagishi and Cook 1993), *pure* generalized exchange, characterized by no fixed structure of giving and receiving, most closely corresponds to the unconditional sharing in academia (Ekeh 1974; Takahashi 2000).
Generalized exchange is generally vulnerable to the free-rider problem of social dilemmas, in which self-interested actors have incentive to receive without giving (Molm 1994; Takahashi 2000; Yamagishi and Cook 1993). The existence of free riders makes it less probable for givers with goodwill to have their future requests fulfilled, so rational actors do not engage in such exchange, and therefore, generalized exchange would not emerge in the first place. To explain why generalized exchange does exist in reality, several lines of literature have proposed solutions for the free-rider problem. One is that generalized exchange is driven by norms or cultural beliefs (Ekeh 1974; Lévi-Strauss 1969). In this setting, actors are not regarded as complete egoists and they are supposed to care about other’s outcome. Gouldner (1960) proposes the norm of reciprocity, suggesting that people feel obliged to return the benefits they received from others. Free riding is avoided because it is a violation of this norm (e.g., Ekeh 1974; Uehara 1995). Assuming that actors are rational benefit seekers (e.g., Emerson 1981; Molm 2010), another argument is that free riding is resolved by selective incentives such as rewarding and sanctioning mechanisms (Coleman 1990; Hechter 1987; Kollock 1998; Olson 1965). Such mechanisms may be enforced by external authorities (Hardin 1968) or internally implemented by exchange participants (Ostrom 1990). Yamagishi (1986) suggests actors who value the benefits of collective actions and are worried about free riding are willing to participate in such sanctioning mechanisms. A third solution draws on individual-level behavioral strategies, independent of collective mechanisms. Among the strategies that could overcome the free-rider problem, Takahashi (2000) proposes the “fairness-based selective-giving strategy,” in which actors give resources without direct reciprocity to the recipients chosen based on the giver’s fairness criterion. Because stingy actors are not given to, free riders are eventually eliminated and pure generalized exchange is sustained. In this strategy, actors need to know who is
cooperative and who is not, so social information (e.g., reputation, rumor) plays an essential role in sustaining generalized exchange (Nowak 2006; Ohtsuki and Iwasa 2004).

These solutions are observed in scientific communities in an intertwined manner. The norm for unconditional sharing is conceptualized as the communism norm (Merton 1973) and articulated in policies and rules, which form the basis of the incentive structure. Scientists who encounter stingy recipients can spread this information, affecting reputations. Given such information, not only direct victims but also other scientists in the community would not support stingy scientists anymore. In this way, generalized exchange in academia seems to be sustained with a high compliance rate.

**Impact of Academic Entrepreneurship**

Drawing on the above argument, I discuss how the entrepreneurial regime could jeopardize sharing based on generalized exchange. First, the sharing norm would be weakened by the increase in entrepreneurial scientists. Since they tend to withhold and act as free riders, the increase in entrepreneurial scientists means a decrease in norm followers, which makes the norm less effective because of loss of positive externalities (Coleman 1990). In addition, the total quantity of sharable resources in the community falls, and the probability of being denied rises. This should lower the collective benefit from unconditional sharing and the rationality to follow the norms (Festre 2010). Furthermore, because the economic incentives emphasized in the entrepreneurial regime contradict the sharing norm, scientists might doubt the legitimacy of the traditional norm. The introduction of economic incentives can change the actors’ perceptions of social norms and lead them to act in accordance with economic rationality and deviate from the sharing norms (Akerlof 1980; Festre 2010).

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3 For example, free riders can be restricted from further funding and admonished by their universities (NAS 2003).
Second, the incentive structure would not function properly. Sanctioning mechanisms in academia are not completely centralized. Individual scientists have to take part even if funding agencies and academic institutions may play primary roles (NAS 2003). Free-riding entrepreneurial scientists may be uninterested in sanctioning other free riders (Sugden 1986). More importantly, the weakening norms and generalized exchange system compromise the rationale for all scientists to participate in sanctioning mechanisms (Coleman 1990; Hechter 1987; Lindbeck 1997; Olson 1965). Third, behavioral strategies based on social information would be destabilized (Nowak 2006; Ohtsuki and Iwasa 2004). With more free riders, actors’ capacities to deal with the social information can be overwhelmed, and erroneous social information can be produced. Since imprecise social information impairs fairness-based strategies, free riders would not be eliminated effectively (Ohtsuki and Iwasa 2004).

This whole process should be progressively aggravated: weakening norms allow more scientists to engage in entrepreneurial activities (Bercovitz and Feldman 2008; Stuart and Ding 2006), further accelerating the above process. In sum, the entrepreneurial regime should undermine the unconditional sharing norm and lead scientists to more frequently deny generalized exchange-based sharing, even among those who do not engage in academic entrepreneurship.

**Hypothesis 1:** The higher the level of academic entrepreneurship in a field, the higher the denial probability for generalized exchange-based sharing.

**Shift in Sharing Forms**

In the face of a malfunctioning generalized exchange system, scientists needing other’s
materials have a few options aside from giving up their research. For one, they can offer incentives to the owner of the material, such as co-authorship or acknowledgments in their publications, promise of future support, or paying money. Such a transaction is substantially different from unconditional sharing and looks more like market exchange. Social exchange theory refers to this exchange between two actors who directly contribute to each other based on mutual agreement as negotiated exchange, one form of direct exchange (Emerson 1981; Molm 1994). For its joint-decision process, where two actors know what they give and receive in advance, negotiated exchange substantially reduces the risk of non-reciprocity (Cheshire, Gerbasi, and Cook 2010; Molm 1994; Molm, Collett, and Schaefer 2007). Another strategy that may secure cooperation is to restrict the scope of the generalized exchange network, decreasing the cost of monitoring free riders (Molm 1994). The extreme case is a two-actor network, where each actor independently cooperates with the other, expecting the other to reciprocate in the future. This is referred to as reciprocal exchange, another type of direct exchange (Emerson 1981). Unlike negotiated exchange, reciprocal exchange is initiated without a joint agreement but with a reasonable expectation of future reciprocity (Molm 1994; Molm et al. 2007). Since both types of direct exchange are characterized by lower risk of non-reciprocity, I expect that scientists increasingly choose direct exchange over generalized exchange when the risk of exploitation by free riders increases.

Several lines of research suggest the plausibility of a shift towards direct exchange. The literature on social dilemmas and psychology argues that smaller networks (including dyads) are favored under conditions prone to free riding (e.g., Bonacich et al. 1976; Fox 1985; Kollok 1998). This is because larger networks make it more difficult for actors to monitor one another.

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4 It is considered safer than generalized exchange but less certain than negotiated exchange because non-reciprocity is possible (Molm 1994; Molm et al. 2007).
and communicate the information of free riders effectively (Olson 1965), and thus, enables anonymous defection (Dawes 1980). The literature also argues that a low level of general trust and social uncertainty facilitate commitment formation, where actors continue transactions with previous exchange partners (i.e., repetitive direct exchange) (Cook, Rice, and Gerbasi 2004; Yamagishi, Cook, and Watabe 1998). General trust should decline in the entrepreneurial regime because scientists know that increasingly scientists will not follow the traditional norms. In addition, the regime shift should lead to higher uncertainty about givers being reciprocated in the long term because increasingly entrepreneurial scientists tend to withhold. Taken together, the entrepreneurial regime should facilitate repetitive direct exchange among limited partners. Between the two forms of direct exchange, the literature suggests that negotiated exchange is preferred to reciprocal exchange under especially high uncertainty (Cook et al. 2004). Negotiated exchange is complete in itself, leaving no obligations for the future and requiring lower degrees of trust (Molm, Schaefer, and Collett 2009).

The shift toward negotiated exchange can be attributed to scientists’ changing perceptions of scientific norms. Empirical studies on the economics of social norms show that economic incentives intended to facilitate voluntary activities (e.g., blood contribution, donation) actually decreased them, and moreover, the level of those activities did not recover even after the incentives were withdrawn (Frey and Goette 1999; Gneezy and Rustichini 2000). In academia, the traditional norms prescribe that scientists do science for the sake of scientific discoveries and that rewards be restricted to recognition and esteem (Merton 1973). However, the entrepreneurial regime reinforces economic incentives (Slaughter and Leslie 1997), which could crowd out the *General trust refers to an actor’s expectation that his potential exchange partners have goodwill in dealing with the actor (Yamagishi and Yamagishi 1994).*

*Because social uncertainty in the previous literature refers to the risk of actors being abused directly by their exchange partners (Kollock 1994; Lawler and Yoon 1996; Yamagishi et al. 1998), it is somewhat different from the “uncertainty” in generalized exchange that recipients might not give to someone else. Nevertheless, since the latter ultimately leads to the uncertainty that givers may not be reciprocated, both types of uncertainty share the feature that an actor’s giving may not pay off.*
scientific norms. If such a transition occurs, the most likely form of exchange is negotiated exchange because scientists can engage in explicit bargaining over terms of exchange in an attempt to maximize their own benefit (Molm et al. 2009).

