MANAGING KNOWLEDGE ASSETS IN ORGANIZATIONS:
ROLE OF INCENTIVES AND INFORMATION SYSTEMS

A Thesis in
Business Administration
by
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Abstract

Incentives and information systems are two major enablers for managing organizational knowledge assets. Prior research in knowledge management focuses either on managerial or technical perspectives, independently. On the one hand, various studies investigate the knowledge management strategies and influential factors for knowledge diffusion. On the other hand, research is abundant in the construction and mechanisms of knowledge management systems. Our research studies the joint role of incentives and information systems in facilitating knowledge sharing and learning within organizations in three closely related essays. The first study demonstrates that incentive rewards for knowledge sharing and learning can be offered in linear proportion to the sharing and learning amounts to achieve knowledge-sharing(learning) alignment, full-knowledge sharing, and truthful reporting of knowledge levels. In addition, the adoption of appropriate knowledge-transfer policies, either mandatory learning(ML) or voluntary learning(VL), depends on the level of information systems. This framework is then extended to the analysis about how to properly allocate internal knowledge assets so that knowledge discoveries can be successfully created, retained, and disseminated to improve organizational productivity, maximizing profits. The equilibria among knowledge pioneers who engage in knowledge innovation are investigated under two incentive policies: individual winner reward(IWR) and aggregate team reward(ATR). Information systems are found to assume the critical role of facilitating knowledge innovation and increasing organizational profitability in the knowledge creation, retention, and diffusion processes. The third model examines the design of reward structures for participants in the internal knowledge market as well as its IT support in diffusing organizational knowledge. The knowledge providers’ signalling strategy and the firm’s optimal design of reward structures are shown based on different types of knowledge recipients.
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Chapter 4

$C_i$ the $i$ th worker’s cost function for exerting effort
$C_i^l$ the $i$ th worker’s cost function for learning knowledge
$C_i^s$ the $i$ th worker’s cost function for sharing knowledge
$e_i$ the $i$ th worker’s efficiency level
$k_i$ the $i$ th worker’s original knowledge level
$k_i'$ the $i$ th worker’s knowledge level after learning
$k_i^l$ knowledge learned by the $i$ th worker
$k_i^s$ knowledge shared by the $i$ th worker
$\lambda_i$ allocation proportion of output
$n$ total number of workers
$R$ reward function for knowledge sharing and learning
$\rho$ linear reward for unit amount of sharing(learning)
$T$ the level of technology to support knowledge sharing and learning
$x$ team’s profit function
Chapter 5

\( \beta \) discount rate in the second period

\( c_s(\cdot) \) cost of sharing knowledge

\( c_l(\cdot) \) cost of learning knowledge

\( e \) research effort exerted by each pioneer

\( i \) index of the production output, \( i = L, H \)

\( M \) team size for knowledge innovation

\( N \) total number of knowledge workers

\( \rho^i(\cdot) \) individual success rate of the discovery

\( \rho^G(\cdot) \) group success rate of the discovery

\( \phi \) reward policy

\( q(M) \) synergy for a team of size \( M \)

\( \psi \) team elasticity of synergy

\( r_i \) individual winner reward

\( R \) aggregate winner reward

\( T \) level of information systems

\( U_e \) reservation utility of executors

\( U_p \) reservation utility of pioneers

\( U_d \) market value of a knowledge discovery

\( w_p(\cdot) \) wage contract for production in two periods

\( w \) wage payment for pioneers in the first period

\( x_i \) production output
Chapter 6

\( \alpha(k_j) \)  signal active threshold function

\( \beta(k_j) \)  signal expiring threshold function

\( B \)  benefit of knowledge transfer

\( c_i(s_i, k_i) \)  cost of signalling for worker \( i \)

\( k_i \)  worker \( i \)'s knowledge level

\( k_j^a \)  worker \( j \)'s active threshold knowledge level

\( k_j^\beta \)  worker \( j \)'s expiring threshold knowledge level

\( k_j^l \)  worker \( j \)'s learning inhibition threshold knowledge level

\( L(k_j) \)  learning inhibition cost function

\( p(s_i, k_j) \)  p.d.f. of worker \( j \) learning \( k_i \) given the signal \( s_i \)

\( P(s_i, k_j) \)  probability of worker \( j \) learning \( k_i \) given the signal \( s_i \)

\( r_l \)  learning reward

\( r_s \)  sharing reward

\( s_i \)  worker \( i \)'s signal of her knowledge \( k_i \)

\( \theta(k_i) \)  p.d.f. of worker \( i \)'s knowledge level

\( V(q_2) \)  IT investment with \( q_2 \) probability of monitoring learning

\( w_i \)  participation reward for signalling
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Chapter 1

Knowledge Sharing and Learning within Organizations: Role of Incentives and Information Systems

The Internet has fundamentally reorganized the whole business world, forcing organizations to continuously upgrade their Knowledge Quotients™, the innovative ability of organizations to systematically create, acquire, synthesize, share, and utilize knowledge assets to gain a competitive edge. Therefore, managing knowledge assets is assuming greater importance for organizations that rely on the critical momentum of internal information and knowledge flows in the eBusiness arena [32]. More and more firms have realized the importance of knowledge management and begun to take knowledge management initiatives to build a competitive edge. For example, Xerox has been consciously managing knowledge since 1990 and is one of the top five “Most Admired Knowledge Enterprises” chosen by senior executives at Fortune’s Global 500 companies [33]. Best Buy’s knowledge management journey started at 1999 and has now entered its expansion phase toward successful knowledge management [4]. Unisys Corp. regards knowledge management as a system of structures, processes, and technologies that inspire people to share what they know and use what they learn to achieve organizational goals [18].

Knowledge can be interpreted from various perspectives. From the process per...
spective, knowledge is understood as a process of applying expertise. Accordingly, the focus of knowledge management is on the flows of knowledge and the whole iterative and interactive processes of creation, storage, transfer, and application of knowledge [2]. Among all these processes, knowledge transfer assumes the most critical position to streamline the entire knowledge process cycle. Therefore, how to effectively facilitate knowledge transfer becomes pivotal for managing internal knowledge assets. This research views knowledge management from the process perspective as well and proposes several incentive-related mechanisms to enable knowledge transfer within organizations.

The remaining of this chapter is organized as follows. Next section motivates the importance of knowledge transfer and the role of information systems and incentives as its enablers. §1.2 poses three streams of research questions related to knowledge transfer, which will be studied in its detail through three related analytical models in Chapter 4, 5, and 6, respectively.

1.1 Knowledge Transfer, Information Systems, and Incentives

Knowledge transfer plays a crucial role in successful implementations of knowledge management practices. The proactive practices of sharing knowledge and learning among knowledge workers facilitate the entire knowledge management process. Without knowledge sharing, knowledge management cannot be sustained and the organization will gradually lose its competitive edge. For knowledge workers, interactive communication serves as an effective and direct means to improve their knowledge levels. However, sharing knowledge with direct communication becomes more and more difficult, especially for those firms in a distributed environment that adopt work arrangements or virtual office programs which allow employees to work at home or at a customer site. Although firms and employees both benefit from these arrangements, they actually lower the frequency of direct knowledge sharing or informal knowledge transfer [20]. In this regard, knowledge transfer within these processes is not totally frictionless. Although knowledge is sometimes inexpensive to transmit, some specific knowledge is costly to transfer
among agents [38]. Generally, knowledge transfer costs can be categorized into
cognitive cost and incentive-related cost and the determinants of these two costs
can be justified from three dimensions: content, channel, and sender&receiver [36].

Therefore, to streamline the entire knowledge management processes and re-
duce the knowledge-transfer costs, information technologies are indispensable. Dav-
enport and Prusak (1998) clearly point out that “techknowledge” is an essential
element of knowledge management. Generally, four critical impediments inhibit
sharing and reusing knowledge via a knowledge management system: heteroge-
neous representations, dialects within language families, lack of communication
conventions, and model mismatches at the knowledge level [56]. Information tech-
nologies overcome these barriers by substantially relaxing the constraints of time
and space in knowledge management, smoothing the knowledge management pro-
cesses. For example, data mining techniques, WWW search & spidering, and in-
telligent agents enhance knowledge creation; knowledge repository databases store
and retrieve knowledge; electronic bulletin boards, discussion forums, and enter-
prise portals enable efficient and accurate transfer of knowledge; and workflow
systems facilitates the application of knowledge [2]. As for the business practices,
Xerox uses Eureka, an intranet system connected with a corporate database, to
help service representatives share repair tips around the world by using their ubiq-
uitous laptops. Therefore, with this system, employees can quickly get the right
knowledge at any time and any place. In Best Buy, KnowledgeZone has the func-
tion to enable knowledge sharing across all levels of the retail organization: stores,
districts, regions, and divisions. Unisys implements an Enterprise Expertise Man-
agement system, an integrated KM solution to map all the 35,000 experts quickly
and accurately, update new expertise continually, and give knowledge workers the
access to share knowledge and collaborate easily across all job functions [40].

However, technology by itself is insufficient in knowledge management because
people are central to creating and sharing knowledge. Information technologies
help to store and transfer knowledge and do not facilitate creation or sharing of
knowledge if a firm does not have a culture favoring these activities [20]. The “in-
ternal stickiness” of knowledge transfer are primarily caused by two sets of factors:
motivational factors and knowledge-related factors. The former is related to the
motivation of the subsidiary manager(s) to devote the necessary time and resources
for conducting the transfer. The latter stems from the tacitness, context-specificity, and causal ambiguity of subject knowledge [72]. From the individual knowledge worker’s perspective, the barriers to knowledge sharing can be summarized as: knowledge is power (not the primary reason); “not invented here” syndrome; ignorance of the importance of knowledge to others; lack of trust; lack of time; and other factors including functional silos, individualism, poor means of knowledge capture, inadequate technology, internal competition and top-down decision making [10, 54, 67, 72]. Therefore, organizations need to adopt appropriate methods to motivate workers to fully utilize knowledge management systems in sharing knowledge and learning. The importance of applying incentives in managing knowledge assets has been emphasized by many studies [2, 7, 9].

Best-practice organizations have recognized for a long time the efficacy of both incentives and information technologies in knowledge management. It has become a common and successful practice for organizations to develop rewards and recognition in conjunction with complementary knowledge management systems to manage knowledge assets. For example, Xerox uses Eureka, an intranet system connected with a corporate database, to help service representatives share repair tips around the world by using their ubiquitous laptops. With this KM system, employees can quickly get the right knowledge at any time and any place. To motivate workers to use the system, Xerox measures and rewards individuals based on their participation and contributions to Eureka [5]. Best Buy uses RetailZone and KnowledgeZone, two primary KM tools, to achieve organizational objectives such as improving sales proficiency, shortening the cycle time of new employee training, and increasing knowledge sharing. Best Buy also uses a framework that includes access, participation, perceived usefulness and timeliness to measure the contribution of employees to the KM system [4]. Unisys implements an Enterprise Expertise Management system, an integrated KM solution, to quickly and accurately map all the 35,000 experts, continually update new expertise, and give knowledge workers the access to share knowledge and collaborate easily across all job functions [40]. Unisys also motivates employees to share and re-use knowledge, to collaborate, and to offer their expertise to their community colleagues across different job functions, business units, and geographies [18]. Siemens measures and rewards individuals for participation in their KM system, ShareNet, as well.
Contributors earn ShareNet shares based on the quality and reusability of their contribution assessed through peer rating. Top ShareNet contributors will be rewarded with an invitation to the ShareNet global knowledge-sharing conference [5].

Despite the demonstrated success of business practices, the impact of information systems on the degree of knowledge sharing and learning, the function of incentives within knowledge-transfer processes, and the complementarity between designed incentives and adopted knowledge management systems are not well understood. Our research addresses this gap by studying the joint role of incentives and information systems in knowledge management.

1.2 Three Streams of Research Questions

Based on the observation from business practices, we study knowledge-transfer issues within the organizational context in which incentives and compatible knowledge management systems are the major enablers to facilitate knowledge sharing and learning. Building on the classical economic incentive models, we explicitly capture the characteristics of both information systems and incentive mechanisms and explore how IT investment complements incentive structures in promoting knowledge sharing and learning.

We address the following three streams of research questions on knowledge sharing and learning from the perspectives of incentives and information systems.

1. What is the joint role of incentives and information systems in motivating workers to share knowledge and learn within a team? Prior research does not explicitly model the sharing and learning processes within a team and assumes that sharing and learning are costless [11, 12, 19, 51]. We explicitly embed incentive issues in knowledge management framework, consider IT as one of the enablers for knowledge sharing as well, and study the synergy between incentives and information systems for knowledge transfer in a team. To be more specific, we address the following questions regarding knowledge sharing and learning within firms with the first model.

First, how do incentive structures affect the degree of knowledge sharing (learning) and outcomes? We study the impacts of incentives on knowledge shar-
ing and learning and address the role of incentives to achieve certain desirable knowledge-transfer characteristics such as knowledge-sharing(learning) alignment, full-knowledge transfer, and complete-knowledge enablement.

Second, how should these incentives be designed? We explicitly show how a firm should design knowledge transfer incentives so that workers will share knowledge and learn as the firms desires.

Third, how does the level of information technology affect knowledge sharing and learning? We analyze the influence of information technologies on knowledge sharing and learning and determine the optimal level of information systems in reducing worker’s sharing and learning costs so that the optimal organizational profit can be achieved.

Finally, how do incentives and information systems affect each other in facilitating knowledge sharing and learning? IT and incentives have been recognized as two major enablers for knowledge sharing and learning. However, their mutual interaction and influence to improve the efficacy of knowledge transfer is not clear. We investigate how incentives and information technologies complement each other and what the tradeoffs are between them to smooth the knowledge transfer process.

(2) How should a firm balance its knowledge assets between knowledge discoveries and routine production to improve its overall productivity and maximize its profit? Prior studies have largely treated knowledge creation and diffusion as two disjointed processes and made optimal decisions separately in accordance (for example, [12], [19], [22], and [6]). The organizational decisions regarding the optimal tradeoff between innovation and production to effectively create, retain, and diffuse knowledge have not been studied. In addition, the impact of information technologies on the knowledge creation and transfer processes is not well understood, either. Our second model explores these important issues of knowledge creation, retention, and diffusion by answering the following questions that provide valuable guidance for managers.

First, how should a firm balance its investment in production and knowledge innovation? The ultimate goal of knowledge innovation for a firm is to improve productivity, satisfy customer demand, and gain a competitive edge so as to sustain its further development. We address the practical question for firms that how much they should invest in R&D so that the goal of innovation can be achieved.
Second, *how should a firm design wage contracts for workers engage in knowledge innovation so that these workers will exert their best efforts in research and once they succeed in knowledge discovery, they will be willing to internally share the discovery with other workers?* In real business world, firms not only care about the success rate of *knowledge innovation*, but also try to retain and diffuse the knowledge discovery once it is made. Firms have to offer rewards to induce successful *knowledge pioneers* to share their discoveries internally because these workers can trade their research fruits on the outside market instead of incurring additional sharing costs to disseminate their discoveries within organizations.

Third, *how should a firm design wage contracts for workers in production positions so that when a knowledge discovery is made, production workers will be willing to learn and adopt new technologies to improve their productivity levels?* Firms should also provide incentives for knowledge workers in production positions to apply new techniques to increase their productivity levels because workers always incur learning costs when they try to *assimilate* and apply new methods in production.

Finally, *what are the impacts of information technologies on the knowledge creation, retention, and diffusion processes?* Information technologies play a critical role in reducing knowledge workers’ sharing and learning costs. However, it is not clear how this cost reduction affects a firm’s decisions on the investment in knowledge innovation and wage contracts for workers as well as workers’ decisions on their participation in knowledge sharing and learning processes.

(3) *How does an internal knowledge market benefit firms in enabling knowledge sharing and learning?* Prior research in knowledge management does not mention the specific designs of incentive mechanisms within internal knowledge markets [20], model the knowledge sharing and learning processes, or investigate the role of information systems for knowledge markets [8]. Our third study addresses these issues of knowledge markets within organizations by specifically answering the following research questions.

First, *how should knowledge management systems support an internal knowledge market?* Based on business practices, we model an internal knowledge market as a place where knowledge workers can signal and share their knowledge as well as learn from others. We describe the necessary support of knowledge management
systems to facilitate the operation of such an internal knowledge market.

Second, how should a firm design its reward mechanism to regulate this internal knowledge market? Firms can regulate the internal knowledge market by offering different reward structures for the participants. By offering rewards for sharing knowledge and participating in the knowledge-transfer processes, workers will be induced to signal on the market to obtain rewards. We study the optimal design of reward structures for knowledge providers as well as receivers.

Finally, What are the roles of rewards and information technologies in facilitating the internal knowledge market? Improving and maintaining the mutual trust between knowledge providers and receivers is the critical element for the success of internal knowledge market. Both information technology and incentive rewards can be applied in enhancing this trust, but with different effects. We study the different influences of information technology and incentive rewards on the internal knowledge market and the firm’s design of reward structures.

The thesis proceeds as follows. Next chapter reviews the related research in knowledge sharing and learning from the sender and receiver framework. Chapter 3 presents the overview of prior studies on the relationships between information systems and knowledge management. Chapter 4 studies the design of incentive rewards for knowledge sharing and learning in a team. Chapter 5 investigates the optimal design of incentives for knowledge creation, retention, and diffusion within a firm. Chapter 6 explores the design of rewards for participants on the internal knowledge market to facilitate knowledge sharing and learning. Chapter 7 concludes the entire thesis with managerial insights and future extensions.
Knowledge Transfer: an Overview of Previous Research

Recent years have seen a continuous growth of studies in knowledge management on IT and incentives. In economics, a well-established collection of research exists on incentives as well. These studies provide a solid framework to understand how incentives function within organizations and how information technologies influence knowledge management. We focus on the literature related to organizational knowledge transfer and summarize various findings with the structure of knowledge transfer shown in Figure 2.1. The structure focuses on the properties of sender and receiver and the transmission link between them with the major factors as incentives, technology, the nature of knowledge, and knowledge environment/market. The sender and receiver can be regarded as individual knowledge workers for knowledge transfer within organizations and entities with groups of workers (for instance, a company, a department, or a unit) for inter-organizational knowledge transfer.

2.1 Nature of knowledge

There exists a rich body of literature on the relationship between the nature of knowledge and knowledge transferability for both intra and inter-organizational knowledge transfer. [72] explored “internal stickiness” of knowledge, i.e., factors that impede the intra-firm transfer of knowledge. He identified two sets of
factors that impede the internal transfer of knowledge: motivational factors and knowledge-related factors. The latter stems from the tacit, context-specific, and ambiguous nature of certain knowledge. Szulanski points out that three most important factors causing the stickiness of knowledge transfer are the lack of absorptive capacity, causal ambiguity, and an arduous relationship between the sender and receiver.

Tacitness, specificity, and complexity are commonly regarded as the three most important characteristics of knowledge that generate the causal ambiguity within a firm in its competency advantage [63]. Within the context of knowledge transfer between partners of strategic alliances, Simonin studies the effects of knowledge ambiguity and these antecedents on transferring marketing know-how. It is found that tacitness and complexity have significant effects on causal ambiguity while specificity does not, that is, how well a technological asset is specialized has no impact on its transferability [66]. In a similar vein, Simonin points out that ambiguity is the full mediator of the effects of tacitness, complexity, experience, and cultural and organizational distance on knowledge transfer [65].

McEvily and Chakravarthy clarify whether and how the complexity, tacitness,
and specificity of a firm’s knowledge affect the persistence of its performance advantages [52]. The complexity and tacitness of technological knowledge are found to be useful for defending a firm’s major product improvements from imitation, but not for protecting its minor improvements. The design specificity of technological knowledge delays imitation of minor improvements.

2.2 Sender and receiver

The characteristics of sender and receiver in the knowledge transfer process may greatly influence its efficacy. In his exploration of the “stickiness” of knowledge transfer, Szulanski investigates the effects of reliability of knowledge source and receiver’s retentive and absorptive capacity on the effectiveness of knowledge transfer [72]. According to his analysis, lack of absorptive capacity is one of the most important factors in causing the friction of knowledge transfer. Szulanski suggests that incentive systems cannot sufficiently alleviate the internal stickiness of knowledge transfer and instead, lack of absorptive capacity, causal ambiguity, and the arduous relationship between senders and receivers are the origins of stickiness.

In the context of international joint venture (IJV), an IJV’s absorptive capacity relative to its foreign parents is also shown to be the critical factor for the effective learning from those parents [46]. Under conditions of greater resource deployment, learning capacity can positively moderate the effects of tacitness, ambiguity, complexity, prior experience, and cultural distance for knowledge transfer in strategic alliances [65].

From another perspective, researchers examine the effects of social and expert status on knowledge sharing among heterogeneous groups [75]. It is found that socially isolated members participate more actively in knowledge sharing than socially connected members.

2.3 Link

There may exist different links or channels for knowledge transfer from the sender to receiver. Research identifies two types of knowledge transfer: replication [74] and adaptation [43]. To copy exactly the entire system is the replication approach to
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<th>Elements</th>
<th>Literature and findings</th>
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<tr>
<td>A. Sender</td>
<td>reliability [72]; social and expert status [75]</td>
</tr>
<tr>
<td>B. Link</td>
<td>types of transfer: replication [74] and adaptation [43]; arduous relationship [72]; strategies: codification and personalization [32]; four types of transfer processes [37]; richness of transmission channel [30]</td>
</tr>
<tr>
<td>C. Receiver</td>
<td>absorptive capacity [46, 72], retentive capacity [72];</td>
</tr>
<tr>
<td>D. Incentive-related</td>
<td>importance of incentives [2][7] and [9]</td>
</tr>
<tr>
<td>E. D → A</td>
<td>lack of motivation [72]; motivational disposition to share [30]</td>
</tr>
<tr>
<td>F. D → B</td>
<td>n/a</td>
</tr>
<tr>
<td>G. D → C</td>
<td>lack of motivation [72]; motivational disposition to learn [30]</td>
</tr>
<tr>
<td>H. Technology-related</td>
<td>process facilitation [2, 77]; support &amp; guidance [76]; explicit/tacit conversion [48, 50]</td>
</tr>
<tr>
<td>I. H → A</td>
<td>fast access to sources [59]</td>
</tr>
<tr>
<td>J. H → B</td>
<td>agile and traditional methods [16]</td>
</tr>
<tr>
<td>K. H → C</td>
<td>group support system [17]</td>
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<tr>
<td>L. K-environment</td>
<td>knowledge-hostile environment [54]; barren organizational context [72]; culture distance, organizational distance [65]</td>
</tr>
<tr>
<td>M. K-nature</td>
<td>tacit and explicit [58, 62]; tacitness [66, 73]; causal ambiguity [65, 72, 73]; conscious, collective, objectified [37]; specificity [63, 66]; complexity [66, 78]; codifiability, teachability, system dependence, product observability [78]</td>
</tr>
<tr>
<td>M ↔ B</td>
<td>mentoring and storytelling: tacit knowledge [71]</td>
</tr>
<tr>
<td>M ↔ H</td>
<td>tacitness and information technology [69]; tacit &amp; explicit conversion [50]</td>
</tr>
</tbody>
</table>

**Table 2.1.** Summary of literature and findings on knowledge transfer
transfer knowledge within an organization. In contrast, the adaptation perspective views knowledge transfer within organizations as a dynamic and adaptive process for firms to learning new knowledge by combining their current capabilities under uncertain environments.

By mainly focusing on the tacit nature of knowledge, [32] suggests two strategies in facilitating knowledge transfer within firms: codification and personalization. Knowledge primarily tacit within organizations should be transferred with a “soft” approach, personalization, by promoting more personal interactions among knowledge workers, whereas organizations whose knowledge can be easily explicated and documented should use the “hard” approach to facilitate knowledge transfer by constructing a sophisticated IT platform. [37] identifies four types of knowledge transfer processes used by alliance partners: technology sharing, alliance-parent interaction, personnel transfers, and strategic integration. Along the two dimensions of knowledge-tacitness and collectiveness, they propose the focus of knowledge transfer for each process. [23] summarizes four network-level knowledge-sharing processes: supplier association, consulting teams, learning teams, and employee transfers, from the knowledge-sharing practices in Toyota. [72] empirically tests the significance of arduous relationship between sender and receiver in knowledge transfer.

With a nodal level of analysis, knowledge outflows from subsidiaries to their parent corporation or peer subsidiaries (or inflows from the parent corporation and peer subsidiaries to themselves) are higher when the subsidiaries are more closely integrated with the rest of corporation with the formal integrative mechanism, or when the subsidiary heads are more actively involved with the parent corporation and other subsidiaries through other loose mechanisms [30]. In terms of the effect of motivational dispositions on knowledge flows within multinational corporations, it is found that knowledge outflows do not relate too much with a subsidiary’s motivational disposition to share, but knowledge inflows do depend on the motivational disposition to learn of a subsidiary. Specifically, knowledge inflows increase when a subsidiary operates under more subsidiary-focused, rather than network-focused, incentives [30].
2.4 Incentive

Incentives have been identified as the third dimension in designing knowledge management systems to facilitate knowledge sharing and learning [7, 9]. Incentives related to knowledge-management efforts are essential in creating a knowledge-sharing culture [72]. [73] considers knowledge transfer as a process including initiation, implementation, ramp-up, and integration, and explores the correlation between knowledge transfer and motivational factors which are related to the motivation of the subsidiary manager(s) to devote the necessary time and resources for conducting the transfer. According to [72], using only intensive-related methods is not sufficient for knowledge transfer and an motivated receiver may intensify the difficulty of knowledge transfer during the ramp-up stage. [30] confirms the impact of transmission channels, motivational disposition to acquire knowledge, and absorptive capacity on knowledge flows into subsidiaries. However, they find that motivational disposition to share knowledge with other units does not have significant effect. Studying the knowledge transfer programme in a manufacturing MNC, Kalling concludes that the smooth internal knowledge transfer requires a great deal of recipient motivation, i.e., motivation is central to transfer success [39]. In contrast to the focus on the role of such factors as tacitness, causal ambiguity and absorptive capacity, Kalling suggests that motivation needs to be in place first. If motivation is not naturally present within organization, managers can redesign local and corporate management control routines as well as reorganize organization structure to improve the motivation.

There is also a rich body of studies on incentive issues related to knowledge sharing and learning in economics literature. Classical principal-agent models explore the optimal incentive structure under incomplete information and the relationship between first best and second best solutions. For example, [34] and [28] study the moral hazard problem within the context of single principal and single agent. [68] introduces the important idea of signalling in a model where employees signal their productivity levels via educational levels in the job market. These early studies provide significant insights into how the principal can use incentives to induce agents to optimally exert unobservable efforts. However, in their analysis, they do not include agent’s ability and only consider the change of output with agent’s
effort levels.

Theory of teams [49] introduces important ideas for team-based incentive systems. Appropriate incentives can align team members’ interests within an organization with two common incentive systems—the paid worker and profit sharing incentive structures [29]. However, in a team with multiple agents, group incentive cannot achieve efficiency without breaking the budget-balancing constraint [35]. While, under certain conditions, a contract linear to output can be optimal for a team and monitoring does not improve the team output [51]. But in these models, agents’ ability levels are fixed and cannot be improved during the whole production process.

In R&D environments, the problem of knowledge sharing has been studied. [11] and [12] study the efficiency problem for a research joint venture with a Blackwell ordered sharing and learning function. [19] generalizes the above results and shows that even when the ‘most knowledgeable’ partner cannot be identified (i.e., the sharing and learning are not Blackwell ordered, but through a general function), the first best solution with perfect disclosure can still be reached with a balanced contract arrangement. However, when they implement the first-best solution, they assume the output is binary, either success or failure. In addition, they consider learning and sharing as costless exogenous processes and they do not show how learning and sharing interact with agents’ decisions on optimal effort levels.

2.5 Technology

Information technologies are crucial to the growth and maintenance of organizational knowledge [15] with the fundamental role in the following four aspects: support & guidance [76], process facilitation [2, 77], explicit/tacit conversion [48, 50], and functional enablement [18]. Various techniques can be applied in building knowledge management systems, such as semantic web [70], agent-based theory [45], peer-to-peer structure [13], and weblogs tools [57]. Next chapter is devoted explaining the role of information technology in knowledge management.

There are generally four critical impediments to share and reuse knowledge from the technical perspective of a knowledge management system: heterogeneous representations, dialects within language families, lack of communication conven-
tions, and model mismatches at the knowledge level [56]. Various technologies are available to remove these barriers and support knowledge sharing and learning between the sender and receiver. [17] investigates the effects of group support systems (GSS) and content facilitation on individual knowledge acquisition in general. [69] studies the relationship between tacit knowledge and information technology and suggests that intranet documents can be used to make tacit knowledge tangible without becoming explicit. [16] presents a comparison of two knowledge sharing approaches between agile and traditional methods in software development teams. The proposed agile methods rely heavily on socialization through close collaboration and communication among knowledge workers, and can be used to facilitate the transfer of tacit knowledge more effectively at a team level.

2.6 Knowledge environment & market

The environment or culture around the sender and receiver within a firm may encourage or deter sharing knowledge and learning. Drawing from the insights of six case studies, [54] elaborates on the knowledge sharing hostile environment by focusing on its typical symptoms such as knowledge hoarding, apprehension about failures, and the “Not-invented-here” syndrome. In order to transform a knowledge sharing hostile environment into a knowledge sharing embracing one, the firm has to initially force the knowledge sharing process instead of encouraging or stimulating knowledge sharing [54]. In other words, in a sharing-hostile environment, knowledge sharing has to be mandated or required in workers’ daily jobs so that a sharing-embracing environment may be graduated cultivated.

Simonin [65] investigates the influence of some other factors related to knowledge environment and culture, including prior experience, partner protectiveness, cultural distance, and organizational distance, on technological knowledge transfer. Relating the environmental impact with the nature of knowledge, he concludes that tacitness significantly correlates with ambiguity during knowledge transfer, while specificity does not [65].

Applying knowledge market principle to facilitate knowledge transfer has gained growing attention in research. Davenport and Prusak first illustrate the concept of internal knowledge market within organizations. The necessary IT support as
well as the indispensable incentives are summarized to build an effective internal knowledge market for knowledge transfer [20]. Following this initial idea of knowledge market within organization, [8] demonstrates that knowledge components can be optimally traded with a Grove-Clarke like mechanism with different bundles in an internal organization market so that a firm can optimally choose the knowledge bundles for investment. [55] formally considers the electronic marketplace as the approach to sharing knowledge assets. The characteristics of knowledge as tradeable goods to be transacted on the e-marketplace are investigated within two types of frameworks: the pricing system and the quality evaluation method. In addition, internal knowledge market is compared with the inter-organizational knowledge market from various perspectives in this study. Drawing lessons from mini-cases, [21] defines the necessary components of an internal knowledge market and outlines several important caveats in association with economics literature when devising the market: market of lemons, chicken-and-egg predicament, black markets, and advertising strategies, by comparing it with physical and electronic markets.

In summary, these studies separately address IT and incentive issues and do not explicitly investigate the synergetic role of incentive systems and information technologies in knowledge management. We show that both incentives and their complementary support from information systems are crucial for the success of knowledge management in an organization.
Chapter 3

Information Systems for Knowledge Management

In previous chapter, §2.5 briefly captures prior studies on technologies related to the knowledge transfer structure. This chapter is devoted to a more extensive and systematic review of the role of information systems in knowledge management. Next section discusses the role of information technologies in knowledge management from various perspectives. §3.2 focuses on the knowledge management system (KMS) by summarizing its framework, metrics, and various available techniques.

3.1 Role of IT in KM

The role of information technologies in knowledge management is explored in this section. From prior studies, five different perspectives can be summarized as follows, which, although may not be comprehensive, can provide an overview of the critical relationship between information technologies and knowledge management.

3.1.1 Support and Guidance Perspective

Information can be categorized into supportive and guidance classes and, therefore, applications of information technologies should provide both supportive and guidance information to successfully implement knowledge management [76]. Figure 3.1
Knowledge is the medium for these messages. Interpretation occurs when an individual's thinking occurs, and meaning is achieved. Figure 3.1 demonstrates the implication of knowledge in this perspective, where knowledge is regarded as the interpretation of both supportive and guidance information and IT provides the effective medium to exploit the information. Eventually, with the help of information technologies, the information is transformed into profitable and productive actions. Different information technologies are available in either or both of the supportive and guidance roles. For instance, database systems basically provide support information, but can be enhanced to be the repositories of guidance; workflow systems support rules of business processes in transferring information, but they offer little guidance to the roles within these processes; personal productivity applications like wizards provide guidance for users, but there is normally no sufficient supportive information associated with them; enterprise information portals can be used to offer both supportive and guidance information to achieve various benefits.