In sum, with prevailing academic entrepreneurship, I hypothesize that suppliers’ preferences for direct exchange (reciprocal or negotiated) over generalized exchange increases. This should have two consequences. First, the presence or absence of reciprocity should have a greater impact on suppliers’ decisions to share. When entrepreneurship is uncommon and the sharing norm functions effectively, the supplier’s decision is made regardless of expected return. However, when entrepreneurship prevails and the sharing norm weakens, sharing is encouraged by expected return.

**Hypothesis 2:** The higher the level of academic entrepreneurship in a field, the greater the effect of reciprocity in decreasing the denial probability (i.e., the difference in the denial probabilities between direct-exchange-based and generalized-exchange-based sharing should be greater in fields with high levels of entrepreneurship than in fields with low levels).

Second, suppliers will demand reciprocity more frequently and consumers will take it as an ordinary condition. Hence, direct exchanges should account for a larger proportion of material requests.

**Hypothesis 3:** The higher the level of academic entrepreneurship in a field, the larger the proportion of direct exchange-based sharing (versus generalized exchange).
Overall Transactions

The shift in exchange forms can also affect the overall frequency of sharing transactions although the direction is ambiguous. On the one hand, the shift toward direct exchange reduces the risk of non-reciprocity (Molm 1994; Molm et al. 2007), which could motivate exchange between specific pairs of scientists, and thus, boost the overall number of transactions. However, I suppose that this positive effect should be limited. In general, when the scope of the exchange network is restricted and actors commit to limited partners for direct exchange, it also limits their choices for exploring better opportunities that might exist outside current relationships (Kollock 1994; Rice 2002; Yamagishi et al. 1998). This can be especially problematic in academia, where individual scientists specialize in a narrow scientific area but draw on diverse knowledge sources and skills. Scientists cannot necessarily find what they need from limited fixed suppliers. This limitation is even more serious in negotiated exchange where two scientists have to simultaneously find useful resources from each other’s pool of resources. Considering that money is almost never used in resource sharing in academia, the lack of a universal means of exchange should lead to the common limitation of barter economies. Negotiated exchange is prone to the risk of failing to reach an agreement of exchange while avoiding the risk of non-reciprocity (Cheshire et al. 2010). In addition, direct exchange incurs immediate costs for consumers. This forces scientists to think carefully about making requests and they may refrain from bearing the cost of reciprocity, especially for early-stage or exploratory research with low probability of success (Heller and Eisenberg 1998). Furthermore, direct exchange is especially vulnerable in a system characterized by inequality in goods of exchange, a key characteristic of academia (Fox 1983; Lotka 1926; Zuckerman 1988). A few productive scientists have many resources and are repeatedly asked to supply, while the majority of scientists may have little of
value to trade. This imbalance gives the productive scientists significant power (Cook et al. 1983); they can demand more than reasonable reciprocity for their resources (such as first authorship, or control over the research project) while less productive scientists may have to take such exchanges in order to do research in that field. This inequality would make direct exchange-based sharing too expensive and deter potential consumers from requesting resources.

In sum, I hypothesize that under the entrepreneurial regime, where direct exchange-based sharing is more common, scientists should make fewer requests.\textsuperscript{7}

\textbf{Hypothesis 4:} The higher the level of academic entrepreneurship in a field, the fewer the requests for exchange.

\section*{MATHEMATICAL MODELS AND SIMULATIONS}

Equivalent or related concepts of social exchange have also been intensively studied in the literature of evolutionary game theory and evolutionary biology (e.g., Axelrod and Hamilton 1981; Sigmund 2010; Weibull 1997). The fundamental question in the literature is how cooperation can emerge when free riding is possible. Not only in the human society but also animal world are often observed the cases where non-cooperative action is systematically taken although mutual cooperation is more desirable. To answer the question, a line of literature has drawn on the iteration of games. For example, although defection is the rational choice in a one-shot prisoner’s dilemma (PD) game, cooperative strategies can emerge when a player participates in games with a certain player many times (Trivers 1971). Many variations in game

\textsuperscript{7} Hypothesis 4 refers to the number of transactions regardless of whether they are fulfilled. We also test the effect on the overall transactions actually fulfilled, which is ambiguous because it is a function of the denial probability (H1,H2), the relative proportion of exchange forms (H3), and the number of requests (H4).
settings and strategies have been examined (e.g., tit-for-tat) (Sigmund 2010: Ch.3), but the common feature is the iterative game participation between fixed two players. This is relevant to reciprocal exchange, a type of direct exchange, in the word of social exchange theory. As for generalized exchange, a seminal study was published by Nowak and Sigmund (1998), who proposed the use of social information to sustain cooperation between changing pairs of players. Simply put, if the reputation of free riders is known to other players, they can avoid helping free riders, whereby free riders are eliminated. In this setting, the reputation must be formed on the basis of player’s prior actions, and various reputation rules have been examined in subsequent studies (Ohtsuki and Iwasa 2004; Sigmund 2010: Ch.4). Based on these studies, I examine the above-discussed hypotheses.

**Generalized Exchange**

As a model of generalized exchange, this study draws on the framework of the Donation game, where a donor decides whether to pay a certain cost, \(c\), to give a benefit to a recipient, \(b (>c)\). This resembles academic cooperation where a supplier gives his resource without any return (, thus, has to bear the cost of the resources) and a consumer receives it (, and earns some benefit from the advancement of research). Apparently, the strategy to always defect (not paying the cost) as a donor is the rational consequence, and if all players follow the defection strategy, no cooperation takes place. However, with the aid of reputation, a cooperative strategy can emerge, as illustrated later.

This study follows the typical analytical setting (Sigmund 2010: Ch.3). Assuming an infinitely large population of players, two players are randomly chosen to engage in a one-short game. Each player has a strategy, based on which he decides whether to cooperate (C) or to
defect (D). If a donor cooperates, he pays cost, $c$, while a recipient receives benefit, $b$ ($b > c$). If a donor defects, he pays no cost and a recipient receives no benefit. After certain rounds of games are repeated, the total payoff for each player is calculated as $b \times (#\text{cooperation received}) - c \times (#\text{cooperation made})$, and high-performing strategies increase while low-performing strategies decrease. The first model employs three donation strategies (Table 1A). ALLC and ALLD are the two extremes, one always cooperating and the other always defecting. If only ALLC and ALLD exist, ALLD always dominates ALLC. Thus, the third strategy which makes use of reputation is introduced. For simplicity, this study assumes that the reputation takes dichotomous values of 0 (bad) or 1 (good). Although various reputation-based strategies are conceivable (Ohtsuki and Iwasa 2004), this study employs the DISC strategy that cooperates with good recipients and defects bad recipients. ALLC and DISC are regarded as advocates of generalized exchange while ALLD is free riders.

The reputation is formed on the basis of only the last one game that each player participated in as a donor. Among many possible reputation rules (Ohtsuki and Iwasa 2004), this study uses the one consistent with the DISC strategy. That is, cooperation with good players and defection with bad players are regarded as good, while defection with good players and cooperation with bad players are regarded as bad (Table 2). Let $x_i$ denote the proportion of $i$-th strategy players (1: ALLC, 2: DISC, 3: ALLD). The strategy composition is in the invariant simplex, $S_3 = \{x = (x_1, x_2, x_3) \in \mathbb{R}^3 \mid x_i \geq 0, \sum x_i = 1\}$. To examine the dynamics of these strategies, first the proportion of good players is calculated. Although the proportion of good players changes in the course of repeating games, this study takes the equilibrium state for simplicity (Brandt and Sigmund 2005). Let $h$ and $h_i$ denote the rate of good players in the whole

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8 If a strategy is based only on the reputation of a recipient (dichotomous), $4 (=2^2)$ strategies are possible. If donor’s reputation is only taken into consideration (third-order evaluation), $16 (=2^4)$ strategies are possible.

9 This strategy is also called CO (Sigmund 2010: Ch.4.7).
population and among \(i\)-th strategy, respectively. An ALLC player always cooperates, so he becomes good after encountering a good recipient but becomes bad after encountering a bad recipient. Thus, \(h_i = h\). To the contrary, because an ALLD player always defects, she becomes bad after encountering a good recipient and becomes good after encountering a bad recipient. Thus, \(h_2 = 1 - h\). Since the action of DISC is accordance with the reputation rule, the probability of DISC being good should be 1. However, I introduce a parameter to address the limitation of the DISC strategy. That is, the reputation information may not always be available (Sigmund 2010: Ch.3). Thus, let \(q\) denote the probability of knowing recipient’s reputation \((0 < q < 1)\). It indicates perfect information that \(q_1 = 1\), where DISC players judge recipient’s reputation precisely. When the reputation is not available, this model assumes that a DISC player regards his recipient good. With this setting, \(h_3 = h + q - h q\). Since \(h\) is the equilibrium, it should follow that \(h = \sum h_i x_i\), or

\[
h = \frac{x_2 + qx_3}{2x_2 + qx_3} \ldots (1).
\]

Next, the payoff of each strategy, \(P_i\) for the \(i\)-th strategy, is calculated. ALLC always pays the cost of cooperation as a donor, which results in the payoff of \(-c\). It receives cooperation when meeting an ALLC donor \((bx_1)\). When meeting a DISC donor, an ALLC recipient gains benefit if he is good \((h_1 bx_3)\), and if he is bad but his reputation is not known \(((1 - h_1)(1 - q)bx_3)\). All taken together,

\[
P_1 = -c + bx_1 + b(1 - q + h_1 q)x_3 \ldots (2a).
\]