3.1.2 Process Perspective

Knowledge may be understood as a process of applying expertise. In this respect, the focus of knowledge management is on the management of knowledge flows and the entire iterative and interactive processes of creation, storage, transfer, and application of knowledge, as show in Figure 3.2. A variety of information systems and technologies provide support to streamline knowledge management processes, especially the flow of explicit knowledge by enabling knowledge capturing, storing, categorizing, indexing, searching, and publishing [77]. For example, data mining techniques such as neural networks find new patterns in data, WWW search & spidering, intelligent agents, and brainstorming enhance knowledge creation; knowledge repository databases store and retrieve knowledge; electronic
bulletin boards, discussion forums, knowledge directories, enterprise portals, “face to face” in-person meetings, and other knowledge networks enable efficient and accurate transfer of knowledge; and workflow systems, indexing, context analysis, taxonomies, and XML codify the application of knowledge [2].

3.1.3 Explicit and Tacit Perspective

The explicit and tacit perspective emphasizes the roles of information technologies in the cyclic conversion of knowledge. The “tacit-explicit model” identifies information technologies as the essential support in knowledge conversion and transfer [58]. For example, document management tools and knowledge portals are widely used in explicit-to-explicit knowledge transfer; collaboration and communication technologies support a tacit-to-explicit knowledge conversion; knowledge discovery and e-learning tools help the explicit-to-tacit conversion of knowledge; and the support of peer-to-peer networks can be tacit-to-tacit or tacit-to-explicit [48].

By using Nonaka’s model as a framework, information technologies that contribute to knowledge management can be reviewed with the explicit and tacit perspective [50]. Currently, the strongest technological contribution to enable knowledge management deals largely with explicit knowledge, such as search and classification. Contributions to the formation and communication of tacit knowledge, and support for making it explicit, are currently weaker, although some
encouraging solutions are under development, such as the use of text-based chat, expertise location, and unrestricted bulletin boards.

3.1.4 Functional Perspective

In the functional perspective, information technologies help companies to implement knowledge management, gaining various core competencies by focusing on different functions, including innovation, expertise, content, relationship, branding, and coordination [18]. For example, enterprise information portals, data mining, business intelligence software, knowledge repository, web-based enterprise management tools boost innovation; best-practice repositories, enterprise information portals, web-based enterprise management tools, and web-based training/learning are good at delivering skilled service, insights, or advice to effectively manage expertise; search engines, enterprise information portals, web-based enterprise management tools are efficient in creating valuable intangibles to manage corporate content; workflow systems, best-practice repositories, business intelligence software, and web-based enterprise management tools attract and keep a good relationship with customers, suppliers, and shareholders; business intelligence software, enterprise information portals, search engine, and web-based enterprise management tools generate recognition and intangible assets of the company; workflow systems, data mining, web-based enterprise management tools, and web-based training/learning coordinate the whole knowledge management processes by providing right knowledge to right person at the right time.

3.1.5 Business Practice Perspective

Table 3.1 summarizes the perspective of business consulting companies with respect to the role of information technologies in knowledge management.

Meta Group’s view is that only three technologies are essential to successful Knowledge Management: email, intranet, and search engine. E-mail enables knowledge sharing and learning and becomes the corporate knowledge base, intranet is a structured repository for collaboration, and search engine complements the growing corporate intranet. It is more important how an organization uses

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1Adapted from www.knowledge-portal.com/knowledge_management_technologies.
<table>
<thead>
<tr>
<th>Company</th>
<th>Essential Technology</th>
<th>View of IT in KM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meta Group</td>
<td>email, intranet, search engine</td>
<td>appropriate application of IT is more important</td>
</tr>
<tr>
<td>Gartner</td>
<td>no technology is KM technology</td>
<td>a business program with creation, organization, access, and reuse</td>
</tr>
<tr>
<td>Forrester</td>
<td>content management</td>
<td>contributing, collaborating and controlling content</td>
</tr>
</tbody>
</table>

**Table 3.1.** Role of IT in knowledge management: business perspective

Technology than which technology it uses. Organizations must focus on the appropriate deployment of these basic technologies, aligning the corporate culture more closely with Knowledge Management principles.

Gartner stresses that no technology is Knowledge Management Technology, which implies that any technology can be applied in knowledge management when it is appropriate. They simply focus on the processes of knowledge management and how technologies can be utilized to facilitate the processes.

Forrester views content management technologies as essential to knowledge management technologies. In this regard, technologies must provide the ability for contributing to, collaborating on and controlling web content in knowledge management.

Based on the discussion in this section, some representative information technologies applied in knowledge management are summarized in Table 3.2 from the above five perspectives.
<table>
<thead>
<tr>
<th>Information Technologies</th>
<th>Support &amp; Guidance</th>
<th>KM Process</th>
<th>Explicit &amp; Tacit</th>
<th>Functional Competency</th>
</tr>
</thead>
<tbody>
<tr>
<td>collaboration technologies</td>
<td>support, guidance</td>
<td>creation, transfer</td>
<td>tacit to explicit</td>
<td>relationship</td>
</tr>
<tr>
<td>database/repository</td>
<td>support</td>
<td>store/retrieve, transfer</td>
<td>explicit to explicit</td>
<td>expertise management</td>
</tr>
<tr>
<td>document management</td>
<td>support</td>
<td>store, application</td>
<td>explicit to explicit</td>
<td>content delivery</td>
</tr>
<tr>
<td>enterprise portals</td>
<td>support, guidance</td>
<td>transfer</td>
<td>explicit to explicit</td>
<td>branding</td>
</tr>
<tr>
<td>knowledge discovery</td>
<td>guidance</td>
<td>creation</td>
<td>explicit to tacit</td>
<td>innovation/coordination</td>
</tr>
<tr>
<td>peer-to-peer networks</td>
<td>support, guidance</td>
<td>transfer</td>
<td>tacit to explicit/tacit</td>
<td>relationship</td>
</tr>
<tr>
<td>workflow systems</td>
<td>support</td>
<td>application</td>
<td>explicit (tacit) to explicit (tacit)</td>
<td>coordination</td>
</tr>
<tr>
<td>WWW search &amp; spidering</td>
<td>support</td>
<td>creation</td>
<td>explicit to explicit/tacit</td>
<td>expertise</td>
</tr>
</tbody>
</table>

*Table 3.2.* Role of representative information technologies from different perspectives
3.2 Knowledge Management Systems

Various information systems and technologies are integrated into knowledge management systems adopted by organizations in managing knowledge assets. For instance, in Xerox, DocuShare was developed in 1996 to enable companywide employees to share information and visit the “virtual” office space on the corporate intranet to obtain electronic documents and a KM portal is also used to allow workers to capture, search, and retrieve knowledge. In Best Buy, RetailZone and KnowledgeZone are the two primary KM tools to achieve organizational objectives, such as improving sales proficiency, shortening the cycle time of new employee training, and increasing knowledge sharing. Unisys built the Enterprise Knowledge Portal, a low-risk and easy-to-implement solution that integrates legacy business systems and data to partially eliminate the complexities of knowledge management [18]. Based on prior research, we summarize the current framework, metrics, and techniques for knowledge management systems.

3.2.1 KMS Framework

A knowledge management system can be constructed based on two dimensions: the locus of knowledge (either artifact or individual) and the *a priori* structure of contents (either structured or unstructured) [31]. According to this framework, a knowledge management system will fall into one of four categories. The first category of KMS manages knowledge artifacts with an inherent structure. The second one includes systems where knowledge resides in each individual that are catalogued in a structured manner by the KMS (e.g., a database of expert). The third one refers to those systems with artifact knowledge but without a priori structure. The last one has no a priori structure and knowledge is associated with each individual. According to this framework of knowledge management systems, several challenges exist in three phases of KMS development: balance between information overload and potential useful content in KMS setup phase, balance between additional workload and accurate content in KMS maintenance phase, and balance between exploitation and exploration for the long-term effects of KMS.

Based on the functionality, knowledge management systems can be classified
into three types: information-based, technology-based, and culture-based [1]. The information-based KMS focuses on providing readily accessible, real-time, and actionable information, the technology-based KMS emphasizes the information technology infrastructure, specifically, about the integration of cross-functional systems worldwide, and the culture-based KMS is devoted to enable organizational communication, intellectual-property protection, and culture development.

From another aspect, the system advance level, knowledge management systems can be classified into three types: Informational Knowledge Systems, Knowledge Management Tools, and Dynamic Knowledge Systems [61]. Informational Knowledge Systems (IKS) typically store, manage, and apply knowledge on a “just in case it’s needed” basis. Knowledge Management Tools (KMT) have the main aim of simplifying access or providing direction to the knowledge and information within KM systems, in a timely manner by reducing the quantity of information available to the user. Dynamic Knowledge Systems (DKS) are systems which elicit on-demand, in-context, timely, and relevant information and knowledge from people when it is needed by somebody else.

3.2.2 KMS Metrics

Knowledge management systems are a critical part of the knowledge management initiatives within organizations. There exist plenty of studies and discussions on the measures of knowledge management investment. Using metrics for knowledge management allows organizations to set targets, assess success, estimate ROI, track ongoing viability, and learn lessons [64]. The need for measurement of knowledge management follows a bell curve pattern through a business life cycle. Formal measurement is not really required for the early-stage knowledge management initiatives. When knowledge management becomes more mature, the need for measurement steadily increases. Finally, when knowledge management becomes the routines of company business, the importance of measurements for knowledge management diminishes and the metrics for knowledge-intensive business processes will be needed instead [41].

Four major measurement systems currently popular among practitioners for knowledge management have been identified: 1) human resource accounting (HRA);
2) economic value added (EVA); 3) the balanced scorecard (BSC); and 4) intellectual capital (IC) [14]. Each of them has different assumptions, details, operationalization procedures, as well as strengths and shortcomings. For instance, the HRA system has extensive internal use in certain service industries, but is based on many unrealistic assumptions. The EVA system closely ties with budgeting, financial planning, goal setting, and incentive compensation, but requires complicated adjustment procedures. The BSC system is based on powerful logic and clearly correlates indicators with financial performances, but is static and rigid. The IC systems is flexible and applies also to non-for-profit organizations, but is still at its early development stage and concentrates too much on stocks [14].

Based on the four different types of knowledge management, valuing knowledge (PLS-Consult, Denmark), exploiting intellectual property (Boeing 777), capturing project-based learning (McKinsey and Bain & Co.), and managing knowledge workers (Analog Devices), a balanced scoreboard method can be applied in measuring knowledge management investment [24]. Fairchild proposes two approaches from the balanced scoreboard perspective to measure knowledge management. The first approach is based on the four different capitals available in organizations: human, intellectual, structural, and social capital. The second approach combines the balanced scoreboard perspective with the resource management based approach [24].

Global Knowledge Economics Council proposed several candidate metrics to measure knowledge management [26]. Summarizing prior related metrics, they suggested the following eight categories of candidate metrics: social network measures, the learning curve, diffusing S-curve and normality, critical mass, the Bass model for forecasting the rate of diffusion, innovation time-cost tradeoffs, the four levels of evaluating training programs, and return on investment [26]. These categories of metrics are supported by related theories from prior studies in different areas. For example, from the social network theories, different measures can be regarded as the knowledge management metrics, such as measures of interpersonal network, commitment network, assignment network, substitute network, needs network, and precedence network [26].

Following upon the discussion on the measurement of knowledge management, the metrics of knowledge management systems can be designed and implemented
in a similar fashion. The Corporate Executive Board evaluates the performance of knowledge-management Intranets from the following perspectives, which can be applied to a general KMS. These perspectives include knowledge sharing, quality, determining use of intranet, and knowledge efficiency [60]. In general, metrics for knowledge management systems include system usage, number of users, information quality, information currency, user feedback, maintenance costs, staff efficiency, printing costs, distributed authoring, process efficiency (reduced time), and transaction costs [64]. Among these metrics, information usage can be measured by web usage statistics, search engine usage, message sent and posted, knowledge use, and other knowledge creation measures. Information quality can be monitored by user rankings, expert evaluation, edits required, usability testing, and links created [64]. Related to the systems metrics, there are also customer service metrics and culture metrics for measuring knowledge management benefits. The customer service metrics can be used to ensure consistent, high-quality customer service through knowledge management and culture metrics to measure how knowledge management initiatives impact organizational culture to match strategic needs.

Based on the knowledge conversion theory [58], the performance for knowledge sharing can be assessed from tacit to tacit, explicit to tacit, tacit to explicit, and explicit to explicit perspectives [47]. Especially, to monitor the performance of tacit to tacit knowledge transfer, the social network theory and analysis can be applied to generate the following measures: the number of links per respondent, frequency of advice seeking, individual with highest nominations, ratio of internal to external links, and proportion of total inward/outward contacts, which can be interpreted as the measurements of knowledge sharing density, intensity, expert identification, expertise distribution, etc.

### 3.2.3 KMS Techniques

Various techniques can be applied in building a knowledge management system. This section reviews the current major techniques in knowledge management systems at a conceptual level.
3.2.3.1 Process-oriented KMS on Semantic Web

A knowledge management system can be built upon the platform of semantic web [70], where the domain ontology and inference engine provide the fundamental support for all the functional units (Figure 3.3). This system captures the following knowledge management processes in a sequence: knowledge capturing, knowledge representation, knowledge processing, knowledge sharing, and using of knowledge. Four types of knowledge sources are identified and treated in the knowledge capturing phase: expert knowledge, legacy (rule-based) systems, metadata repositories, and documents, each of them associated with certain semantic-web tools [70].

3.2.3.2 Agent-based KMS

In Figure 3.4, a knowledge management system is built on agency theory with agent communication language (ACL). In this system, there are five agents providing different functions. Three types of knowledge can be captured: explicit technical knowledge (from internal structure and staff competence), tacit process knowledge or process experience (from internal structure and staff competence), and explicit relational network knowledge (from internal and external structure). The shared ontology agent is shared by all members to provide the concept of
3.2.3.3 P2P KMS

Most of the knowledge management systems of complex organizations are based on technological architectures that are in contradiction with the social processes of knowledge creation. In particular, centralized architectures are adopted to manage a process that is intrinsically distributed. Assuming a Distributed approach to Knowledge Management (DKM), [13] proposes that technological and social
architectures must be reciprocally consistent and a peer-to-peer architecture is suggested.

3.2.3.4 Weblogs, web-services, and KMS

Blogs can be used as a KM tool in two dimensions: selective forgetting & knowledge mining and synthesizing information [57]. Many knowledge management systems only focus on codifying and transferring knowledge, which is not advantageous because these systems only try to elicit and transfer the explicit dimension of tacit knowledge and their implementations depend heavily on outside incentives. Therefore, weblog-based KMS is proposed as a good solution to enable the transfer of tacit knowledge within organizations.

As demonstrated in Figure 3.5, weblog-based KMS share some common basic features. First, all blogs are listed in a corporate blog directory, which is categorized by topics, groups, or other criteria. Readers subscribe to the blogs they are interested in from corporate blog directory and all subscribed blogs would appear on one page and be updated on a real-time basis. Second, all the blogs have intensive archival and search features that make it easy to find relevant posts. Third, not all the blogs are available to the public on the Internet. Those blogs that are related to organizational confidentiality should be confined to the Intranet, while others can be published through the Internet. Finally, each team can develop and maintain their own blogs in the organization based on their functional role, for instance, marketing, finance and accounting, product development, research, and sales.
Various technologies and their standards in web services can be applied in publishing weblogs and building knowledge management systems. For instance, [3] outlines a knowledge capture, publication, and awareness system based on the XML and soap platform.

### 3.2.3.5 KM Portals

According to the Delphi Groups Corporate Portal Report from Knowledge Management Magazine (April 2000, page 42), three types of organizational portals can be used as knowledge management systems in business-to-employee (B2E), business-to-consumer (B2C), and business-to-business (B2B) scenarios, respectively [60], as shown in Table 3.3.

The corporate portal is used for intra-organizational knowledge sharing and learning, the customer portal is applied to the knowledge management between companies and consumers for managing customer relationship, and the vertical portal is generally adopted for inter-organizational knowledge transfer and collaborations.
<table>
<thead>
<tr>
<th></th>
<th>Corporate</th>
<th>Customer</th>
<th>Vertical</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other name</td>
<td>enterprise information portal</td>
<td>premier pages</td>
<td>industrial web site</td>
</tr>
<tr>
<td>Target user</td>
<td>employees, professional in a single discipline</td>
<td>customers</td>
<td>business professional in a single discipline</td>
</tr>
<tr>
<td>Purpose</td>
<td>provides individual and role based view of business content and resources; provides access to productivity and role-based applications such as HR, purchasing, etc.</td>
<td>provides a company-specific view of products, prices, services, and transaction history</td>
<td>provides original content, links to resources, and community in a business discipline, commerce, too.</td>
</tr>
<tr>
<td>Content</td>
<td>corporate reports, training manuals, competitive analyses, performance status, resource links, best practices, news feeds, employee directories</td>
<td>product catalogs, manuals, FAQs, reports on accounts and activities</td>
<td>articles, books, industry reports, software, directories, job listings, product catalogs, shopping guides</td>
</tr>
<tr>
<td>Applications</td>
<td>email, calendar, travel, conferencing, expense reports, function specific applications</td>
<td>procurement, help desk, online customer service</td>
<td>discussions, web site creation, web hosting, software downloads</td>
</tr>
</tbody>
</table>

**Table 3.3.** Summary of different portals in knowledge management (source: [60])
Prior studies provide a solid framework to understand how incentives function within organizations [34, 28, 51], while incentives that explicitly induce agents’ knowledge-sharing and learning behaviors and their interactions with information systems, which are the focus of this chapter, have not been fully investigated yet. In this chapter, in addition to the traditional incentives to induce agents’ best efforts, we also study the role of incentive structures to motivate agents’ knowledge sharing and learning behaviors which impact the organizational and individual welfare, and explore the interactions between these two sets of incentives. Building on the team incentive models, we explicitly model both the rewards and costs for knowledge sharing and learning, capture the characteristics of both information system and incentive schemes, study how the investment of information technology impacts the incentive structure of knowledge sharing, and explore the tradeoff between incentive schemes and investment of information technology for enabling knowledge transfer in organizations.

The chapter proceeds as follows. Next section develops the outline of our model, §4.2 details our findings, §4.2.4 discusses the implication, particularly expounding the relationship between information systems and incentives, and §4.3 summarizes the chapter.
4.1 The Model of Knowledge Sharing

We model the most critical process of knowledge management—sharing and learning—within an organization and discuss the impact of information technologies and incentive mechanisms on knowledge transfer. We first outline the setting of the knowledge transfer process via a knowledge management system applied in an organization. Then we model the sharing and learning among workers as a team incentive problem in which workers participate in a team project and the organization applies incentives to induce them to share knowledge and learn to achieve a maximal profit.

4.1.1 The Knowledge Transfer Framework

In this section, we describe the framework of knowledge transfer for managing and coordinating knowledge workers within organizations.

The organization applies a knowledge management system (for instance, Lotus Discovery Server from IBM\(^1\) to maintain its knowledge map and facilitate knowledge transfer among workers (Figure 4.1). Specifically, the organization controls the knowledge server of the knowledge management system, monitoring and coordinating the KM processes among all the workers. Generally, there are many KM processes within an organization. In this paper, we focus on those related to knowledge transfer, including registration, update, notification, search, sharing, and other functionalities.

and learning. Among these processes, registration, update, notification, and search take place between knowledge workers and the KMS, while sharing and learning only occur among knowledge workers. In this regard, KMS helps to identify potential knowledge providers and seekers, while knowledge flows among knowledge workers.

When a knowledge worker initially participates in the processes coordinated by the KMS, she is required to register her expertise. After she acquires new knowledge, she can update her registration. If a knowledge worker wants to find the new documents or know-how residing in the organization to help in her work, she will initialize the search process and inform the knowledge server of her needs. In this framework, knowledge is only associated with knowledge workers, i.e., the knowledge server does not store any codified knowledge. Therefore, to enable knowledge transfer, the knowledge server will check the knowledge map, match the potential knowledge hoarders with seekers, and establish the link (e.g., email, instant messages, wireless conferences, or other peer-to-peer technologies) between these workers to help them share knowledge and learn. In summary, the KMS provides the “hard” support for knowledge transfer in the organization. It helps to create a knowledge directory to identify potential knowledge hoarders and knowledge seekers and facilitates the transfer of knowledge.

However, since KMS only works as the platform for workers to interact, incentives are indispensable for the organization to get an accurate knowledge map and streamline the transfer of knowledge. We next formulate a model to investigate the important role of incentives in providing the “soft” support for knowledge transfer.

4.1.2 The Model of Knowledge Sharing

We consider \( n \) knowledge workers functioning as a team in a risk-neutral firm. These workers belong to one of two types with either high or low knowledge level. Each worker \( i \) has a certain knowledge level \( k_i \), known only to the worker herself. Other team members and the firm will perceive worker \( i \)'s knowledge level from a distribution \( G(k_i) \). Assume that the density function \( g(k_i) \) exists and is continuous. The knowledge level affects a worker’s ability to understand and work with the other member and yield the team output \( x \) of the project. Generally, knowledge
levels in an organization can be specified according to different criteria such as knowledge scope and knowledge depth [44]. In addition, knowledge can be classified into different categories such as tacit, explicit, causal, procedural, and pragmatic [2]. However, following the standard economic literature [19, 8, 68], we assume that the knowledge in completing the project can be simplified into a single dimension and increased simply by absorbing the same kind of new knowledge. Further, we assume that knowledge learning is accumulative, i.e., people cannot learn the knowledge at higher level unless they acquire the knowledge at the lower level.

In contrast to earlier studies as [35], [11], [12], and [19], in the context of knowledge organizations, we model worker’s knowledge level to increase the team’s output just as her effort level does, which is similar to the assumption in [51]. Specifically, the output $x$ is a concavely increasing function of each worker’s efficiency level $e_i$, and $x = x(e_1, e_2, \theta)$, where the parameter $\theta$ reflects the stochasticity in the outcome. The efficiency unit $e_i$ contains both the effort and knowledge level of a worker $i$. Additionally, we assume that $\partial^2 E[x]/\partial e_i \partial e_j \geq 0$, $\forall i, j = 1, 2, i \neq j$. The moral hazard problem originates from the uncertain nature and unobservable efficiency units.

We map the whole knowledge transfer process while completing the project into the following four stages. In the first stage, the firm announces a sharing rule

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_i$</td>
<td>the $i$th worker’s cost function for exerting effort</td>
</tr>
<tr>
<td>$C_i^l$</td>
<td>the $i$th worker’s cost function for learning knowledge</td>
</tr>
<tr>
<td>$C_i^s$</td>
<td>the $i$th worker’s cost function for sharing knowledge</td>
</tr>
<tr>
<td>$e_i$</td>
<td>the $i$th worker’s efficiency level</td>
</tr>
<tr>
<td>$k_i$</td>
<td>the $i$th worker’s original knowledge level</td>
</tr>
<tr>
<td>$k_i'$</td>
<td>the $i$th worker’s knowledge level after learning</td>
</tr>
<tr>
<td>$k_i^l$</td>
<td>knowledge learned by the $i$th worker</td>
</tr>
<tr>
<td>$k_i^s$</td>
<td>knowledge shared by the $i$th worker</td>
</tr>
<tr>
<td>$\lambda_i$</td>
<td>allocation proportion of output</td>
</tr>
<tr>
<td>$n$</td>
<td>total number of workers</td>
</tr>
<tr>
<td>$R$</td>
<td>reward function for knowledge sharing and learning</td>
</tr>
<tr>
<td>$\rho$</td>
<td>linear reward for unit amount of sharing(learning)</td>
</tr>
<tr>
<td>$T$</td>
<td>the level of technology to support knowledge sharing and learning</td>
</tr>
<tr>
<td>$x$</td>
<td>team’s profit function</td>
</tr>
</tbody>
</table>

Table 4.1. Summary of Notation: the model of knowledge sharing
and reward structures for sharing knowledge and learning. Motivating workers’ best efficiency units, this sharing rule $s_i(x, \tau)$ allocates the team’s total output to each individual in a specific way based on the achieved outcome $x$ and workers’ reported knowledge level $\tau$. The reward structure is based on workers’ reported knowledge level $\tau_i$ and the amount being shared or learned which can be monitored by the KMS. In the second stage, each individual $i$ reports her knowledge level $\tau_i$ to the firm. In the third stage, each individual exerts effort, shares or learns knowledge, and completes the project. In the fourth stage, workers get their allocations according to the preannounced sharing rule and knowledge-sharing or learning reward if applicable.

Each risk-neutral knowledge worker has to choose a non-observable efficiency level $e_i \in E_i = [0, \infty)$, keeping in mind the sharing rule designed by the firm. The cost $C_i$ for exerting effort is a convexly decreasing function of an individual’s knowledge level and a convexly increasing function of her efficiency level, which is consistent with the assumption in prior literature [11, 12, 19, 51]. We also assume that $\partial^2 C_i / \partial e_i \partial k_i < 0$, implying that a worker with higher knowledge level incurs less cost for exerting same efficiency units.

In addition, workers decide how much knowledge $k^s_i$ to share and how much $k^l_i$ to learn, given the reward structure announced by the firm. A worker’s cost of sharing knowledge $C^s_i$ is a nondecreasing convex function of $k^s_i$ and a decreasing function of $k_i$ and we assume $\partial^2 C^s_i / \partial k^s_i \partial k_i < 0$, which implies that the unit cost for sharing knowledge is lower for a worker at a higher knowledge level. Similarly, the cost of learning $C^l_i$ is assumed to be a nondecreasing convex function of $k^l_i$ and a decreasing function of $k_i$ and $\partial^2 C^l_i / \partial k^l_i \partial k_i < 0$, i.e., the unit cost for learning is lower for a worker with higher knowledge level. Our above assumptions about knowledge sharing and learning stems from the observation of KM practices and differentiates our study from prior research which assume that sharing and learning are costless. Furthermore, both the sharing and learning costs are parameterized by the firm’s IT level $T$ of the knowledge management system utilized for knowledge sharing and learning. Generally, there are four critical impediments to share and reuse knowledge from the technical perspective of a knowledge management system: heterogeneous representations, dialects within language families, lack of communication conventions, and model mismatches at the knowledge level [56].
Information technologies overcome these barriers to knowledge transfer: the more advanced (a higher $T$) the knowledge management system, the lower the sharing and learning costs. For example, a network connecting knowledge workers with advanced learning and sharing tools including collaborative systems, expert systems, knowledge portals, and e-learning analysis software will reduce costs and improve knowledge sharing and learning. In this model, we assume that the firm’s investment $I$ in information technologies convexly increases with the level $T$ of information systems.

As for the knowledge-transfer policy, we investigate two commonly adopted ones—Mandatory Learning (ML) and Voluntary Learning (VL), both rewarding knowledge sharing $R_s(k^*_i, \tau_i)$ or learning $R_l(k^i, \tau_i)$ based on the amount of knowledge being shared $k^*_i$ or learned $k^i$ and the reported knowledge level $\tau_i$. However, in the first case, workers are forced to learn whenever other workers share knowledge useful to them, i.e., $k^i = k^*_j$, $\forall i, j = 1, 2$ and $i \neq j$. Tests will be conducted to check whether workers have reached certain desirable knowledge levels. While, in the second case, workers can choose how much to learn independently, i.e., $k^i \leq k^*_j$, $\forall i, j = 1, 2$ and $i \neq j$.

These two knowledge-transfer policies are summarized as observed in business practice. Some companies, in particular, knowledge-based learning organizations, make learning mandatory to promote the knowledge culture within organizations. Typically, employees are required to learn to acquire the necessary skills for their jobs. For example, at O’Hagan, Smith & Amundsen LLC, certification of basic IT skills is mandatory for everyone [42], from the top partners to the lowest-paid clerical worker. Employees have to go through training and pass a series of certification tests to fulfill their basic job requirements. Insurance company USAA in San Antonio also requires similar training for its employees [27]. In fact, the organizations that are on the list of Computerworld’s 10 Best Places to Work in IT, all tie training goals to the performance measurements of their employees. In contrast, offering direct reward to induce workers to participate in knowledge sharing and learning is a practice adopted by some other leading companies. For example, Siemens measures and rewards individuals for participation in ShareNet. Contributors earn ShareNet shares based on the quality and reusability of their contribution assessed through a peer rating. Top ShareNet contributors will be
rewarded with an invitation to the ShareNet global knowledge-sharing conference. Hewlett-Packard Consulting creates the Knowledge Masters Award to recognize the employees whose knowledge mastery best exemplifies the balance of innovation with reuse and significantly contributes to promoting knowledge culture in business. Winners receive not only the company-wide recognition, but also an all-expense-paid trip or cash award [5].

In summary, the firm designs sharing rules \( s_i(x, \tau) \), specifies sharing reward \( R_s(k^s_i, \tau_i) \) and learning reward \( R_l(k^l_i, \tau_i) \), \( i = 1 \) and \( 2 \), for all possible \( x \), and chooses a level \( T \) of information systems to maximize its profit. Formally, the firm’s problem \([P]\) can be modelled as

\[
\max_{(s, R, T)} E\{x - I(T) - \sum_{i=1}^{2} [s_i(x, \tau) + R_s(k^s_i, \tau_i) + R_l(k^l_i, \tau_i)]\} \tag{4.1}
\]

subject to workers’ incentive-compatibility constraints (IC)

\[
(e^*_i, \tau^*_i, (k^l_i)^*, (k^s_i)^*) = \underset{(e, \tau, k^l, k^s)}{\arg\max} E[\pi_i],
\]

and individual-rationality constraints (IR)

\[
E[\pi_i] \geq 0, \tag{4.3}
\]

in which \((e^*_i, \tau^*_i, (k^l_i)^*, (k^s_i)^*)\) is the equilibrium with \(e^* = \{e^*_1, e^*_2\}, \tau^* = \{\tau^*_1, \tau^*_2\}, k^*_i = \{(k^l_i)^*, (k^s_i)^*\}, \) and \( k^*_s = \{(k^s_i)^*, (k^s_j)^*\}. \pi_i = s_i(x, \tau) - C_i(e_i, k^l_i) - C_i(k^l_i, k^s_i, T) - C_i(k^s_i, k^s_i, T) + R_s(k^s_i, \tau_i) + R_l(k^l_i, \tau_i)\) is each knowledge worker’s expected payoff where \( k^l_i = k_i + k^l_i \), \( 0 \leq k^l_i \leq k^s_i \leq |k_j - k_i|^+, \forall i, j = 1, 2, \) and \( j \neq i \). It is assumed that each worker may only share her knowledge beyond the other worker’s reported knowledge level. Therefore, \( k^l_i = k_i + k^l_i \) and \( k^s_j \) is bounded by \([k_j - k_i]^+, \forall i, j = 1, 2 \) and \( j \neq i \), which is formally shown in Lemma 2.

Workers may have different beliefs about others’ knowledge levels. In this paper, we investigate the sharing and learning processes during which workers believe that everyone else is induced to report her true knowledge level and they act accordingly. We analyze the effects of two knowledge-transfer policies (ML&VL) on knowledge sharing and learning. We next introduce some definitions of desir-
able knowledge transfer characteristics and motivate the importance of knowledge sharing and learning.

Knowledge-sharing(learning) alignment: Individuals acting independently are induced to share(learn) the same amount of knowledge as desired by the organization.

Full-knowledge transfer: The knowledge shared by the high-knowledge worker is fully absorbed by the low-knowledge worker.

Complete-knowledge enablement: The high-knowledge worker shares knowledge completely so that the low-knowledge worker may reach her knowledge level.

4.2 Analysis and Discussion

We present our analysis and results about the impact of different incentive policies and information technology levels on knowledge sharing and learning in this section. We begin with the characterizations of the optimal solution to the problem \([P]\). Then we show that under certain conditions, the firm can design a linear contract to induce workers to truthfully report their knowledge levels and achieve the optimal profit. After that, we demonstrate the role of incentives and information technologies in facilitating knowledge-sharing(learning) alignment, full knowledge transfer, and complete-knowledge enablement. Finally, we discuss the relationship between incentives and information technologies in facilitating knowledge transfer.