Similarly, the payoffs of ALLD and DISC are calculated as follows:

\[
P_2 = bx_1 + b(1 - q + h_2 q)x_3 \ldots (2b)
\]

\[
P_3 = -c\{(1 - q + h_1 q)x_1 + (1 - q + h_2 q)x_2 + (1 - q + h_3 q)x_3\}
+ bx_1 + b(1 - q + h_3 q)x_3 \ldots (2c)
\]

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To examine the strategy dynamics, I draw on the replicator equation of continuous replicator dynamics (Hofbauer and Sigmund 1998), as follows:

\[ \dot{x}_i = x_i (P_i - \bar{P}) \]  \( \text{(3)} \)

where \( \bar{P} \) is the average payoff, \( \sum x_i P_i \) and \( \dot{x}_i = \frac{dx_i}{dt} \). Based on Equations 1 - 3, a numerical phase plot is shown in Figure 1. The figure illustrates how strategy composition shifts over time. This dynamics has two sets of stable equilibria, and that the simplex is divided into two parts: one converges to \textit{ALLD} and the other converges to a mixture of \textit{ALLC} and \textit{DISC}. The former is achieved when the initial condition is below the separatrix (the curve from the \textit{ALLC} corner to \( F_{23} \)), while the latter is reached when the initial condition is above it. Thus, a certain proportion of \textit{DISC} players are necessary to suppress free riders and maintain generalized exchange. The coordinate of \( F_{23} \) is \( (x_1, x_2, x_3) = (0, q(b - c)/A, c(2 - q)/A) \), where \( A = 2c(b - q) + q^2 \).

For this to be inside the simplex, it must follow that \( q > c/b \). In other words, unless reputation availability is larger than the cost-benefit ratio, the whole strategy space converges to \textit{ALLD}. Thus, in the following sections, I assume that \( q > c/b \) so that generalized exchange (\textit{ALLC} or \textit{DISC}) is feasible. With fixed \( q \), the separatrix moves upward when the cooperation cost (\( c/b \)) rises, allowing \textit{ALLD} players to prevail more easily.

\textit{Academic Entrepreneurship}

The environment of academic entrepreneurship can be modeled in many ways, but this study focuses on the aspect that more entrepreneurial condition involves more scientists who participate in commercial activities. For simplicity, this study sets the following assumptions.

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10 For example, the bottom edge is the combination of \textit{ALLC} and \textit{ALLD} (without \textit{DISC}). On the edge, the arrow directs rightward and eventually reaches pure \textit{ALLD} (the right bottom corner). When the strategy composition is in the center of the simplex, \( (\frac{1}{3}, \frac{1}{3}, \frac{1}{3}) \), it moves toward the edge \textit{ALLC-DISC}. 

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First, commercial participants earn sufficient benefit for survival even if they receive no cooperation. Second, they never cooperate because cooperation should decrease the benefit from commercial activities. Thus, their behavioral strategy is \textit{ALLD}. Third, since it takes time and effort to engage in commercial activities, commercial no-participants cannot engage in commercial activities (at least in the short term) and the commercial participants do not exit from commercial activities. In sum, this study models academic entrepreneurship as exogenous introduction of \textit{ALLD} players.\textsuperscript{11} Let $y$ denote the proportion of exogenous \textit{ALLD}, or the extent of entrepreneurship ($0 < y < 1$). The payoff for endogenous strategies is shown as follows:

$$
P_1 = -c + b[x_1 + (1 - q + h_1 q)x_3](1 - y) \quad (4a)$$

$$
P_2 = b[x_1 + (1 - q + h_2 q)x_3](1 - y) \quad (4b)$$

$$
P_3 = -c[(1 - q + h_1 q)x_1 + (1 - q + h_2 q)x_2 + (1 - q + h_3 q)x_3](1 - y)$$

$$+ b[x_1 + (1 - q + h_3 q)x_3](1 - y) \quad (4c)$$

, where $(x_1, x_2, x_3) \in \mathbb{R}^3, x_i \geq 0$, and $\sum x_i = 1$.\textsuperscript{12} With this setting, phase plots with varying $y$ are shown in Figure 2A. They show that the simplex is similarly divided into two parts, and that the separatrix shifts upward so that the condition is more prone to (endogenous) \textit{ALLD}.\textsuperscript{13} As an indicator of vulnerability to free riders, the ratio of the area converging to (endogenous) \textit{ALLD} and the coordinate of F23 is shown in Figure 2B. The graph shows that F23 approaches the pure \textit{DISC} corner and that the area converging to (endogenous) \textit{ALLD} is expanding as $y$ increases. Therefore, with the invasion of more commercial participants, ordinary players are also inclined toward \textit{ALLD} even though they do not engage in commercial activities. This is consistent with Hypothesis 1.

\textsuperscript{11}Exogenous \textit{ALLD} is also called “phenotypic \textit{ALLD}” (Sherratt and Roberts 2001).

\textsuperscript{12}Since the ratio of endogenous players is $1 - y$, $x_1$ is replaced by $x_1(1 - y)$, $x_3$ by $x_3(1 - y)$, and $x_2$ by $x_2(1 - y) + y$ from Eqs.2.

\textsuperscript{13}Analytically, the coordinate of F23 is $\left(0, \frac{u(w - c - b)^2(1 - u) - c^2}{\lambda'}, \frac{c(2 - u)}{\lambda'}\right)$, where $\lambda' = 2u(1 - u) + u^2(b - by + cy)$. The second coordinate monotonously decreases as $y$ increases ($\frac{dx_2}{dy} < 0$).
Direct Exchange

To examine the direct exchange simultaneously, I extend the Donation game with the option of rewarding, or the Trust game (Sigmund 2010: Ch.5.8). That is, if a donor decides to give a benefit to the recipient in a Donation game, the recipient has the option to give the donor a reward, $\beta$, with the cost of $\gamma$. If a donor cooperates and a recipient rewards, the payoff is $\beta - c$ for a donor and $b - \gamma$ for a recipient, respectively. This resembles that consumers of research tools provide co-authorship to the supplier scientists, where the consumer pays a certain cost by reducing the extent of credit in his publication. $\beta$ and $\gamma$ may be unequal because, for example, the value of co-authorship is generally different for supplier and consumer scientists. Further, this study assumes that donors know whether their recipients will reward or not (through negotiation).

To examine the option of rewarding, this section introduces two recipient’s strategy, $R$ for rewarding and $NR$ for not rewarding (Table 1B), and a donor’s strategy, $PAY$ (Table 1A). $PAY$ cooperates only if cooperation is beneficial (i.e., if a recipient is $R$ and $\beta - c > 0$). The drawback of $PAY$ strategy is that the reward offered by recipients may not always be sufficient (it can be that $\beta < c$). To incorporate this limitation, this study considers two values of $\beta$: one greater than $c$ (which occurs with a probability of $p$) and the other smaller than $c$ (with a possibility of $1 - p$). This $p$ is an indicator of the universality in the value of rewarding medium. Further, for simplicity, the former value equals $\gamma$ ($> c$) and the latter is 0. Since $PAY$ dominates $ALLD$ with this setting, this section examines $ALLC$, $DISC$, and $PAY$ as donor’s strategies. With two recipient’s strategies, six strategies are possible. Let $x_{ij}$ denote the proportion of $i$-th recipient’s and $j$-th donor’s strategy, where $x = (x_{01}, x_{02}, x_{04}, x_{11}, x_{12}, x_{14}) \in \mathbb{R}^6, x_{ij} \geq 0,$ and $\sum x_{ij} = 1.$
Table 3 summarizes the payoff for a certain donor’s strategy and a certain recipient’s strategy. The payoff of \( j \)-th donor’s strategy, \( P_{jD} \), is as follows:

\[
P_{1D} = -c \sum x_{0j} + \{p(\beta - c) + (1 - p)(-c)\} \sum x_{1j} \ldots (4a)
\]

\[
P_{2D} = p(\beta - c) \sum x_{1j} \ldots (4b)
\]

\[
P_{4D} = -c \sum h_j x_{0j} + \{p(\beta - c) + (1 - p)(-c)\} \sum h_j x_{1j} \ldots (4c)
\]

, where \( h_j \) is the proportion of good players for \( j \)-th donor’s strategy and \( h_4 = hp \sum x_{1j} + (1 - h) \sum x_{0j} + (1 - h) \sum x_{1j} (1 - p) \). The payoff of \( i \)-th recipient’s and \( j \)-th donor’s strategy, \( P_{ijR} \), is as follows:

\[
P_{0iR} = b \left[ \sum x_{i1} + (1 - q + h_i q) \sum x_{i3} \right] \ldots (4d)
\]

\[
P_{1iR} = (b - \gamma) \left\{ \sum x_{i1} + p \sum x_{i2} + (1 - q + h_i q) \sum x_{i3} \right\} \ldots (4e)
\]

Put together, the payoff of \( i \)-th recipient’s and \( j \)-th donor’s strategy is \( P_{ij} = P_{iD} + P_{jR} \).