First, we summarize some features of the optimal solutions.

Lemma 1. The firm gets the same optimal profits for both policies.

Lemma 2. The low-knowledge worker should not share and the high-knowledge worker should start her sharing point beyond the low-knowledge worker’s level of knowledge.

In optimality, the firm will only induce workers to share if the shared knowledge will be completed absorbed by other workers. Otherwise, the firm will incur additional cost without any benefit. In this regard, under both VL and ML policy, the sharing amount from the high-knowledge worker equals the learning amount from the low-knowledge worker. Therefore, the firm achieves the same profit under
both policies. Next, we characterize the firm’s optimal solution in the following lemma.

**Lemma 3.** If the firm makes payments \( s_i \) and rewards sharing and learning to workers such that

1. each worker’s expected surplus is zero when her real knowledge level is at zero,
2. workers exert efficiency levels, share knowledge, and learn as

\[
(e_1^*, e_2^*, (k_{1s}^*)^*, (k_{2l}^*)^*) = \arg\max \left\{ \text{expected team output} - \text{investment in IT} \right.
\]
\[
- \text{firm’s inferred costs for production, learning, and sharing},
\]

then payments \( s_i \), sharing reward \( R_s \), and learning reward \( R_l \) maximize the firm’s expected profit subject to workers’ individual-rationality and incentive-compatibility constraints.

The first condition is essentially a reduced individual participation constraint. In other words, when a worker reports her true knowledge level that is greater than zero, her expected payoff should always be greater than zero (see Equation (A.3)). The second condition defines the optimal efficiency levels, sharing, and learning amounts for the maximal organizational profit, in which the production, sharing, and learning costs inferred by the firm is higher because the firm does not know the workers’ actual knowledge levels. Specifically, the inferred production cost includes the actual production cost and the cost of inducing the workers to reveal their true knowledge levels. Similarly, the sharing cost and learning cost perceived by the firm contains two terms as well (see Appendix A.3 for details).

### 4.2.1 Linear Contract for Payment and Reward

A payment and reward functions to satisfy the conditions in Lemma 3 may not exist. However, we show next that under certain broad conditions, a simple payment structure, linear in output \( x \), and a simple sharing and learning structure, linear in the amount being shared and learned, are optimal.
In Table 4.2, the necessary components for the linear contracts are summarized under both VL and ML policies. For example, a high-knowledge worker’s linear contract under VL policy is

\[
\text{linear contract for high-knowledge worker under VL policy} = \text{allocation of output} + \text{sharing reward} + \text{optimal efficiency cost} + \text{optimal sharing cost} + \text{expected profit},
\]

in which the allocation for output is linear in the final team output, the sharing reward is linear in the amount being shared, and optimal efficiency and sharing costs are used to compensate high-knowledge worker’s actual costs for exerting effort and sharing knowledge. For detailed mathematical formulation of these linear contracts, please see Appendix A.4 and A.5.

<table>
<thead>
<tr>
<th>Linear Contract</th>
<th>VL policy</th>
<th>ML policy</th>
</tr>
</thead>
<tbody>
<tr>
<td>knowledge worker</td>
<td>high</td>
<td>low</td>
</tr>
<tr>
<td></td>
<td>high</td>
<td>low</td>
</tr>
<tr>
<td>allocation of output</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>sharing reward</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>learning reward</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>optimal efficiency cost</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>optimal sharing cost</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>optimal learning cost</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>expected profit</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Table 4.2. Linear contracts for VL and ML policies

To ensure the incentive-compatibility and individual-rationality of these linear contracts, the firm has to enforce some broad conditions. We next propose the conditions under both VL and ML policies in the following proposition.

Proposition 1. Under conditions in Table 4.3, the firm can design linear contracts for both VL and ML policy to achieve the optimal efficiency levels and sharing and learning amounts as characterized in Lemma 3 when there is no complementarity between worker’s efficiency levels.

Given the incentive-compatible conditions in Table 4.3 that are essential in inducing workers to report their true knowledge levels, the firm can design a linear
Table 4.3. Summary of conditions for optimal linear contracts

<table>
<thead>
<tr>
<th>Conditions</th>
<th>VL policy</th>
<th>ML policy</th>
</tr>
</thead>
<tbody>
<tr>
<td>output sharing term</td>
<td>$\frac{\partial \lambda_{VL}}{\partial k_i} \geq 0$</td>
<td>$\frac{\partial \lambda_{ML}}{\partial k_i} \geq 0$</td>
</tr>
<tr>
<td>optimal efficiency units</td>
<td>$\frac{\partial c_i^<em>}{k_i} \geq 0$, $\frac{\partial^2 c_i^</em>}{k_i^2} \geq 0$</td>
<td>$\frac{\partial c_i^<em>}{k_i} \geq 0$, $\frac{\partial^2 c_i^</em>}{k_i^2} \geq 0$</td>
</tr>
<tr>
<td>optimal sharing &amp; learning amount</td>
<td>$\frac{\partial k_i^<em>}{\partial k_1} \geq 0$, $\frac{\partial k_i^</em>}{\partial k_2} = -1$, $\frac{\partial^2 k_i^*}{\partial k_1^2} \geq 0$</td>
<td>$\frac{\partial k_i^<em>}{\partial k_1} \geq 0$, $\frac{\partial^2 k_i^</em>}{\partial k_1^2} \geq 0$</td>
</tr>
</tbody>
</table>

contract to motivate workers to exert best efficiency units and share and learn the optimal amount of knowledge required by the firm when there is no complementarity between worker’s efficiency levels. However, in the existence of positive complementarity between workers’ efficiency levels as we assume in our model formulation, some other minor conditions about the output and cost functions are needed along with the above conditions. Please see Appendix A.7 for details. Basically, these conditions requires that the output does not increase so fast in the complementarity as in each workers’ efficiency level and the cost for exerting efficiency units does not increase so fast in the complementarity between efficiency units and knowledge level as in either of them alone.

Among all the conditions for this linear contract under VL policy, the sharing term condition indicates that the sharing term of the final output is nondecreasing in each worker’s knowledge level. Notice that this term depends on both worker’s knowledge levels. With the sharing term defined in (A.8) and (A.9), each worker sets her marginal cost of efficiency to her marginal return from the output.

The conditions for optimal efficiency units under VL policy imply that the efficiency level of the high-knowledge worker is a weakly convex and nondecreasing function of the low-knowledge worker’s knowledge level, while the efficiency level of the low-knowledge worker is a weakly concave and non-decreasing function of the high-knowledge worker’s knowledge level. Optimally, a worker will work harder to increase her efficiency level if her partner is more knowledgeable. However,
this increasing rate is different with respect to different workers, which is useful
to ensure the concavity of workers’ payoff with respect to the sharing or learning
amount.

The last set of conditions under VL policy for optimal sharing and learning
amounts indicates that the optimal sharing amount is a weakly convex and non-
decreasing function of the high-knowledge worker’s knowledge level and the opti-
mal learning amount is a negatively linear function of the low-knowledge worker’s
knowledge level. The condition for the high-knowledge worker implies that the
firms wants her to share more if she reports higher knowledge level. The condition
for the low-knowledge worker says that the low-knowledge worker should always
reach a knowledge level after learning which is required by the organization and
independent of the learning amount. In equilibrium, the optimal sharing amount
from the high-knowledge worker equals the learning amount by the low-knowledge
worker. Therefore, by combining the conditions for sharing and learning, the opti-
mal sharing function is

\[ k_s = \alpha(k_1) - k_2 \]

where \( k_2 \leq \alpha(k_1) \leq k_1 \). The final knowledge
level after learning is \( k'_2 = \alpha(k_1) \) for the low-knowledge worker. This \( \alpha \) function
does not change with the knowledge level \( k_2 \) of the low-knowledge worker.

The conditions under ML policy bear the same interpretations as those under
VL policy. However, the last set of conditions for optimal sharing and learning
amounts is less restrictive. It only requires the optimal sharing amount to be a
nondecreasing function of the high-knowledge worker’s knowledge level and a non-
increasing function of the low-knowledge worker’s knowledge level. When the ML
policy is implemented, the firm will preannounce that a test will be conducted after
learning to verify whether the low-knowledge worker has enhanced her knowledge
level to a fixed constant level (as we observe from business practice, firms imple-
menting the ML policy all require their employees to pass certain certification tests
after learning or training).

The linear contracts under these two policies show that knowledge workers get
the same proportion of output allocation, same sharing reward for unit sharing
amount, and same expected profits under both polices. The difference only resides
in the learning part: under the VL policy, the firm needs to reward learning to
induce the low-knowledge worker to learn optimally; while under the ML policy,
no additional incentive is needed since learning is mandatory.
Proposition 2. The reward for sharing is non-decreasing in one’s knowledge level and the reward for learning is non-increasing in one’s knowledge level.

Given the optimal conditions listed in Table 4.3, the firm should offer more sharing reward for a worker with a higher knowledge level to induce her to share more knowledge. Similarly, the firm should offer more learning reward for a worker with a lower knowledge level in order to induce her to learn more.

4.2.2 Role of Incentives

We demonstrate that incentives play a critical role in achieving the truthful reporting of knowledge levels, knowledge-sharing(learning) alignment, and full knowledge transfer, greatly facilitating the knowledge sharing and learning process.

First of all, incentives induce knowledge workers to truthfully report their knowledge levels. Under VL policy, conditions in Table 4.3 ensure that workers will not under-report their knowledge levels. First, if they report a lower knowledge level, they will get a lower sharing proportion according to the sharing-term condition. Second, the condition for optimal efficiency units indicates that the firm will ask a worker to work harder if her partner has a higher knowledge level, which will discourage one to under-report her knowledge level since this worker’s share from the final output (that increases with the other worker’s efficiency level) will decrease. Third, if a high-knowledge worker under-reports her knowledge level, she will be asked to share less knowledge and get less sharing reward. Finally, when the low-knowledge worker reports a knowledge level \( \tau_2 < k_2 \), she only needs to learn the amount of \( \tau_2 + k_l(\tau_2, k_1) - k_2 \), but she can pretend to learn \( k_l(\tau_2, k_1) \) to get additional learning reward. However, this additional reward is not large enough to compensate the loss from output allocation because of her under-report. Therefore, the low-knowledge worker will not under-report her knowledge level either.

On the other hand, incentives prevent workers from over-reporting their knowledge levels as well. In prior studies by [11], [12], and [19], they assume that knowledge levels cannot be over-reported because the principal can always intelligently verify whether an agent has done that. In our model setting without such assumption, no matter which policy is adopted, workers will not over-report their knowledge levels. Firstly, when a worker claims a higher knowledge level, she
will be required by the firm to share more knowledge which might be beyond her real knowledge level. Secondly, when the reported knowledge level by the low-knowledge worker is higher than her real one, the actual amount learned by the low-knowledge worker will be zero because in this case, there is a gap between $k_2$ and $k^*_l$. Therefore, the low-knowledge worker will not be able to learn with the existence of this gap according to our assumption, which will easily expose her over-reported identity. Finally, a worker has to exert more effort if she claims a higher knowledge level, which will let her incur a higher cost for effort at her real knowledge level.

Next, incentives are used to accomplish knowledge-sharing(learning) alignment as well and under certain conditions, knowledge sharing and learning may be autonomous. The role of sharing reward is actually to achieve knowledge-sharing alignment. Because the increased output from sharing may not completely compensate the high-knowledge worker’s sharing cost, the firm has to provide additional sharing reward to induce the high-knowledge worker to share the optimal amount of knowledge. Similarly, the role of learning reward under the VL policy is to achieve knowledge-learning alignment. The firm has to provide learning reward as well to ensure that the optimal amount of knowledge will be learned since learning is independent of sharing under the VL policy. Without the appropriate learning reward, the low-knowledge worker would not learn the same amount desired by the firm if the increased output from learning cannot adequately compensate her learning cost. However, under the ML policy, the firm does not have to provide additional reward because learning is always optimally aligned.

Finally, incentives can help the firm to facilitate full-knowledge transfer. [20] points out that knowledge transfer is knowledge transmission plus knowledge absorption and if knowledge is not absorbed, then it has not been transferred. In this sense, full knowledge transfer is a desirable property that the firm wants to obtain during its implementation of knowledge management practices while maximizing its profit. Obviously, knowledge cannot be fully transferred from the high-knowledge worker to the low-knowledge worker without the incentives contained in the linear contract. Under the ML policy, because of mandatory learning, full-knowledge transfer is artificially achieved. Under the VL policy, the linear contract functions delineate an equilibrium where the sharing amount from the high-
knowledge worker is tantamount to the learning amount by the low-knowledge worker. Besides, both workers act in such a way that their sharing and learning amounts converge to this equilibrium so that they both achieve optimal surplus themselves.

4.2.3 Role of Information Systems

We turn next to analyze the role of information systems in facilitating knowledge transfer when the firm adopts the linear incentive policies. In the following, we show the existence of an optimal level $T^*$ of information systems for the firm to achieve the maximal profit and demonstrate the threshold level $T^C$ of information systems in achieving complete-knowledge enablement.

**Proposition 3.** The optimal level $T^*$ of information systems can be derived from

$$T^* = \arg\max_T \left\{ \text{expected team output} - \text{investment in IT} \right. \left. - \text{firm’s inferred costs for production, learning, and sharing} \right\}.$$

The degree of sophistication in technology adopted by a firm not only increases the firm’s profit, but also greatly influences the process of knowledge transfer—knowledge sharing and learning. Generally, there exists one threshold to attain complete-knowledge enablement for the firm.

**Proposition 4.** When the level of information technology exceeds the threshold level $T^C$, complete-knowledge enablement is achieved.

![Figure 4.2. The sharing-coefficient $\alpha$ vs. IT level $T$](image)
In Figure 4.2 (see Appendix A.11 for the numerical example, where $\alpha$ is the coefficient in $k_s = \alpha k_1 - k_2$), we show that the sharing-coefficient $\alpha$ is increasing when the level of information technology increases within the range from 0 to the IT threshold $T^C$. While beyond this IT threshold $T^C$, $\alpha = 1$, i.e., complete-knowledge enablement is achieved and the low-knowledge worker reaches the same knowledge level as that of the high-knowledge worker.

The previous discussions imply that given a sufficiently high level of information systems, the firm may use incentives to induce high-knowledge worker to completely share her knowledge, enabling the high-performance team.

**4.2.4 Relationship of Incentives and Information Systems**

In this section, we investigate the relationship of incentives and information systems in facilitating knowledge transfer by beginning with the general discussion from a knowledge market perspective.

From a knowledge market perspective [20], both incentive policies and information technologies assume the roles as follows: (a) identifying potential knowledge buyers and sellers, i.e., knowledge hoarders and seekers; (b) facilitating knowledge transaction, i.e., the flow of knowledge from knowledge providers to knowledge absorbers.

Information technologies and knowledge-sharing(learning) complement each other by providing hard and soft support for knowledge transfer. Information technologies set up the market place for the potential buyers and sellers to meet and establish the link for knowledge to flow from sellers to buyers. However, since knowledge is unobservable and sometimes intangible, incentives can induce buyers and sellers to register their real knowledge expertise to the knowledge server, resulting in an accurate knowledge map within organizations. The incentive policy also induces the seller and buyer to transact knowledge in the exact amount desired by the organization. Essentially, knowledge-sharing(learning) incentives ensure that both buyers and sellers benefit from the knowledge transaction.

Ideally, the firm wants to exploit the full potential of its knowledge assets, yielding a maximal expected output. To obtain this goal, incentives and information technology are both indispensable. In linear contracts, incentives help
to align individual goal with organization one, while information technology facilitates the implementation of the linear contracts. Under the VL policy, the conditions for optimal sharing and learning require the optimal sharing function to be 

\[ k_s = \alpha(k_1) - k_2 \text{ where } k_2 \leq \alpha(k_1) \leq k_1. \]

This condition can not be easily satisfied because the sharing amount generally changes with the knowledge level of the low-knowledge worker. However, if the level of information technology is high enough such that complete-knowledge enablement is facilitated, then the optimal sharing and learning amount always equal 

\[ k_1 - k_2 \text{ where } \alpha(k_1) = k_1, \text{ independent of } k_2 \text{ and non-decreasing of } k_1, \]

which satisfies the conditions for optimal sharing and learning. In this respect, information technology can implement the VL policy by facilitating complement-knowledge enablement. While, if the level of information technology is not sufficiently high, the ML policy has to be adopted by the firm to ensure the truth-reporting of knowledge levels and achieve the optimal profit because in this situation, the ML policy mandatorily enforces the optimal sharing and learning condition 

\[ k_s = \alpha(k_1) - k_2. \]

To summarize the role of IT in facilitating the implementation of incentive policies, we show in Figure 4.3 the best knowledge-transfer policy with different level of information technology. When the optimal IT level \( T^* \) is within the range from 0 to \( T^C \), IT level is not sufficiently high to achieve complete-knowledge enablement. Hence, ML policy has to be adopted to mandatorily implement the truth-telling mechanism. While, if the optimal IT level \( T^* \) is in \((T^C, \infty]\), complete-knowledge enablement will be enabled and workers will always report their true knowledge levels. In this case, it is best to implement the VL policy, which might promote a better organization culture by allowing free participation in knowledge sharing.
and learning. The implications from this figure coincide with our observations of business practices. When firms have a sufficiently high IT level to facilitate knowledge transfer (for example, Siemens, Hewlett-Packard, and Chevron), they can just announce the reward policies (for example, participation rewards at Siemens) for sharing and learning and let workers to voluntarily participate in the process of knowledge transfer. While if the IT infrastructure is not so sophisticated (for example, the law firm O’Hagan, Smith & Amundsen LLC and insurance company USAA), learning and sharing costs are relatively high. Therefore, in this situations, firms should adopt the ML policy to mandate workers to learn so as to elicit workers’ truthfully-reported knowledge levels and their best sharing and learning behaviors.

### 4.3 Summary

This chapter investigates the impact of IT investment and incentives on knowledge transfer in organizations. Extending team incentive models, we incorporate both an incentive structures for rewarding knowledge sharing and learning and the influence of information technologies. Our detailed analysis in this chapter provides valuable guidance for knowledge managers to appropriately invest in information technology to facilitate knowledge transfer, and design incentive mechanisms to reward and induce knowledge sharing and learning while taking into account the level of IT investments.
Incentives for Knowledge Discovery and Diffusion

It remains unclear how to reward knowledge workers such that potential knowledge discoveries can be successfully made, retained, and disseminated to other workers to improve a firm’s overall performance and how research workers’ effort levels and the firm’s profit change when the level of information technologies increases to reduce worker’s sharing and learning costs. In a large firm, knowledge experts normally reside in the research department which is responsible for discovering new knowledge. The firm wishes to improve not only the success rate of knowledge discovery, but also the dissemination of knowledge discovery to all workers to enhance its overall productivity. Therefore, the firm is interested in assembling the best team size for knowledge discovery, specifying the optimal wage contracts for production workers and researchers, choosing the appropriate reward for successful researchers, and understanding the impact of information technologies on the above decisions.

This chapter is devoted to addressing the above questions. We consider a firm that wants to employ some of its labor force in knowledge innovation to discover new method or know-how to improve its overall productivity. The knowledge innovation team is assembled by the firm internally and will be dismantled at the end of the research period. Each knowledge pioneer, acting independently, exerts a certain level of effort, generating a success rate for new knowledge discovery. In this setting of unobservable effort, the typical problem of shirking may arise,
because each individual can choose to exert less or no effort in the first period while enjoying other knowledge innovators’ fruit of success in the second period. To fully understand and characterize knowledge workers’ behaviors in this situation, we analyze the equilibrium that can be reached among knowledge innovators under different reward policies and study the tradeoffs between team size and incentive rewards for knowledge innovation. In addition, we also investigate how information technology influences the firm’s optimal profit, wage contracts, and rewards for successful discoveries.

Some studies have analyzed the best team size for research in the multi-period setting. Dutta and Prasad investigate a multi-period model in which workers can decide whether or not to participate in research in each period and once a researcher succeeds, his discovery will be disseminated automatically to the whole firm [22]. However, the firm does not specify the number of teams and knowledge transmission is also assumed to be costless. In a simplified model, Arditti and Levy study how to optimally choose the number of teams to do research to develop a new product to increase a firm’s net worth [6]. However, they do not discuss how this new product or discovery increases the firm’s net worth, what factors impact the success rate of the discovery, and what the necessary incentives are to increase the success rate of a discovery in conjunction with the optimal number of teams.

In this chapter, we extend their simple construction to a knowledge management framework and capture the properties of knowledge transmission process to improve productivity. In particular, we explicitly model the knowledge management processes including creating, retaining, and transferring of knowledge within a firm and study the role of organizational incentives in facilitating these processes. In addition, we model the impact of information technologies to lower the sharing and learning costs in knowledge transfer among knowledge workers and investigate how this reduction of sharing and learning costs influences the knowledge creation, retention, and transmission processes.

The chapter proceeds as follows. Next section outlines the model for knowledge discovery and diffusion. §5.2, §5.3, and §5.4 present our detailed analysis. §5.5 briefly summarizes the entire chapter.
5.1 The Model of Knowledge Discovery and Diffusion

We assume there are $N$ knowledge workers in a firm. These workers contribute identically either in routine production or knowledge discovery.

A two-period model as shown in Figure 5.1 is considered in our framework. In the first period, $M$ knowledge workers (knowledge pioneers) are selected by the firm to participate in knowledge discovery and the remaining $N - M$ knowledge workers (knowledge executors) engage in routine production. In the second period, the team of knowledge innovation is dismantled and all the $M$ knowledge pioneers return to their original positions in the normal production process, working at certain productivity level. If a knowledge discovery is made in the first period, all those who make the discovery will be rewarded by the firm, either individually or collectively, so that they will be induced to share their discoveries with the rest of knowledge workers (including those unsuccessful knowledge pioneers), improving each individual’s productivity level.

A knowledge worker’s effort in production is normalized to be zero. Hence, knowledge executors only decide whether or not to participate in production in each period to maximize their total expected net payoffs. The output in production for each knowledge worker when applying the current technology is $x_L$. Knowledge workers get payments $w_p(x_L)$ for production according to the contract designed by the firm.

If a knowledge worker is selected to be in the knowledge innovation team, she has the additional option to choose the effort $e$ to exert in research, resulting in an expected success rate $\rho^I(e, M)$ for the knowledge discovery, given the innovation team size is $M$. The probability of individual success $\rho^I(e, M)$ is independent and identical for each knowledge pioneer. We assume that $\rho^I(e, M)$ is a concavely increasing function of the innovation effort level $e$ exerted. Given the effort exerted by each pioneer and the innovation team size $M$, the available team success rate of knowledge innovation will be $\rho^G(E, M)$, where $E$ is the set of effort levels of all $M$ pioneers. If a discovery is made, the production output for each worker when applying the new technology will be increased to $x_H$ and workers get wage payment $w_p(x_H)$ for yielding this output. Lastly, knowledge pioneers get a fixed
payment $w$ in the first period and will be compensated in the same way as other knowledge executors after they return to production positions.

Overall, the firm selects the number of knowledge pioneers $M$ to do research, determines the wage contract $w(\cdot)$ for production, chooses the fixed wage $w_r$ for knowledge pioneers, and allocates rewards to induce knowledge pioneers to exert their best efforts and share their knowledge discoveries. Two organizational reward policies are examined in this paper: *individual winner reward* (IWR) and *aggregate winner reward* (AWR). Successful knowledge pioneers individually get the reward $r$ under IWR policy and all $M$ team members equally share the aggregate reward $R$ under AWR policy.

Given the identically individual innovation effort level $e$, the team success rate $\rho^G(E, M) = 1 - (1 - \rho^I(e, M))^M$.

### 5.1.1 Knowledge Worker’s Payoff

Next we formulate the net payoff for knowledge workers in two periods, including knowledge executors and knowledge pioneers.

A knowledge executor’s net payoff in two periods is

$$\pi_e = \frac{w_p(x_L)}{\text{payoff in 1st period: wage payment}}$$

\[ (5.1) \]
subject to the learning-participation constraint (LPC)

\[ w_p(x_H) - c_l(T) \geq w_p(x_L) \]  \hspace{1cm} (5.2)

and the individual-rationality constraint for knowledge execution (IR-E)

\[ \pi_e \geq U_e, \]  \hspace{1cm} (5.3)

where \( \beta \) is the discount rate and \( c_l(T) \) is the learning cost for knowledge executors who learn the knowledge discovery in the second period. Constraint (5.3) is the individual-rationality constraints for knowledge executors in which \( U_e \) is the reservation utility. Constraint (5.2) implies that it is always in a knowledge executor’s interest to learn the new knowledge given the wage contract \( w(\cdot) \) and learning cost. To investigate the impact of information technology, we assume that the learning cost depends on the level \( T \) of the information system applied by the firm in knowledge transfer. We assume that \( c_l(T) \) convexly decreases with respect to \( T \)-the higher the level of information systems, the lower the learning cost.

For a knowledge pioneer \( \kappa \) in the knowledge discovery team, her expected net payoff in two periods is

\[
\bar{\pi}_p = \underbrace{w - c(e)}_{\text{payoff in 1st period: wage - effort cost}} + \underbrace{\beta \rho^I(e, M)[w_p(x_H) + \phi_1 - c_s(T)]}_{\text{payoff in 2nd period when } \kappa \text{ succeeds}} + \underbrace{\beta(1 - \rho^I(e, M))p^{M-1}_{\eta=0}w_p(x_L)}_{\text{payoff in 2nd period when everyone fails}} + \underbrace{(1 - \rho^I(e, M))(1 - p^{M-1}_{\eta=0})[w_p(x_H) + \phi_2 - c_l(T)]}_{\text{payoff in 2nd period when } \kappa \text{ fails and at least one of other pioneers succeeds}},
\]
subject to the *sharing-participation constraint* (SPC)

\[
\phi_1 - c_s(T) \geq U_d
\]  

(5.5)

and the *individual-rationality constraint* for knowledge innovation (IR-P)

\[
\pi_p \geq U_p,
\]  

(5.6)

where the reward policy for knowledge pioneers is

\[
\phi_1 = \begin{cases} 
  r & \text{IWR policy}, \\
  \frac{R}{M} & \text{AWR policy},
\end{cases}
\quad \text{and} \quad
\phi_2 = \begin{cases} 
  0 & \text{IWR policy}, \\
  \frac{R}{M} & \text{AWR policy}.
\end{cases}
\]  

(5.7)

Here, Constraint (5.6) is the individual-rationality constraint for knowledge pioneers in which \( U_p \) is the reservation utility. Constraint (5.5) indicates that the firm always tries to retain and diffuse potential knowledge discoveries among knowledge workers so that a successful knowledge pioneer always prefers to share her knowledge discovery with other workers rather than hoarding and trading it on the market to get additional utility \( U_d \). If a knowledge pioneer fails, she will produce in the second period at the low productivity level if no other pioneer makes the discovery and she will learn to improve her productivity level while incurring the learning cost \( c_l(T) \) if at least one of the other \( M - 1 \) knowledge pioneers succeeds. On the contrary, if a knowledge pioneer succeeds, she can share her knowledge discovery to get reward while incurring the sharing cost \( c_s(T) \). The reward for a knowledge pioneer is \( r \) if she succeeds under the IWR policy and \( R/M \) under the AWR policy as long as the whole team succeeds. The sharing cost \( c_s(T) \) is assumed to be convexly decreasing in \( T \) as well.
### Parameters

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>discount rate in the second period</td>
</tr>
<tr>
<td>$c_s(\cdot)$</td>
<td>cost of sharing knowledge</td>
</tr>
<tr>
<td>$c_l(\cdot)$</td>
<td>cost of learning knowledge</td>
</tr>
<tr>
<td>$i$</td>
<td>index of the production output, $i = L, H$</td>
</tr>
<tr>
<td>$N$</td>
<td>total number of knowledge workers</td>
</tr>
<tr>
<td>$\rho_f(\cdot)$</td>
<td>individual success rate of the discovery</td>
</tr>
<tr>
<td>$\rho_G(\cdot)$</td>
<td>group success rate of the discovery</td>
</tr>
<tr>
<td>$\phi$</td>
<td>reward policy</td>
</tr>
<tr>
<td>$T$</td>
<td>level of information systems</td>
</tr>
<tr>
<td>$U_e$</td>
<td>reservation utility of executors</td>
</tr>
<tr>
<td>$U_p$</td>
<td>reservation utility of pioneers</td>
</tr>
<tr>
<td>$U_d$</td>
<td>market value of a knowledge discovery</td>
</tr>
<tr>
<td>$x_i$</td>
<td>production output</td>
</tr>
</tbody>
</table>

### Decision Variables

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e$</td>
<td>research effort exerted by each pioneer</td>
</tr>
<tr>
<td>$M$</td>
<td>team size for knowledge innovation</td>
</tr>
<tr>
<td>$r$</td>
<td>individual winner reward</td>
</tr>
<tr>
<td>$R$</td>
<td>aggregate winner reward</td>
</tr>
<tr>
<td>$w_p(\cdot)$</td>
<td>wage contract for production in two periods</td>
</tr>
<tr>
<td>$w$</td>
<td>wage payment for pioneers in the first period</td>
</tr>
</tbody>
</table>

Table 5.1. Summary of Notation: the model of knowledge discovery and diffusion

#### 5.1.2 Organizational Decisions on Incentives and Team Size

We formulate the firm’s total payoff in two periods and define the firm’s optimization problem in this subsection. In the first period, the firm’s net payoff is

$$
\pi_1 = \left( N - M \right) \left( x_L - w_p(x_L) \right) - M w
$$

(5.8)

in which $M$ knowledge workers participate as knowledge pioneers in knowledge innovation and the rest of workers as knowledge executors in routine production.

In the second period, knowledge will be transferred from the successful knowledge pioneers to other workers, including both unsuccessful knowledge pioneers and knowledge executors, improving each individual’s productivity level. To enable the knowledge transmission, the firm has to choose a reward policy to motivate successful pioneers to share. Hence, the firm’s expected payoff in the second period
\[ \pi_2 = \beta N \left( 1 - \rho^G(E, M) \right) (x_L - w_p(x_L)) + \beta N \rho^G(E, M) (x_H - w_p(x_H)) \]

\[ - \beta \Delta \left[ \text{expected reward for knowledge pioneers} \right] \]

where the \emph{expected reward} (ER) is

\[ \Delta = \begin{cases} \sum_{k=1}^{M} \rho_{\eta=k}^{M} k r & \text{IWR policy}, \vspace{0.5cm} \\
\rho^G(E, M) \frac{R}{M} & \text{AWR policy}. \end{cases} \]

In summary, the firm specifies the wage contract \( w_i(\cdot) \) in two periods for production and \( w_r \) for knowledge innovation in the first period, chooses the number of knowledge workers \( M \) to engage in knowledge innovation, and determines the appropriate reward \( r \) for IWR and \( R \) for AWR) for diffusing knowledge discoveries to maximize its total profit. Formally, we define the firm’s problem \([P]\) as

\[ \max_{w_i(\cdot), w_r, M, r \text{ or } R} \pi_1 + \pi_2, \]

subject to IR-E, IR-P, LPC, SPC,

\[ E \in \text{Equilibrium set } E^*, \]

\[ 0 \leq M \leq N \text{ and } M \text{ is integer}, \]

where Constraint (5.12) is the incentive-compatibility constraint (IC) for knowledge innovation in which \( E^* \) is the equilibrium set of innovation effort levels among \( M \) knowledge pioneers.

We next present our analysis and discussion in this section. First, we demonstrate the solutions to the special cases with effort-independent success rate, which serves as the benchmark and suggests solution techniques to the complete problem. Second, we show the existence and properties of the symmetric equilibrium for both IWR and AWR policies with the binding learning-participation constraint. Finally, we discuss the impacts of information technology.
5.2 Effort-independent Success Rate

We investigate the benchmark case in which the individual success rate of knowledge innovation is exogenous determined as a fixed parameter $\rho$, which simplifies our original formulation. In addition, $\rho^G(M) = 1 - (1 - \rho)^M$. Since the success rate of individual knowledge discovery is independent of the effort levels of knowledge pioneers, the firm does not have to consider the reward issue and only needs to determine the appropriate team size and wage payments. We focus on the discussion and insights on innovation team size in this subsection.