First, every strategy pair is compared in Figure 3A. It indicates two stable equilibria on the edges; pure \( PAY-R \) and the combination of \( DISC-NR \) and \( ALLC-NR \). For the face including these three strategies, Figure 3B shows a numerical phase plot. The relative advantage between the two equilibrium strategies can be gauged by the position of separatrix (curve from \( F_{01-14} \) to \( F_{03-14} \)) or, more simply, by the position of \( F_{03-14} \). The closer to the \( DISC-NR \) corner \( F_{03-14} \) is, the easier \( PAY-R \) is to prevail. To analyze the sensitivity to parameters, Figure 3C shows the coordinate of \( F_{03-14} \) with varying \( p \) and \( q \), suggesting that higher \( p \) (greater universality in reward value) and lower \( q \) (smaller availability of reputation) allows \( PAY-R \) to prevail.

\[\text{footnote}{14} \text{ Although any combination of } ALLC-NR \text{ and } DISC-NR \text{ (close enough to } DISC-NR \text{) is stable, } ALLC-NR \text{ is relatively in a weak position compared to } DISC-NR \text{. For example, when a very small exogenous } ALLD \text{ is introduced, pure } DISC-NR \text{ is stable but the combination of } DISC-NR \text{ and } ALLC-NR \text{ turns no longer stable. In addition, minimum error in donor’s decision (a donor defects when he is supposed to cooperate) makes } ALLC-NR \text{ unstable. For this reason, I emphasize more the competition between } DISC-NR \text{ and } PAY-R.}\]
Next, exogenous *ALLD-NR* is introduced in order to examine the effect of entrepreneurship. Figure 4A illustrates the bi-strategy comparison and how the equilibria shifts as exogenous *ALLD* increases. As an indicator of *PAY-R* invasiveness, the coordinate of $F_{03-14}$ with the ratio exogenous *ALLD* is shown in Figure 4B (higher $x_{03}$ coordinate indicates greater invasiveness of *PAY-R*). It suggests that under highly entrepreneurial environment, reward-based cooperation will prevail. This transition toward direct exchange is consistent with Hypotheses 2 and 3.

**Abstention from Cooperation**

Furthermore, I extend the model by adding another to abstain from participating in the Donation game, or *ABST* (Sigmund 2010: Ch.6.7). *ABST* players do not engage in the game, and instead, they direct their efforts for producing some benefit for themselves alone. In practice, this option may be taken when scientists hesitate to ask for cooperation that is too costly or unlikely to work but would rather concentrate on their independent research. By foregoing potential benefit of cooperation, *ABST* earns a limited benefit, $\sigma$, automatically, which is sufficiently small so that participation in a Donation game makes sense ($0 < \sigma < b - c$). Since the previous section suggests that *DISC-NR* and *PAY-R* are the stable strategies, this section examines the competition between *DISC-NR*, *PAY-R*, and *ABST*. Let $x_{25}$ denote the proportion of *ABST*. The payoff of *ABST*, $P_{25} = \sigma$. Figure 5A illustrates a numerical phase plot. It shows three stable equilibria at the three corners of the simplex, and three unstable equilibria on each edge, and an internal unstable equilibrium. When $\sigma$ increases, $F_{14-25}$ shift upward and $F_{03-25}$ rightward, and the area converging *ABST* expands. Likewise, exogenous *ALLD-NR* is introduced, and the strategy space converging to each strategy is calculated with Monte-Carlo simulation (Figure 5B). It indicates
that increasing exogenous $ALLD$-NR allows $ABST$ to overwhelm $DISC$-NR and $PAY$-R. Thus, under highly entrepreneurial environment, scientists are more likely to work alone, reducing the total volume of cooperative transaction, which is consistent with Hypothesis 4.

EMPIRICAL ANALYSIS BASED ON SURVEY

To test our hypotheses, I conducted a survey of life and material scientists in Japan, focusing on their entrepreneurial activities and their experience in the sharing of research material (“material transfer”). I include data from life sciences, where the impact of academic entrepreneurship has been a major issue (NAS 2003). To move beyond prior work, I also added materials science, where UIRs play an important role and the sharing of materials is common. In total, our sample consists of 16 fields. 15 These fields are well integrated into the international science community (Adams et al. 2010). 16 As for the entrepreneurial context, policy makers began to implement a series of policy reforms, modeled on the US system in the 1990s (Kneller 2007; Nagaoka et al. 2009: 11; Walsh et al. 2008). In this trend, Japanese scientists have recognized their new role in the entrepreneurial regime (Baba and Goto 2007) and increasingly engaged in patenting, licensing, startups, and contracts with industry (Kneller 2007; Nagaoka et al. 2009: 186; Walsh et al. 2008). Nevertheless, from our interviews with scientists, I expected these fields to vary significantly in the prevalence of entrepreneurial activity. Our analytic strategy takes advantage of this variance across fields and compares sharing behavior in fields with more and less prevalence of entrepreneurship.

15 Life sciences are divided into 12 fields such as basic biology, clinical medicine and agricultural science. Materials science consists of four fields including compound chemistry and nano-chemistry.
16 For example, our respondents published the majority of their papers in international peer-reviewed journals.
As survey respondents, I chose full and associate professors because they are the primary decision-makers in material transfer in Japanese universities. In addition, to focus on active researchers, I selected scientists in the top 45 research universities who received national funds in the prior five years. Drawing on the list of recipients of national funds, I prepared our sampling frame of 8,013 scientists.\textsuperscript{17} The survey instrument was developed building off prior surveys and semi-structured interviews with 30 Japanese scientists. To validate the instruments, I did cognitive interviews with ten scientists to detect unclear or inappropriate questions. The revised survey was mailed to 1,674 randomly sampled scientists (stratifying by university, field and rank). The survey was conducted from February through April, 2009. I received 698 responses (42\% response rate).\textsuperscript{18} Eighty-three percent of our respondents are life scientists while 17\% are material scientists. On average, they obtained their highest degree (Ph.D. or MD) in 1988, had worked in 2.8 laboratories in their career, and have been working in their current laboratory for 13 years. The mean laboratory size was six researchers. The mean number of publications for the last two years was 12.

**Measures**

**Academic entrepreneurship.** I measured academic entrepreneurship from three aspects drawing on prior work (Blumenthal et al. 1997; Blumenthal et al. 2006; Walsh et al. 2007). First,

\textsuperscript{17} This covers 62\% of the grantees across all universities who satisfy our population criteria, and accounts for about 80\% of all research funding
\textsuperscript{18} We tested for non-response bias as follows. First, we obtained publication data from the Web of Science for 100 scientists in each of the response and non-response groups, and found no significant difference in publication productivity between the two groups (7.4 vs. 9.1 publications per year, p = 0.22). Second, using a Japanese patent database\textsuperscript{18}, we examined the number of patent applications for the two groups, and found no significant difference (0.27 vs. 0.34 applications per year, p = 0.49; 74\% vs. 73\% with no patents). Third, we tested for differences in response rate by scientific field. Although we did not find significant differences (p = 0.11), as a robustness check, we tested our hypotheses excluding the fields with the highest and lowest response rates and confirmed a similar pattern of results. Fourth, we compared the response rate across organizational ranks, and found that full professors were somewhat less responsive than associate professors (38\% vs. 46\%, p < 0.01). To alleviate a potential bias due to the overrepresentation of associate professors, we randomly dropped some respondents to balance the proportion of full and associate professors. Using this subsample, we obtained qualitatively similar results.
I asked if respondents were involved in commercial activities in the two year period 2007 to 2008, including: negotiations with industry, planning a new business, establishing a start-up firm, development of new technologies for commercial purposes, and earning licensing income. Respondents involved in at least one commercial activity are assigned a value of one on a dummy variable (*individual-level commercial involvement*), zero otherwise (Campbell et al. 2002). Second, following Hong and Walsh (2009), I asked respondents to list up to seven recent collaborators. If at least one collaborator was from industry, a dummy variable is coded one (*individual-level industry collaboration*). Third, I asked the proportion of research funds from industry. If industry funding was greater than zero, a dummy variable is coded one (*individual-level industry funding*) (Campbell et al. 2002; Hong and Walsh 2009). These three individual-level measures are averaged at the field level to obtain measures of field-level academic entrepreneurship (*field-level prevalence of commercial involvement, industry collaboration, and industry funding*, respectively).

**Material transfer transactions.** Following Walsh et al. (2007), I asked respondents how many material transfer requests they made as a consumer in the two years of 2007-2008 (#*request made*) and how many were fulfilled (#*material received*). Likewise, I asked how many requests they received as a supplier in the same period (#*request received*) and how many were fulfilled (#*material provided*). I also asked how many received requests included an offer of co-authorship. I then calculated the percentage of requests that included co-authorship in return (%

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19 We also prepared continuous measures for the three types of entrepreneurial activities (number of types of commercial activities, number of industry collaborators, and percentage of industry funds). Averaging these, we calculated three field-level entrepreneurship measures. Regressions using these variables show similar patterns (results available from author). For simplicity, only the results for dichotomous measures are presented.