The firm’s profit in this case is

$$\pi_{EIS} = (N - M)(x_L - w_p(x_L)) - Mw + \beta N(1 - \rho)^M(x_L - w_p(x_L)) + \beta N(1 - (1 - \rho)^M(x_H - w_p(x_H))),$$

which is concavely increasing in $M$. After investigating the first order condition of the firm’s profit with respect to $M$, we find that the optimal innovation team size $M^*$ can be achieved when

$$\text{marginal benefit of knowledge innovation} \quad (\text{marginal success rate of knowledge innovation team}$$

$$\times \text{payoff from N workers when new technology is applied})$$

$$= \text{marginal cost of knowledge innovation}$$

$$\quad (\text{marginal opportunity cost for knowledge innovation}$$

$$+ \text{marginal cost for fixed wage payment of knowledge innovation}).$$

For the convenience of graphical presentation, we move the term “payoff from $N$ workers when new technology is applied” in Equation 5.14 to the RHS and obtain the following equation

$$\lambda(M^*) = \tau,$$
Figure 5.2. Marginal knowledge innovation ratio and marginal team innovation index with respect to the success rate; \( \tau \) is the marginal knowledge innovation ratio (horizontal line); \( \lambda(M) \) is the marginal team innovation index with team size \( M \) (concave function of the success rate \( \rho \)).

where

\[
\tau = \frac{(x_L - w_p(x_L)) + w}{\beta N[(x_H - w_p(x_H)) - (x_L - w_p(x_L))]},
\]

\[
\lambda(M) = -(1 - \rho)^M ln(1 - \rho).
\]

\( \tau \) can be interpreted as the marginal knowledge innovation ratio. When the firm shifts one knowledge worker from production to knowledge innovation, the numerator of \( \tau \) is the summation of the firm’s marginal opportunity cost \( (x_H - w_p(x_H)) \) and wage payment \( w \) for knowledge innovation in the first period and the denominator is the firm’s marginal discounted benefit to apply new discovery in production from all knowledge workers in the second period. Therefore, \( \tau \) is the ratio of marginal cost to marginal benefit for the firm to engage an additional worker in knowledge innovation. \( \lambda(M) \) can be understood as the marginal team innovation index for a fixed success rate \( \rho \) with the team size \( M \), which exactly reflects the overall marginal success rate of the innovation team when the firm adds a member to the innovation team. The firm should determine the optimal team size such that the marginal knowledge innovation ratio equals the marginal team innovation index.

In Figure (5.2), we show how the optimal team size can be chosen by examining
the curves of \( \tau \) and \( \lambda(M) \). \( \tau \) is a fixed straight line with respect to \( \rho \) and is affected by other parameters including the output levels, productivity improvement, and wage contracts. \( \lambda(M) \) is a concave function for \( \rho \) between 0 and 1. There are \( N \) curves of \( \lambda(M) \) for a team with 1 to \( N \) knowledge pioneers. For a fixed \( \rho \) (for example, \( \hat{\rho} \) in the figure), to choose the optimal team sizes \( M^* \), the firm can compute the actual value for each \( \lambda(M) \) at \( \rho = \hat{\rho} \) and then find the successive team size \( m \) and \( m + 1 \) such that the \( \tau \) value is between \( \lambda(m) \) and \( \lambda(m + 1) \). For example, because \( \tau_1 \) is found to be in \( (\lambda(m), \lambda(m + 1)) \) at \( \rho = \hat{\rho} \), the optimal team size \( M^* \) can be fixed by comparing \( \pi(m) \) and \( \pi(m + 1) \). When \( \tau \) is very large, in other words, when the marginal cost-to-benefit ratio is higher (for instance, \( \tau_2 \) in the figure), there is no intersection between \( \tau \) and \( \lambda(M) \). Hence, the firm will not assemble the knowledge-innovation team. In contrast, when the marginal ratio is very low (for instance, \( \tau_3 \) in the figure), there exists a range of success rates where all the knowledge workers will be asked to participate in knowledge innovation, i.e., \( M^* = N \). In addition, if \( \tau \) is tangential to \( \lambda(M) \) (\( \tau_4 \) in the figure), \( M \) achieves its maximal value \( Z \), i.e., the maximal team size the firm can choose.

5.3 Optimal Incentives for Knowledge Discovery

We first separate the knowledge discovery and diffusion processes and investigate the optimal incentives for knowledge discovery alone. In this case, the firm chooses the number \( M \) of researchers in innovation and offers the wage structure for knowledge pioneers with IWR policy as follows

\[
\text{wage payment} = \begin{cases} 
  w & \text{unsuccessful pioneers,} \\
  w + r & \text{successful pioneers.}
\end{cases}
\]

Under the individual reward policy, a knowledge pioneer \( i \)'s expected net payoff is

\[
\pi_p = w - c(e_i) + \rho'(e_i, M) \cdot r, \quad (5.15)
\]

where \( e_i \) is her best effort exerted based on the wage \( w \) and reward \( r \) offered by
the firm. Accordingly, the firm’s net payoff is

\[ \pi = \rho^G(E, M)B - M \cdot w - \sum_{i} \rho^I(e_i, M) \cdot r. \] (5.16)

To maximize its expected profit, the firm specifies the wage payment \( w \) for knowledge innovation, chooses the number of knowledge workers \( M \) to engage in knowledge innovation, and determines the appropriate individual reward \( r \). Formally, we define the firm’s problem \([P]\) as

\[ \max_{w,M,r} \pi, \] (5.17)

subject to

\[ E \in \text{Equilibrium set } E^*, \]
\[ \pi_p \geq U_r, \]
\[ w \geq 0, \]

where the first constraint is the incentive-compatibility constraint (IC) for knowledge innovation in which \( E^* \) is the equilibrium set of innovation effort levels among \( M \) knowledge pioneers, the second constraint is the individual-rationality constraint (IR) in which \( U_r \) is the reservation utility, and the last one is to ensure a positive wage payment.

Alternatively, when the aggregate team reward policy is applied, the individual’s payoff and firm’s profit can be formulated accordingly. We next introduce two lemmas, based on which the firm’s problem can be greatly simplified.

**Lemma 4.** There always exists a unique symmetric equilibrium for workers’ effort levels when the individual winner reward policy is applied.

*Proof.* The first order condition of each individual’s payoff with respect to her effort level shows that \( c'(e_i) = \rho_i^I(e_i, M) \cdot r \). Therefore, each individual’s effort level is determined by the team size \( M \) and individual reward \( r \), not related to others’ effort levels. ■

Based on Lemma 4, we simplify the notation \( e_i \) as \( e \) for all the individual
efforts under the individual winner reward policy and the incentive-compatibility constraint is reduced into

\[ e \in \arg\max_{\tilde{e}} \{ w - c(\tilde{e}) + \rho(\tilde{e}, M) r \}. \]

**Lemma 5.** The individual-rationality constraints are always binding for each individual.

**Proof.** (can be proved by contradiction) ■

Lemma 5 allows us to further simplify the firm’s problem into

\[ \max_{(r, M)} \pi = -M[c(e) + U_r] + \rho^G(e, M) B \]

subject to

\[ e \in \{ \tilde{e} | c'\tilde{e} = \rho^I(\tilde{e}, M) r \}, \]

\[ c(e) - \rho^I(e, M) r + U_r \geq 0. \]

In this section, the base model is investigated from the three perspectives summarized in Table 5.2. In addition to the two alternative reward policies, we also identify the other two dimensions for analysis.

First, we differentiate a team as either synergistic or non-synergistic. In a non-synergistic team, individual success rate does not depend on the total number of researchers. Hence, the individual success rate can be defined as \( \rho^I(e, M) = \rho(e) \), which is independent of the team size \( M \). Then the team success rate is just

\[ \rho^G(e, M) = 1 - (1 - \rho(e))^M = 1 - (1 - \rho(e))^M. \]

In a synergistic team, individual success rate depends on the total number of researchers in the team. Because of the synergy within the research team, individual success rate may increase when more researchers engage in the innovation. In this regard, we define the individual success rate as

\[ \rho^I(e, M) = 1 - (1 - \rho(e)) \frac{\tilde{e}(M)}{M}, \]
Table 5.2. Three dimensions for the analysis of base model

<table>
<thead>
<tr>
<th></th>
<th>non-synergistic</th>
<th>synergistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>individual reward</td>
<td>aggregate reward</td>
</tr>
<tr>
<td>3</td>
<td>Homogeneous researchers</td>
<td>Heterogeneous researchers</td>
</tr>
</tbody>
</table>

then the team success rate is just

$$\rho^G(e, M) = 1 - (1 - \rho^I(e, M))^M = 1 - (1 - \rho(e))^{q(M)},$$

where $q(M)$ can be used to measure the actual synergy generated among $M$ researchers. When $q(M) = M$, there is no synergy within the team, which is the same as the above non-synergistic case. When $q(M) > M$, there is favorable synergy within the team, which helps to improve the individual success rate $\rho^I(e, M)$. When $q(M) < M$, team size will have opposite and negative effect on the individual success rate, which eventually reduces the team success rate $\rho^G(e, M)$. In general, we assume that $q(M)$ is a concave function, first increasing then decreasing in $M$ with the properties that $q(0) = 0$ and $q(1) = 1$. The existence of synergy within a team is critical for the firm to design optimal incentives. To capture how the synergy changes with a team size, we define the team elasticity of synergy $\psi$ as

$$\psi = \frac{Mq'(M)}{q(M)},$$

(5.18)

which represents the marginal change of synergy with respect to the team size. For a positive $\psi$, the larger it is, the larger the team synergy.

Second, we explore the different equilibria and designs of contracts when there exist homogeneous or heterogenous researchers on the labor market. When researchers are heterogenous with respect to their success rates and costs in the innovation team, the firm can not explicitly differentiate researchers’ types and have to design contracts to induce them to self-select the contracts specifically formulated for them.
5.3.1 Homogeneous pioneers

We begin with the analysis of homogeneous pioneers. First, the optimal solution is discussed for a non-synergistic team with individual reward. Second, various conditions are explored with the focus on the team elasticity of synergy in a synergistic team. Finally, we investigate the impacts of aggregate team reward policy on the equilibria of pioneers’ effort levels.

5.3.1.1 Non-synergistic team with individual reward

For a non-synergistic team, we next show that the firm can only achieve the second-best solution by offering each individual a zero wage payment.

Assumption 1. \( \rho''(e)(1 - \rho(e)) + [\rho'(e)]^2 \leq 0. \)

Lemma 6. Under Assumption 1, the Hessian matrix of the firm’s profit for non-synergistic team is always negative definite.

Proof. Please see Appendix B.1

The condition about the success rate in Assumption 1 implies that the function

\[
f(e) = \frac{\rho'(e)}{1 - \rho(e)}
\]

is nonincreasing in the optimal effort level \( e^* \) because \( f'(e) \leq 0. \) \( f(e) \) can be understood as the hazard function of effort level \( e. \) Under this condition, the stationary point \( (e^*, M^*) \) will be the optimal solution for the firm. Suppose there exist such optimal solution, we want to ensure that the optimal solution can be implemented, i.e., the firm can both achieve a positive profit and offer a positive wage payment to pioneers.

Proposition 5. The firm cannot implement the first-best solution with a non-synergistic team and only the second-best solution can be implemented. The reward and optimal effort level can be determined from

\[
r = \frac{c'(e)}{\rho'(e)}
\]

\[
U_r = \frac{\rho(e)}{\rho'(e)} c'(e) - c(e).
\]
Proof. Please see Appendix B.2

The reason that the first-best solution cannot be achieved lies in the contradiction that the firm cannot obtain a positive profit while maintaining a positive wage payment. Figure 5.3 explains this intuition by showing the individual’s iso-utility wage contours and the firm’s indifference curve when there is no synergy.

Figure 5.3. Worker’s iso-utility wage contours and firm’s indifference curve: no synergy

Since individual’s effort is solely determined by \( c'(e)/\rho'(e) = r \), which is not related to the team size \( M \), therefore, \( dr/dM = 0 \), which implies that iso-utility wage contours are horizontal lines. Figure 5.3 shows these lines for the reservation utility \( U_r \). The firm’s substitution rate is

\[
\frac{dr}{dM} = -\frac{\partial \pi}{\partial M} = -\frac{\rho_M B - w - \rho(e)r + (\rho_e^B B - M\rho'(e)r)\frac{\partial e}{\partial M}}{\rho_e^G B - M\rho'(e)r}\frac{\partial e}{\partial r}
\]

which is zero at point \((M^*, r^*)\) that satisfies the following two conditions

\[
\rho_M^G B = w + \rho(e)r = c(e) + U_r,
\]

\[
\rho_e^G B = M\rho'(e)r = Mc'(e).
\]

These two conditions suggest that the optimal effort level \( e^* \) is characterized by

\[
\frac{c'(e^*)}{\rho'(e^*)} = \frac{c(e^*) + U_r}{-(1 - \rho'(e^*))ln(1 - \rho'(e^*))}.
\]
When the wage payment is zero, individual’s effort level can be obtained from
\[
\frac{c'(e_0)}{\rho'(e_0)} = \frac{c(e_0) + U_r}{\rho(e_0)}.
\]

Since \(-(1 - \rho'(e))\ln(1 - \rho'(e)) < \rho(e), \forall e > 0\), it follows that \(e^* > e_0\), or \(r^* > r_0\), which implies that the firm’s indifference curve for maximal profit can never intersect with individual’s iso-utility wage contours for utility \(U_r\). Therefore, the firm can only achieve the second-best solution by lowering \(r^*\) to \(r_0\), offering zero wage payment to individual workers. \(M^*\) remains unchanged in both first-best and second-best cases. In summary, in the non-synergistic case, the firm cannot achieve the first-best effort level from knowledge pioneers. The second-best effort level can be obtained by offering a zero wage payment and paying the knowledge pioneer a proportion of the innovation benefit upon their successes.

### 5.3.1.2 Synergistic team with individual reward

For a synergistic team, it is possible to achieve a first-best solution under some conditions. Next, the possible cases are shown by investigating the lagrangian function of the firm’s profit.

By introducing the lagrangian multiplier \(\lambda\), the firm’s profit can be reformulated as
\[
\pi = -M[c(e) + U_r] + \rho G(e, M)B + \lambda[c(e) - \rho^I(e, M)r + U_r],
\]
whose necessary conditions for an optimal solution are
\[
\frac{\partial \pi}{\partial r} = [-Mc'(e) + \rho G B] \frac{\partial e}{\partial r} - \lambda \rho^I = 0,
\]
\[
\frac{\partial \pi}{\partial M} = -c(e) - U_r + \rho^G B + [-Mc'(e) + \rho G B] \frac{\partial e}{\partial M} - \lambda \rho^I r = 0,
\]
\[
\frac{\partial \pi}{\partial \lambda} = c(e) - \rho^I(e, M)r + U_r \geq 0,
\]
\[
\lambda \geq 0,
\]
\[
\lambda[c(e) - \rho^I(e, M)r + U_r] = 0.
\]

There are two cases for the optimal solutions.
1) When $\lambda = 0$, $-Mc'(e) + \rho_G^G B = -c(e) - U_r + \rho_B^G M_B = 0$ and $c(e) - \rho^I(e,M) r + U_r > 0$.

2) When $\lambda > 0$, $c(e) - \rho^I(e,M) r + U_r = -c(e) - U_r + \rho_B^G M_B = 0$ and $-Mc'(e) + \rho_G^G B > 0$.

Therefore, the firm’s problem can be regarded as choosing the best $e$ and $M$ to maximize the profit for either a positive or zero wage payment. We investigate these two cases in details as follows.

**I. Positive wage payment**

The first case is when $\lambda = 0$, the firm will be able to offer a positive wage payment to achieve a first-best solution. In other words, the firm can induce workers to exert efforts as if they could be observed. When effort levels are observable, the firm does not have to offer a reward for successful pioneers. Instead, only a wage payment that satisfies workers’ individual rationality constraints will be enough. In contrast, when effort levels are unobservable, the firm has to offer a reward to induce workers to exert efforts as it desires. However, in order to achieve the same optimal profit, the firm has to redesign the wage payment for workers by subtracting their expected reward. Therefore, in some cases, the wage payment may becomes negative after this substraction, which is not implementable. In this subsection, we show some conditions which allow the implementation of achieving the first-best solutions with individual reward policy.

**i. Complementarity between $e$ and $M$**

We first analyze the complementarity between the effort level and team size for the firm’s optimal solution by examining the Hessian matrix. The following lemma establishes the sufficient condition for a feasible optimal solution.