20 To validate our self-report measure of commercial involvement we compared published lists of professors who were board members of a private company (available for some universities) with our survey responses on whether a respondent was involved with a firm (foundation of start-ups or development of new technologies for commercial purposes), finding a high correlation ($r = 0.64, p<0.001$). In addition, we compared self-reported patent applications with the Japanese patent database PATOLIS for 100 randomly selected respondents and again find a strong correlation (Spearman’s $\rho = 0.59, p<0.001$). These checks indicate reasonable reliability of our survey measures.
coauthorship requests received). Following Walsh et al. (2007), I asked several questions focusing on the latest request received as a supplier, to reduce recall bias and allow more detailed questions about the specific transaction. First, I asked if they had denied or fulfilled the request (denial for the latest request). Regardless of whether they denied or fulfilled the request, I asked if the respondent had expected any return from the consumer if she fulfilled the request, including (non-exclusively): co-authorship, acknowledgment, data/materials in exchange, or monetary compensation. If respondents believed that co-authorship would be given, assuming that the consumer’s research was published, a dummy variable is coded one (co-authorship). As another measure of direct exchange, I asked if the respondent believed she would benefit from the relationship with the consumer in the future (future benefits). Taking the maximum of co-authorship and future benefits, I created an additional dummy variable (expected return).

Control variables. I included the following dummy variables regarding the latest request. First, because competition affects sharing (Vogeli et al. 2006; Walsh et al. 2007), I asked if the respondent believed the consumer’s research would compete with her own (competing relationship). Second, although previous studies have shown commercial involvement reduces sharing (Campbell et al. 2002; Walsh et al. 2007), I assume this effect may depend in part on whether the sharing interferes directly with commercial activities or not. Thus, I asked if the requested material was related to the respondent’s commercial activities (commercial material). Third, as previous relationships can affect sharing, I asked whether the consumer was a previous collaborator with the respondent (previous collaborator).

I also controlled for respondent’s total funding because this may affect capacity for handling requests (Walsh et al. 2007). I asked the amount of research funding in the year 2008,

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21 The condition of co-authorship is often explicitly mentioned by consumers (e.g., in the e-mail requesting the material), so the respondents can answer this question even if they did not provide the material.
on a seven-point scale from ‘less than 5 million JPY’ to ‘more than 100 million JPY’ (¥ funds) [roughly, less than $50,000 to over $1 million]. The number of publications is also controlled (Campbell et al. 2000). Since frequency of publication differs significantly across fields, publication counts were standardized by field means and standard deviations (#publication). Because employment stability may change attitudes toward cooperation, a dummy variable was coded one if respondents had a permanent or tenured position, and zero if their contract was temporary (permanent position). I also controlled for number of grant awardees in each field (field size), since it might affect efficacy of monitoring mechanisms.

EMPIRICAL RESULTS

Description of Material Transfer Transactions and Entrepreneurial Activities

Table 4 presents the descriptive statistics and correlation matrix of the variables. In two years, 59% of our respondents made at least one request for a material transfer while 60% received at least one request. On average, respondents made 2.1 requests and received 4.7 requests in two years. As for the latest requests received, 8% were denied. The frequency of material transfer requests and ratio of denial varies widely across fields. The frequency of receiving requests is highest in biological sciences and lowest in medical engineering and nanotechnology. The denial rate is highest in veterinary sciences and lowest in molecular biology. In terms of sharing forms, respondents answered that, assuming they provided the requested

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22 To validate this self-report measure, we counted publications in the last two years for 100 randomly-selected respondents in Web of Science, and found this highly correlated with the survey measure (r = 0.73, p<0.001).
23 Sixty-nine percent of requests received were from those who were not former collaborators. The high probability of being a giver and a recipient of materials, as well as the high rate of transactions between unfixed pairs of scientists, suggests this setting shares the characteristics of pure generalized exchange.
24 Six respondents received 100 requests or more. Excluding these outliers, the mean number of received requests goes down to 2.8 in two years.
material, they expected 49% of cases would result in co-authorship, 25% in acknowledgment, 31% in data feedback, and 0.5% in monetary compensation. In addition, 41% of requests would bring about some return from their consumers in the future.

As for entrepreneurial activities, 32% of respondents were engaged in at least one form of commercial activity in the two years of 2007-2008. Fifty percent received industry funds, and 28% collaborated with industry. Figure 6 shows the three field-level measures for prevalence of academic entrepreneurship, which are highly correlated ($r \simeq 0.9$). Analyses of variance (ANOVA) indicate these variables each significantly differ across fields ($p < 0.01$). Academic entrepreneurship is common in medical engineering, molecular biology and material chemistry but relatively rare in basic biology and agricultural science.

**Impact of Academic Entrepreneurship**

*Probability of denial by exchange forms.* Our first hypothesis is that compliance with requests for generalized exchange should be lower in fields with higher levels of academic entrepreneurship, even among those who are not entrepreneurially active. The second hypothesis is that the sharing decision is more strongly affected by exchange forms when academic entrepreneurship is high. To test these hypotheses, I ran logit regressions predicting the denial of the latest request for material transfer (Table 5). First, I use *expected return* as a broad measure of direct exchange. Among the three measures of academic entrepreneurship, only the results for commercial involvement are featured because the other two show the same pattern. I controlled for number of materials received (as a consumer), number of requests received (as a supplier),

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25 Negotiations with industry over their IP rights (29%), founding start-ups or marketing new technologies (8%), or out-licensing of their technologies (9%)

26 Our data has a hierarchical structure with two levels: field and individual, but our preliminary analysis rejected a random effects model, as only 4% of the variance of the dependent variable was attributable to field-level factors ($\chi^2(1) = 0.41, p > 0.1$).
research funds, number of publications, permanent position, and field size. Regarding sharing conditions, I also control for whether the consumer is a direct scientific competitor, whether the consumer is a previous collaborator, and whether the requested material is directly related to the supplier’s commercial activities.

Model 1 shows the results with the control variables and individual-level commercial involvement (ICI), similar to prior models (Campbell et al. 2002; Walsh et al. 2007). I find that ICI has a positive, but not significant, effect on denial of requests for sharing. In Model 2, I add field-level commercial involvement (FCI). Both individual and field-level commercial involvement show insignificant positive coefficients.

These models mix both generalized and direct exchange. To examine the denial likelihood for each exchange form, Model 3 adds the interaction term between FCI and expected return. The significantly positive coefficient of FCI (b = 4.833, p < 0.1) indicates that higher FCI leads to a higher denial probability when no return is expected (i.e., generalized exchange). This supports Hypothesis 1. When return is expected (i.e., direct exchange), higher FCI results in a lower probability of denial (b = -4.968, p < 0.05).²⁷ For better interpretation of the non-linear interaction model (Wiersema and Bowen 2009; Zelner 2009), Figure 7A illustrates the probability of denial with and without return over the observed range of FCI. The expectation of a return (direct exchange) has a bigger impact as commercial involvement becomes more prevalent. To examine the statistical significance of the effect of reciprocity, Figure 7B shows the difference between the two curves in Figure 7A along with a 95% confidence interval. It indicates that the difference of denial probabilities is not significantly different from zero at low FCI, but turns significantly greater than zero when FCI exceeds about 35% (slightly above the

²⁷ The predicted equation is [denial probability] = 4.833×[FCI] – 9.801×[FCI]×[expected return] + other factors. When no return is expected (i.e., [expected return] = 0), the coefficient of FCI (4.833) directly measures its effect. When return is expected (i.e., [expected return] = 1), the effect of FCI is calculated by 4.833 – 9.801×1 = – 4.968.
mean). These results suggest that the advantage of direct exchange (over generalized exchange) increases with field-level prevalence of academic entrepreneurship, supporting Hypothesis 2.

Thus far, ICI does not show a significant effect. To further examine its effects, Model 4 incorporates the interaction between ICI and expected return. Although the interaction effect is weakly positive ($b = 1.875, p < 0.1$), further analyses indicate it is not significant. Thus, individual-level involvement alone does not change the likelihood of sharing or impact of reciprocity.

I also find previous collaboration strongly decreases denial probability in all models. Since the sharing norm is supposed to apply beyond one’s direct network ties, I ran the same regression excluding cases involving previous collaborators and find qualitatively similar results (Model 5). Likewise, I also ran the regression limiting the sample to scientists not involved in commercial activities (Model 6). It shows a similar result, but the focal effects turn insignificant (perhaps due to decreased power of the test).

To distinguish the two types of direct exchange, I also test the effects of co-authorship (negotiated exchange) and expectations for future benefits (reciprocal exchange) separately (Table A1). Figure 7C indicates that the denial probability is substantially lower when co-authorship is offered under higher FCI. When only future support is expected, the denial probability is not as low as when co-authorship is offered. This suggests negotiated exchange is preferred to reciprocal exchange under highly entrepreneurial conditions.

**Proportion of direct exchange-based transactions.** Next, to examine more directly the shift in exchange forms, I estimate the effects of field-level commercial involvement (FCI) on the proportion of direct exchanges among all completed exchanges. As a medium of direct

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28 The Wiersema and Bowen (2009) method indicates that the interaction is not significant. Also, models using other measures of individual-level academic entrepreneurship (based on industry collaboration and industry funding) do not result in a significant interaction effect. Finally, when the effect of ICI is evaluated separately for each type of exchange, it is not significant.
exchange, I focus on co-authorship for its importance in material transfer. In Table 6, I test whether the percentage of direct exchange (vs. generalized) increases as FCI grows (Hypothesis 3). I use hierarchical linear modeling (HLM) regressions. \(^{29}\) Model 1 includes individual commercial involvement (ICI) and Model 2 adds FCI. Model 1 shows ICI is not significantly associated with the proportion of direct exchange, while Model 2 indicates FCI increases the proportion of direct exchange \((b = 0.562, p < 0.05)\). This supports Hypothesis 3. When the percentage of commercially active scientists increases by 10\%, direct exchange transactions increase by 5.6\%. For the subsample of scientists who are not commercially active, Model 3 still shows a significantly positive coefficient for FCI \((b = 0.612, p < 0.1)\), suggesting entrepreneurship prevalence has field-wide effects.

**Overall transactions.** To examine how entrepreneurship affects overall quantity of transactions (Hypothesis 4), I regress total number of requests on ICI and FCI (Table 7). Models 1-3 show requests made by respondents, and, as a robustness check, Models 4-6 show requests received (as supplier). I use the logarithm of request counts to address their extreme skewness. \(^{30,31}\) Model 1 shows ICI is associated with making more requests, which might imply complementarities between commercial and scientific activities at the individual level (Breschi, Lissoni, and Montobbio 2007). Model 2 shows a significantly negative effect of FCI on number of requests made, consistent with Hypothesis 4. A 10\% increase in FCI results in an 18\% decrease in requests made. Model 3 shows that this result holds for non-commercially active scientists. For the supplier side (requests received), Models 4-6 show the same patterns. Model 5

\(^{29}\) We also tested the cross-field variance of the FCI coefficient (i.e., random-coefficient model) but found no significant variance. A Hausman test indicates consistency of the random-effects estimators.

\(^{30}\) Since \#request received (made) can be zero, the natural logarithm of \((1 + \#request received (made))\) is used. When the level measure (\#request received (made)) is used with negative binomial regressions, the same pattern is obtained if outliers of the dependent variable are excluded.

\(^{31}\) I employ HLM regressions with individuals nested in fields. A Hausman test indicates the consistency of the random-effect estimators. The random-coefficient model is rejected.
indicates a significantly negative effect of FCI (b = -1.940, p < 0.01), implying that a 10% increase in FCI leads to an 18% decrease in requests received. This result holds even when commercially active scientists are excluded (Model 6). Thus, I have strong support for Hypothesis 4: a high level of entrepreneurship leads to fewer sharing attempts.

I also ran the same models with number of requests fulfilled as the dependent variable (Table A2). The results show a similar pattern to Table 7. In sum, these results imply that a high prevalence of academic entrepreneurship decreases the total number of material transfer transactions.

**Generation difference.** Although I assume that prevailing entrepreneurship has affected norms and exchange forms, the opposite direction is not implausible. That is, some fields may have had weaker sharing norms, and it might be those fields that most readily adopted academic entrepreneurship. To examine this possibility, I tested our hypotheses splitting the sample into two generations: the older generation who experienced the regime transition late in their career, and the younger generation who experienced the transition early in their career. In terms of denial probability, Tables A3 shows the interaction effect between FCI and expected return is stronger for the younger generation (Models 1 and 2). To statistically test the generation difference, Model 3 includes the interaction term between generation and FCI and restricts the sample to only generalized exchange cases (i.e., expected return = 0). The positive interaction effect suggests the effect of FCI to increase the denial probability is significantly higher in the younger generation than in the older generation. Table A4 shows no significant generation difference in the percentage of exchange forms (Model 1). Models 2 and 3 indicate significant interaction effects, suggesting that the younger generation makes fewer requests and provides fewer materials than the older generation given a high level of FCI. Overall, these results imply
that younger scientists, who should be more sensitive to the regime shift, are more strongly influenced, consistent with our proposed causal order.

**Field effect.** Because our analytic strategy depends on differences across fields to test the effects of academic entrepreneurship, our results might be due to other factors that vary by field and happen to correlate with entrepreneurship. I examine several rival explanations. First, results could be driven by differences in types of materials shared in each field.\(^{32}\) To test this, I re-ran our regressions, respectively excluding the subsample of materials science, clinical science, pharmaceutical sciences, and medical engineering, which our interviews suggested might use special types of materials, and obtained similar results. I also asked about characteristics of requested materials, such as scarcity, reproducibility, and ease of preparation, which might affect willingness to share. When these measures are included, our results were unaffected. Thus, the findings do not seem sensitive to material types. I also considered other field characteristics. I controlled for (domestic) field size in the regressions above, as that could affect sanctioning mechanisms and normative structure. In addition, I controlled for field globalization (proportion of publications in each field coauthored with foreigners), and results were not affected. I considered scientific competition, which might affect willingness to share or preference for direct exchange (Hong and Walsh 2009). However, our survey measure did not show significant difference in competition across fields. Thus, while I cannot rule out the possibility that our results might be driven by unmeasured heterogeneity across fields, our results are largely unaffected when I control for material and other field characteristics.

\(^{32}\) Prior work by Walsh et al. (2007) found little difference in denial probability by material types (gene, organism, protein, unpublished information, etc.) with the exception that (potential) drugs were less likely to be shared.
DISCUSSION AND CONCLUSIONS

Figure 8 summarizes our results. Comparing highly entrepreneurially active fields to less entrepreneurially active fields: (1) likelihood of denial for generalized exchange-based sharing increases; (2) proportion of direct exchange-based sharing increases; (3) total number of requests declines. Also, the likelihood of successful exchange becomes more tied to direct exchange offers. Going beyond prior literature focusing on anti-normative behavior of entrepreneurially active scientists (e.g., Campbell et al. 2000; Walsh et al. 2007), this study suggests a general shift in norms that affects even scientists who are not themselves entrepreneurially active.

Our results address key debates in sociology of science. Prior literature, building on general discussions on scientific norms (Merton 1973), suggests the normative structure can be affected by contextual factors such as historical period, organizational environment, and policy designs (Blume 1974; Hackett 1990). While much of the prior work emphasizes organizational contexts as a key determinant of norms (e.g., Fox and Mohapatra 2007; Long and McGinnis 1981), this study focuses on field-level contexts. In particular, changing policies and growing emphasis on entrepreneurship at the field level affect scientists’ cooperation even when they are not directly engaged in entrepreneurial activities. These findings suggest scientific norms are contingent on the context of scientific fields. Importantly, rather than simply arguing that academic entrepreneurship is associated with a divergence from Mertonian norms, this study shows a shift from unconditional sharing (generalized exchange) toward return-based sharing (direct exchange). This shift of exchange forms is consistent with the notion of hybridization of industry and open science norms (Murray 2010; Owen-Smith 2003). These findings suggest the science system can adapt to changing contexts. Overall decline in transactions and problems of
direct exchange in a system of vast inequality (Fox 1983; Lotka 1926) suggest this direct-exchange based sharing system may reduce overall access to scientific materials, particularly among those not able to offer valuable resources in exchange. The rise of direct exchange may not simply increase publication inequality, but might limit whole research domains to elite scientists who can pay the admission fee with materials or high-quality co-authorships to trade.

Future work could develop our findings in several respects. First, various forms of academic cooperation should be investigated, such as data sharing and discussing on-going research (Blumenthal et al. 2006). Second, the empirical part of this study draws on scientists in Japanese universities. The Japanese science system is well integrated into the global arena. The level of entrepreneurial activity is similar to that in the US (Walsh et al. 2007). The frequency of sharing is comparable to US counterparts, and the denial probability is similar to that of the US 10 years ago (Walsh et al. 2007), consistent with the later policy shift in Japan. Observing sharing behavior soon after the new regime was institutionalized provides a window on how scientists are reacting to the new context. Nevertheless, since local contexts are important for understanding scientists’ behavior (Hackett 1990), comparative studies across institutions and countries are needed. In particular, while the decline of generalized exchange seems consistent with observations in other countries, the shift toward direct exchange might be related to underlying culture (Yamagishi et al. 1998), and should be investigated in different contexts. Third, given our cross-sectional data, I cannot rule out the possibility of the opposite causality, that underlying differences in scientific norms influenced the adoption of academic entrepreneurship.33 Thus, future work is needed to confirm the direction of the causality.

33 Mowery et al. (2001) argue that academic entrepreneurship was driven by underlying science (e.g., biotech revolution in life science) and general policies, suggesting that entrepreneurship differences were not the result of prior normative differences, and our empirical analyses of cohort differences are consistent with our interpretation.
In conclusion, our results suggest growing emphasis on academic entrepreneurship may be having adverse effects on materials sharing, even among those not directly engaged in entrepreneurship. These changes are associated with changes in exchange forms, with greater emphasis on direct exchanges rather than the generalized exchange recommended by scientific communities. These results reflect the contradictions inherent in current science policies that simultaneously exhort scientists to freely share their results and to exploit the commercial potential in their findings. The resulting shift to direct exchange suggests that scientific norms are contingent on institutional contexts. Future work is needed to develop our understandings of the drivers of the normative structures of science and their implications for social exchange and sociology of science.
REFERENCES


Table 1  List of strategies

(A) Donor’s strategy

<table>
<thead>
<tr>
<th>No.</th>
<th>Strategy</th>
<th>Action as a donor</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ALLC</td>
<td>Always cooperate.</td>
</tr>
<tr>
<td>2</td>
<td>ALLD</td>
<td>Always defect.</td>
</tr>
<tr>
<td>3</td>
<td>DISC</td>
<td>Cooperate with a good recipient and detect a bad recipient</td>
</tr>
<tr>
<td>4</td>
<td>PAY</td>
<td>Cooperate if it is beneficial and defect if it is not</td>
</tr>
<tr>
<td>5</td>
<td>ABST</td>
<td>Do not participate in a game</td>
</tr>
</tbody>
</table>

(B) Recipient’s strategy

<table>
<thead>
<tr>
<th>No.</th>
<th>Strategy</th>
<th>Action as a donor</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>NR</td>
<td>Never pay reward</td>
</tr>
<tr>
<td>1</td>
<td>R</td>
<td>Pay reward if a donor cooperates</td>
</tr>
<tr>
<td>2</td>
<td>ABST</td>
<td>Do not participate in a game</td>
</tr>
</tbody>
</table>

Table 2  Reputation rule

<table>
<thead>
<tr>
<th>Recipient’s reputation</th>
<th>Donor’s action</th>
<th>Resulting donor’s reputation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>Cooperate</td>
<td>Good</td>
</tr>
<tr>
<td>Good</td>
<td>Defect</td>
<td>Bad</td>
</tr>
<tr>
<td>Bad</td>
<td>Cooperate</td>
<td>Bad</td>
</tr>
<tr>
<td>Bad</td>
<td>Defect</td>
<td>Good</td>
</tr>
</tbody>
</table>
Table 3  
Payoff matrix

<table>
<thead>
<tr>
<th>Donor</th>
<th>NR</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alice</td>
<td>(-c, b)</td>
<td>(γ - c, b - γ)(^1) &lt;br&gt; (c, b - γ)(^2)</td>
</tr>
<tr>
<td>Disc</td>
<td>(-c, b)(^1)</td>
<td>(γ - c, b - γ)(^1) &lt;br&gt; (c, b - γ)(^2)</td>
</tr>
<tr>
<td></td>
<td>(0, 0)(^2)</td>
<td>(0, 0)(^2) &lt;br&gt; (0, 0)(^2)</td>
</tr>
<tr>
<td>Pay</td>
<td>(0, 0)</td>
<td>(γ - c, b - γ)(^1) &lt;br&gt; (0, 0)(^2)</td>
</tr>
</tbody>
</table>

\(^a\) Left in each parenthesis is the payoff of a donor and the right is that of a recipient. \(^b1\): The value of the donor and the recipient agrees. \(^b2\): The value of the donor and the recipient does not agree. \(^b3\): The recipient is good. \(^b4\): The recipient is bad.
| Variable                                                                 | Mean | S.D. | Min | Max | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9      | 10     | 11     | 12     | 13     | 14     | 15     | 16     | 17     | 18     | 19     | 20     | 21     |
|--------------------------------------------------------------------------|------|------|-----|-----|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| 1. Denial for the latest request                                        | .083 | .276 | .000| 1.000| ~100   |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 2. % Coauthorship requests received                                     | .347 | .393 | .000| 1.000| ~100   |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 3. # Request made (as a consumer)                                       | 2.116| 3.375| .000| 30.000| ~122   | ~173   |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 4. # Request received (as a supplier)                                   | 4.775| 24.455| .000| 400.000| ~554   | ~245   |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 5. # Material received (as a consumer)                                  | 1.854| 3.045| .000| 30.000|        | ~126   | ~147   | ~972   |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 6. # Material provided (as a supplier)                                  | 4.516| 24.175| .000| 400.000| ~611   | ~243   | ~999   | ~226   |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 7. V Funds                                                              | 2.705| 1.442| 1.000| 7.000| ~121   | ~004   | ~268   | ~149   | ~256   | ~148   |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 8. % Publication (standardized)                                         | ~001| 0.927| 1.730| 8.115| ~037   | ~059   | ~188   | ~183   | ~192   | ~177   | ~140   |        |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 9. Permanent position                                                   | .705 | .456 | .000| 1.000|        | ~098   | ~079   | ~013   | ~043   | ~026   | ~045   | ~048   | ~004   |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 10. Field size                                                          | 4.149| 3.444| 1.084| 11.930| ~064   | ~069   | ~016   | ~043   | ~036   | ~043   | ~021   | ~017   | ~274   |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 11. Competing relationship                                              | .088 | .283 | .000| 1.000| ~185   | ~281   | ~019   | ~058   | ~003   | ~054   | ~037   | ~082   | ~019   | ~066   | ~065   |        |        |        |        |        |        |        |        |        |        |        |        |
| 12. Previous collaborator                                                | .313 | .464 | .000| 1.000| ~103   | ~084   | ~058   | ~049   | ~415   | ~833   | ~355   | ~406   |        |        |        |        |        |        |        |        |        |        |        |        |        |
| 13. Commercial material                                                 | .050 | .218 | .000| 1.000| ~129   | ~012   | ~008   | ~005   | ~055   | ~000   | ~076   | ~000   | ~097   | ~069   | ~026   | ~035   | ~122   | ~084   |        |        |        |        |        |        |        |
| 14. Coauthorship                                                        | .487 | .500 | .000| 1.000| ~132   | ~055   | ~076   | ~092   | ~051   | ~089   | ~013   | ~005   | ~037   | ~024   | ~001   | ~045   | ~034   | ~004   |        |        |        |        |        |        |        |
| 15. Future benefit                                                       | .407 | .402 | .000| 1.000|        | ~122   | ~126   | ~082   | ~049   | ~064   | ~090   | ~052   | ~039   | ~037   | ~003   | ~077   | ~022   | ~042   | ~018   |        |        |        |        |        |        |        |
| 16. Expected return (co-authorship OR future benefits)                  | .572 | .495 | .000| 1.000| ~122   | ~126   | ~082   | ~049   | ~064   | ~090   | ~052   | ~039   | ~037   | ~003   | ~077   | ~022   | ~042   | ~018   |        |        |        |        |        |        |        |
| 17. Individual-level commercial involvement (ICI)                        | .317 | .465 | .000| 1.000| ~018   | ~051   | ~075   | ~095   | ~089   | ~093   | ~230   | ~198   | ~030   | ~021   | ~092   | ~076   | ~276   | ~079   | ~000   | ~087   |        |        |        |        |        |        |
| 18. Individual-level industry collaboration                              | .279 | .449 | .000| 1.000| ~045   | ~043   | ~015   | ~048   | ~044   | ~049   | ~418   | ~107   | ~003   | ~025   | ~001   | ~100   | ~209   | ~126   | ~107   | ~131   | ~134   |        |        |        |        |        |
| 19. Individual-level industry funding                                    | .496 | .500 | .000| 1.000| ~045   | ~058   | ~005   | ~023   | ~074   | ~024   | ~224   | ~188   | ~010   | ~051   | ~062   | ~119   | ~187   | ~135   | ~125   | ~157   | ~342   | ~347   |        |        |        |        |
| 20. Field-level prevalence of commercial involvement (FCI)              | .328 | .114 | .174| .667  | ~075   | ~159   | ~200   | ~066   | ~198   | ~065   | ~074   | ~032   | ~065   | ~071   | ~052   | ~106   | ~075   | ~106   | ~090   | ~131   | ~218   | ~213   | ~300   |        |        |        |        |
| 21. Field-level prevalence of industry collaboration                     | .279 | .108 | .130| .538  | ~076   | ~170   | ~251   | ~092   | ~237   | ~088   | ~079   | ~023   | ~092   | ~102   | ~022   | ~155   | ~070   | ~113   | ~126   | ~132   | ~215   | ~241   | ~322   | ~886   |        |        |        |        |
| 22. Field-level prevalence of industry funding                          | .496 | .185 | .182| .818  | ~038   | ~186   | ~256   | ~098   | ~248   | ~094   | ~078   | ~008   | ~12    | ~017   | ~053   | ~039   | ~147   | ~145   | ~166   | ~201   | ~210   | ~370   | ~810   | ~871   |        |        |        |        |

* Bold italic indicates significant correlation (p < 0.05).
Table 5 Logit Regressions Predicting the Probability of Denial for the Latest Request

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td># Material received (as a consumer)</td>
<td>-.641 * (.296)</td>
<td>-.606 * (.301)</td>
<td>-.632 * (.300)</td>
<td>-.588 † (.309)</td>
<td>-.607 † (.311)</td>
<td>-.125 ** (.462)</td>
</tr>
<tr>
<td># Request received (as a supplier)</td>
<td>-.517 † (.273)</td>
<td>-.527 † (.275)</td>
<td>-.552 † (.298)</td>
<td>-.579 * (.291)</td>
<td>-.556 † (.307)</td>
<td>-.439 (3.89)</td>
</tr>
<tr>
<td>¥ Funds</td>
<td>-.329 † (.196)</td>
<td>-.333 † (.197)</td>
<td>-.355 † (.201)</td>
<td>-.289 (.199)</td>
<td>-.334 (.205)</td>
<td>-.499 (.324)</td>
</tr>
<tr>
<td># Publication</td>
<td>.315 † (.191)</td>
<td>.315 † (.190)</td>
<td>.401 † (.196)</td>
<td>.358 † (.192)</td>
<td>.420 * (.208)</td>
<td>.987 * (.424)</td>
</tr>
<tr>
<td>Permanent position</td>
<td>.741 (.519)</td>
<td>.723 (.516)</td>
<td>.751 (.507)</td>
<td>.765 (.515)</td>
<td>.734 (.522)</td>
<td>.974 (.691)</td>
</tr>
<tr>
<td>Field size</td>
<td>-.071 (.088)</td>
<td>-.067 (.087)</td>
<td>-.086 (.086)</td>
<td>-.062 (.083)</td>
<td>-.088 (.088)</td>
<td>-.031 (.100)</td>
</tr>
</tbody>
</table>

Conditions of cooperation

| Competing relationship             | .730 (.637)   | .732 (.633)   | .582 (.707)   | .626 (.633)   | .618 (.724)   | .829 (1.047)   |
| Previous collaborator              | -.2328 * (1.032)| -.2314 * (1.036)| -.2462 * (1.064)| -.2145 * (1.046)| -.1194 (1.348)|               |
| Commercial material                | 1.250 (.904)  | 1.289 (.923)  | 1.228 (.954)  | 1.258 (.870)  | 1.148 (.953)  |               |

Return for material transfer

| Expected return (co-authorship OR future benefits) | -.638 (.421) | -.677 (.463) | 2.524 * (1.221) | -1.464 * (.628) | 2.735 * (1.259) | -.262 (2.174)   |

Academic entrepreneurship

| Individual-level commercial involvement (ICI)      | .326 (.472)  | .283 (.472)  | .220 (.485)   | -.662 (.788)   | .277 (.504)    |               |
| Field-level prevalence of commercial involvement (FCI) | .899 (2.114) | 4.833 † (2.778) | 1.220 (2.192) | 4.828 † (2.812) | 3.860 (4.035)  |               |

Interaction effect

| ICI * Expected return                       | 1.875 † (1.014)|               |               |               |               |               |
| FCI * Expected return                       | -9.801 ** (3.559)|               |               |               |               |               |

χ² test

| 29.845 **                                   | 29.472 **      | 32.038 **      | 33.426 **      | 28.080 **      | 32.570 ***     |

Log likelihood

| -82.312                                     | -82.213        | -79.361        | -80.410        | -74.213        | -44.780        |

Pseudo R²

| .190                                        | .191           | .219           | .208           | .166           | .304           |

N

| 369                                         | 369            | 369            | 369            | 261            | 245            |

*a Unstandardized coefficients and robust standard errors (parentheses). † p<0.10; * p<0.05; ** p<0.01; *** p<0.001 (two-tailed test). Model 5 excludes cases where a request was made by a previous collaborator, so previous collaborator is dropped. Model 6 excludes respondents involved in commercial activities, so ICI and commercial material are dropped.
Table 6  HLM Regressions Predicting the Percentage of Coauthorship Requests Received

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td># Request received (as a supplier)</td>
<td>-.124 *** (.026)</td>
<td>-.121 *** (.025)</td>
<td>-.147 *** (.037)</td>
</tr>
<tr>
<td>¥ Funds</td>
<td>.007 (.015)</td>
<td>.006 (.015)</td>
<td>.006 (.019)</td>
</tr>
<tr>
<td># Publication</td>
<td>.046 * (.022)</td>
<td>.047 * (.022)</td>
<td>.061 † (.035)</td>
</tr>
<tr>
<td>Permanent contract</td>
<td>-.038 (.044)</td>
<td>-.045 (.044)</td>
<td>-.082 (.056)</td>
</tr>
<tr>
<td>Field size</td>
<td>.008 (.010)</td>
<td>.009 (.008)</td>
<td>.001 (.011)</td>
</tr>
</tbody>
</table>

| Academic entrepreneurship                  |                 |                 |                 |
| Individual-level commercial involvement (ICI) | -.044 (.042)    | -.056 (.043)    |                 |
| Field-level prevalence of commercial involvement (FCI) | .562 * (.249)   | .612 † (.368)   |                 |

χ² test | 28.537 *** | 32.631 *** | 21.258 ** |
Log likelihood | -154.693 | -152.646 | -108.256 |
N | 364 | 364 | 241 |

* Unstandardized coefficients and standard errors (parentheses). † p<0.10; * p<0.05; ** p<0.01; *** p<0.001 (two-tailed test).
### Table 7    HLM Regressions Predicting the Number of Requests

Unstandardized coefficients and standard errors (parentheses). † p<0.10; * p<0.05; ** p<0.01; *** p<0.001 (two-tailed tests).

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Requests made (as a consumer)</th>
<th>Requests received (as a supplier)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Funds</td>
<td>.140 *** (.021)</td>
<td>.141 *** (.021)</td>
</tr>
<tr>
<td># Publication</td>
<td>.036 (.034)</td>
<td>.032 (.034)</td>
</tr>
<tr>
<td>Permanent contract</td>
<td>.041 (.064)</td>
<td>.044 (.063)</td>
</tr>
<tr>
<td>Field size</td>
<td>.001 (.025)</td>
<td>-.006 (.017)</td>
</tr>
<tr>
<td>Academic entrepreneurship</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual-level commercial involvement (ICI)</td>
<td>.146 * (.063)</td>
<td>.164 ** (.063)</td>
</tr>
<tr>
<td>Field-level prevalence of commercial involvement (FCI)</td>
<td>-2.040 *** (.463)</td>
<td>-1.914 *** (.532)</td>
</tr>
<tr>
<td>χ² test</td>
<td>71.224 ***</td>
<td>84.418 ***</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-756.374</td>
<td>-749.777</td>
</tr>
<tr>
<td>N</td>
<td>683</td>
<td>683</td>
</tr>
</tbody>
</table>

* Unstandardized coefficients and standard errors (parentheses). † p<0.10; * p<0.05; ** p<0.01; *** p<0.001 (two-tailed tests).
Figure 1  Numerical Phase Plot for Generalized exchange

\[ \text{ALLD} = (0,0,1) \text{ and DISC} = (0,1,0) \text{ are stable while ALLC} = (1,0,0) \text{ is unstable. No interior fixed point, where } P_1 = P_2 = P_3, \text{ is found. } F_{23} (P_2 = P_3 \text{ and } x_1 = 0) \text{ is unstable fixed point. All points on the edge } x_3 = 0 \text{ are fixed. Particularly, } F_{12} \text{-DISC} (x_2 \leq 1 - \frac{c}{b}) \text{ is stable (} F_{12} \text{ is identified by } P_3 = P \text{ and } x_3 = 0). \text{ The simplex } S_3 \text{ is separated into one area converging to DISC-ALLC mix (Blue) and the other converging to ALLD (Orange). } c/b = 0.1, q = 0.8. \]
Figure 2  Introduction of Exogenous $ALLD$ $^a$

(A) Numerical Phase Plot

(B) Shift of separatrix $^b$

---

$^a$ $c/b = 0.1$, $q = 0.8$.

$^b$ Monte Carlo simulation, $N=2,000$. 

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Figure 3  Generalized vs. Direct Exchange

(A) Bi-strategy comparison

(B) Numerical Phase Plot

\( c/b = 0.1, r/b = 0.3, p = 0.5, q = 0.8. \)
(C) Shift of separatrix a

\[ \text{The } x_{03} \text{ coordinate of } F_{03:4} \]

\[ q \]

\[ \rho \]

\[ ^a c/b = 0.1, r/b=0.3. \]
Figure 4  
Introduction of Exogenous \textit{ALLD} to Generalized vs. Direct Exchange

(A) Shift of equilibrium points

(B) Shift of separatrix $^a$

\begin{itemize}
  \item $c/b=0.1$, $\gamma/b=0.3$, $p=0.5$, $q=0.8$.
\end{itemize}
Figure 5  Abstention from Cooperation (Model 3)

(A) Numerical Phase Plot

(B) %Space converging to each strategy with exogenous *ALLD* 

---

\(^a\) c/b = 0.1, r/b=0.3, p=0.5, q = 0.8, σ/b=0.2.

\(^b\) Monte Carlo simulation.
Figure 6  Field-level Prevalence of Academic Entrepreneurship
Figure 7  Probability of Denial across Different Prevalence of Field-Level Academic Entrepreneurship

(A) Denial probability at different levels of FCI

(B) Difference of denial probability

---

\(^a\) The horizontal axis takes the reasonable range of FCI (minimum: 0.17, average: 0.33, maximum: 0.67). To calculate denial probability, all variables are held at their means except for FCI and the expectation of return.

\(^b\) The central solid curve is the difference of the two curves shown in Figure 4(A): \( \text{Prob(Denial} | \text{Return} = 0) - \text{Prob(Denial} | \text{Return} = 1) \). Dashed curves indicate the 95% confidence interval, estimated by Zelner's method (2009) to avoid a bias.
(C) Denial probability for different forms of return
Figure 8    Transition of the Forms and Compliance of Sharing

Low Academic Entrepreneurship

Fulfilled

Denied

Generalized    Direct

High Academic Entrepreneurship

Fulfilled

Denied

Generalized    Direct