**Lemma 7.** Under Assumption 1, the sufficient condition for the Hessian matrix of the firm’s profit to be negative definite with a synergistic team is

$$-q'(M)q(M)ln(1 - \rho(e)) \geq \left| q'(M)[1 + q(M)ln(1 - \rho(e))] - \frac{q(M)}{M} \right|.$$ 

**Proof.** Please see Appendix B.3.

Considering the case when $1 + q(M)ln(1 - \rho(e)) \leq 0$, there always exists negative complementarity between $e$ and $M$, i.e., assembling a larger innovation team
requires the lower effort levels of workers. The above inequality can be simplified as

\[
\frac{q(M)}{q'(M)M} \leq 1.
\]

Next, when \(1 + q(M)\ln(1 - \rho(e)) > 0\), if

\[
[1 + 2q(M)\ln(1 - \rho(e))] \leq \frac{q(M)}{q'(M)M} < [1 + q(M)\ln(1 - \rho(e))],
\] (5.19)

there exists positive complementarity between \(e\) and \(M\), and if

\[
[1 + q(M)\ln(1 - \rho(e))] < \frac{q(M)}{q'(M)M} \leq 1,
\] (5.20)

there exists negative complementarity between \(e\) and \(M\).

When there is no complementarity between the effort level \(e\) and team size \(M\), the Hessian matrix is always negative definite, and, in addition,

\[
\frac{dM}{M} = \frac{dq(M)}{q(M)}[1 + q(M)\ln(1 - \rho(e))].
\]

Since \(q(1) = 1\), therefore,

\[
M^* = q(M^*)(1 - \rho(e^*))^{q(M^*)^{-1}}.
\] (5.21)

Given different scenarios of complementarities between the effort and team size, we next show how they relate to the firm’s first-best solutions.

ii. Positive profit and wage payment

In addition to the requirement of a positive wage payment, the first-best solution has to ensure a positive organization profit for it to be implementable. The next lemma suggests the necessary and sufficient condition for a firm to achieve positive profit under the first-best solution.

Lemma 8. The necessary and sufficient condition for a firm to achieve a positive
Table 5.3. Conditions regarding the team elasticity of synergy

profit under the first-best solution of the individual reward policy is

\[
\frac{q'(M)M}{q(M)} \leq \frac{\rho^G}{-(1-\rho^G)\ln(1-\rho^G)}.
\]

Proof. Please see Appendix B.4.

This Lemma suggests that with the presence of synergy within a team, the team success rate should be sufficiently high so that the firm can achieve the positive profit. As shown in Figure 5.4, when the team elasticity of synergy increases, the feasible area where the firm achieves a positive profit requires a higher team success rate \(\rho^G(e^*, M^*)\). In other words, when the team’s synergy is more productive, the firm should expect the team to generate a higher success rate of innovation such that the positive organizational profit is achievable.

According to the best team size above, the optimal effort level is characterized as

\[
\frac{c'(e^*)}{\rho'(e^*)} = \frac{q(M^*)}{M^*}(1-\rho(e^*))^{q(M^*)-1}B,
\]

which can be induced by offering the optimal reward as

\[
r^* = \frac{c'(e^*)}{\rho'_t(e^*, M^*)} = \frac{(1-\rho(e^*))^{q(M^*)}}{(1-\rho(e^*))^{\frac{2q(M^*)}{M^*}}}B.
\]
When there is no complementarity between the effort level and team size, \( M^* = q(M^*)(1 - \rho(e^*))^{q(M^*)^{-1}} \), the optimal effort level is simply \( c'(e^*)/\rho'(e^*) = B \), independent of the team size \( M \). When there exists positive complementarity between \( e \) and \( M \), \( M^* < q(M^*)(1 - \rho(e^*))^{q(M^*)^{-1}} \), the optimal effort level will be higher than that without complementarity. Finally, when there exists negative complementarity between \( e \) and \( M \), \( M^* > q(M^*)(1 - \rho(e^*))^{q(M^*)^{-1}} \), the optimal effort level will be lower than that without complementarity. Next, as we have discussed before, the firm has to ensure the wage payment to be positive when offering the individual reward under the first-best solution.

Figure 5.4. Team elasticity of synergy \( \psi \) vs. team success rate \( \rho^G \): individual reward

**Lemma 9.** The necessary and sufficient condition for \( w^* \geq 0 \) (or, for the firm to be able to offer a positive wage contract) under individual reward policy is

\[
\frac{q'(M)M}{q(M)} \geq \frac{M\rho^I}{-(1 - \rho^I)ln(1 - \rho^G)}
\]

**Proof.** Please see Appendix B.5.

This lemma indicates that the team synergy has to be sufficiently high with respect to the team’s success rate, in order for the wage payment to be positive. As shown in Figure 5.4, a higher team success rate demands a team with a higher team elasticity of synergy.

Following upon these two lemmas, we next discuss how they relate with the complementarity between effort and team size by the following propositions.
Proposition 6. The necessary condition for a positive firm’s profit is the existence of the negative complementarity between the effort level and team size.

Proof. Please see Appendix B.6.

Proposition 7. The necessary condition for both a positive firm’s profit and wage payment is the existence of negative complementarity between $e$ and $M$.

Proof. Please see Appendix B.7.

As depicted in Figure 5.5, the implementable first-best solution only occurs when there exits the negative complementarity between the team size and effort level. In other cases, either the firm has to obtain the additional funding in supporting the innovation or the firm has to request a prior payment from workers to participate in innovation, in order to achieve the first-best solution. Otherwise, only the second-best solution can be obtained, as the analysis shows in the following subsection.

II. Zero wage payment

The second-best solution has to be implemented when there is no additional external funding for innovation or no worker will be willing to participate in research when requested for a deposit. In this case, workers get no wage payment and the firm’s profit is lower than that in the first-best case.

Proposition 8. The firm can only achieve the second-best solution by paying a
zero wage payment when

\[
\frac{Mq'(M)}{q(M)} < \frac{Mp^l}{-(1 - \rho^l)\ln(1 - \rho^G)}.
\]

Proof. Please see Appendix B.8.  

Since the wage payment is zero, the effort level and reward in this case are determined from

\[
r = \frac{c'(e)}{\rho^l(e, M)},
\]
\[
c(e) = \rho^l(e, M)r - U_r,
\]

and the firm’s profit is always positive

\[
\pi = [\rho^G(e, M) - M\rho^G_M(e, M)]B > 0.
\]

Figure 5.6 demonstrates the iso-utility wage contours for workers between reward and team size. In particular, for a fixed wage payment \(w\) to achieve certain utility, there can be various combinations between \(r\) and \(M\), that is,

\[
\frac{dr}{dM} = -\frac{\partial w}{\partial r} = -\frac{\rho^l_M}{\rho^l_I}r < 0,
\]

and \(d^2r/dM^2 > 0\). Hence, the substitution rate between \(r\) and \(M\) for a fixed wage monotonically decrease.

The firm’s marginal indifference rate between \(r\) and \(M\) for a fixed profit is

\[
\frac{dr}{dM} = -\frac{\partial \pi}{\partial M} = -\frac{\partial \pi}{\partial r} = \frac{\rho^G_M B - w - \rho^l r - M\rho^l_M r + (\rho^G_e B - M \rho^l_e r) \frac{\partial e}{\partial M}}{(\rho^G_e B - M \rho^l_e r) \frac{\partial e}{\partial r} - M \rho^l},
\]

which will equal individual’s substitution rate at the point \((M^*, r^*)\) that satisfies conditions

\[
\rho^G_M B = w + \rho^l r = c(e) + U_r,
\]
\[
\rho^G_e B = M\rho^l_e r = M^c(e).
\]
These two conditions are nothing but the first-order conditions of the firm’s profit with respect to $e$ and $M$. If the optimal point $(M^*, r^*)$ is within the region for worker’s iso-utility contours with utility $U_r$, as shown in Figure 5.6, then the first best solution can be achieved. However, if the optimal point $(M^*, r^*)$ is outside the region for worker’s iso-utility wage contours with utility $U_r$ as shown in Figure 5.7, the firm has to move its indifference curve downward such that it is tangential to the worker’s iso-utility wage contour at $w = 0$. In this case, the firm has to bind worker’s positive wage constraint and achieve a positive second-best profit.

**Figure 5.6.** Worker’s iso-utility indifference curves for a fixed wage: first best

**Figure 5.7.** Worker’s iso-utility wage contours and firm’s indifference curve: second best
5.3.1.3 Synergistic team with aggregate reward

In stead of offering rewards to successful individuals, the firm can reward the whole team when the team succeeds. We first show the similar symmetric equilibrium as that under individual reward policy. Under the aggregate reward policy, asymmetric equilibrium may exist where knowledge pioneers exert efforts at different levels. However, we next show that only the symmetric equilibrium exist as long as all the pioneers in sub-groups collaborate as one group.

I. Symmetric equilibrium

Under aggregate reward policy, a knowledge pioneer’s payoff is

$$\pi_p = w - c(e) + \rho^l(e, M) \frac{R}{M} + (1 - \rho^l(e, M))(1 - \rho_{\eta=0}^{M-1}) \frac{R}{M},$$

subject to the constraints \(\pi_r \geq U_r\) and \(R/M \geq U_d\).

The symmetric equilibrium is obtained when there exists such an effort level that when a pioneer assumes that all the other \(M-1\) workers exert the same effort \(e\), she will be able to exert this effort \(e\) as well. Therefore, the symmetric equilibrium can be captured as

$$\frac{c'(e^s)}{\rho^l(e^s, M)} = [1 - \rho^l(e^s, M)]^{M-1} \frac{R}{M},$$

and the firm’s total payoff under the symmetric equilibrium is

$$\pi = -Mw - \rho^G(e, M)R + \rho^G(e, M)B$$

$$= -M[c(e) + U_r - (1 - (1 - \rho^l(e, M))^M) \frac{R}{M}] - \rho^G(e, M)R + \rho^G(e, M)B$$

$$= -M[c(e) + U_r] + \rho^G(e, M)B.$$

The firm has the same profit function under the aggregate reward policy as that under the individual reward policy. Therefore, the optimal profit remains the same for both cases, but the implementable conditions for the first-best solution is different. Next we show the conditions for the firm to achieve both positive wage payment and profit under the aggregate reward policy.

Lemma 10. The necessary and sufficient condition for \(w^* \geq 0\) (or, for the firm to be able to offer a positive wage contract) under the symmetric equilibrium of AWR
is

\[
\frac{q'(M)M}{q(M)} \geq \frac{M \rho^G}{-(1 - \rho^G) \ln(1 - \rho^G)}.
\]

Proof. Please see Appendix B.9. ■

To maintain the first-best optimal profit, the wage payment has to be redesigned to subtract the expected reward for each individual. Under the symmetric equilibrium of the aggregate reward policy, it requires a higher team elasticity of synergy for a positive wage payment than that under the individual reward policy, as shown in Figure 5.5.

Lemma 11. The necessary and sufficient condition for the firm’s profit to be positive under the symmetric equilibrium of AWR is

\[
\frac{q'(M)M}{q(M)} \leq \frac{\rho^G}{-(1 - \rho^G) \ln(1 - \rho^G)}.
\]

Proof. Please see Appendix B.10. ■

Since the firm achieves the same optimal profit, the implementable condition is the same for a positive first-best profit as that under the individual reward policy. However, because of the effect of aggregate reward, it is impossible to achieve so high a team success rate that both the profit and wage payment are positive, which is presented in the following proposition.

Proposition 9. The first-best solution under the aggregate reward policy cannot be implemented, i.e., the firm cannot both achieve a positive profit and offer a positive wage payment at the same time under the symmetric equilibrium of aggregate reward policy. Only the second-best solution can be implemented under the aggregate reward policy and the effort level and aggregate reward in this case can be determined from,

\[
\frac{R}{M} = c'(e) \frac{\rho^G(e, M)}{\rho^G(e, M)},
\]

\[
c(e) = \rho^G(e, M) \frac{R}{M} - U_r.
\]
Proof. From Lemma 10 and 11, it is never possible for the team elasticity of synergy to satisfy both conditions.

Under the aggregate reward policy, a worker will be rewarded even if she is unsuccessful as long as the entire team has succeeded. Therefore, a worker may not work so diligently as that under the individual reward policy. Hence, the firm has to offer more reward to induce a worker to exert the same effort as that under the individual reward policy, which makes it less implementable in terms of the positive wage payment. In other words, subtracting a higher expected reward will make the net wage payment less probably to be positive. Therefore, in order to engage in the innovation and achieve a positive profit under the symmetric equilibrium of aggregate reward policy, the firm always offers zero wage payment to pioneers.

II. Asymmetric equilibrium

The asymmetric equilibrium is investigated when there exist two or more groups among knowledge pioneers. The following proposition shows that as long as all the workers collaborate as one team and enjoy the benefit of the team synergy, they will always exert efforts at the same level no matter how many sub-groups may actually exist.

Proposition 10. The asymmetric equilibrium does not exist when the firm offers the aggregate reward and all pioneers collaborate as one group.

Proof. Consider the case where there exist \( n \) groups among knowledge pioneers. The effort level for \( m_i \) group can be characterized as

\[
\frac{c'(e_i)}{\rho^l_{e_i}(e_i, M)} = (1 - \rho^l(e_i, M))^{m_i-1} \prod_{j=1, j \neq i}^{n} (1 - \rho^l(e_j, M))^{m_j} \frac{R}{M}, \forall i = 1, 2, \ldots, n,
\]

from their incentive-compatibility constraints and \( \sum_{j=1}^{n} m_j = M \).

Then, the effort level for each group can be rewritten as follows,

\[
\frac{c'(e_i)(1 - \rho^l(e_i, M))}{\rho^l_{e_i}(e_i, M)} = \prod_{j=1}^{n} (1 - \rho^l(e_j, M))^{m_j} \frac{R}{M}, \forall i = 1, 2, \ldots, n.
\]

\[\blacksquare\]
Therefore, all the workers exert same effort levels as long as they enjoy the synergy from the entire group. The optimal solution for the effort, reward, and team size in this case is the same as that under the symmetric equilibrium. However, if there is no collaboration among the sub-groups of workers, then the group success rate will be different and there may exist asymmetric equilibrium among workers, which may be worthwhile for future research; however, it is not the focus of this chapter.

Our above discussion with regard to the aggregate reward policy assumes that the same synergy will be achieved under both individual and aggregate reward policies. However, these two policies may have different effects on pioneers’ motives to collaborate. Under the individual reward policy, a pioneer does not care about the success of other workers, so there may not exist such synergy as assumed in our model. In contrast, under the aggregate reward policy, all pioneers are induced to collaborate to achieve the team success, so the policy itself may motivate workers to collaborate and generate team synergy.

5.3.1.4 Alternative aggregate reward

Following upon our discussion between the differences of individual and aggregate reward policy, we propose an alternative aggregate reward policy which moderates the negative effects of both policies. Under this alternative policy, a pioneer will be rewarded only if she succeeds and the reward is related to the total number of successful pioneers. The more the number of successful pioneers, the higher the reward. In this respect, a pioneer will voluntarily collaborate with others to “help” others succeed. Hence, the team synergy can be clearly justified.

If a symmetric equilibrium is obtained, a pioneer’s total expected payoff is

\[ \pi_i = w_i - c(e) + \rho^i(e, M) \sum_{j=1}^{M} C_{M-1}^{j-1}(\rho^i)^j(1 - \rho^i)^{M-j}r_j, \]

where

\[ C_{M-1}^{j-1} = \frac{(M - 1)!}{(j - 1)!(M - j)!}. \]
\( \rho^I \) is the individual success rate of other \( M-1 \) workers, and \( r_j, \forall j = 1, \ldots, M \), is the reward which increases in \( j \), the total number of successful pioneers.

Therefore, the symmetric equilibrium can be attained when a worker assumes that all the others exert the same efforts and this effort can be represented as

\[
\frac{c'(e)}{\rho^I(e, M)} = \sum_{j=1}^{M} C^j_{M-1}(\rho^I(e, M))^j(1 - \rho^I(e, M))^{M-j}r_j. \tag{5.22}
\]

When applying this alternative reward policy, the firm achieves the total expected profit\(^1\) as

\[
\pi = -Mw_i - M\rho^I(e, M) \sum_{j=1}^{M} C^j_{M-1}(\rho^I)^j(1 - \rho^I)^{M-j}r_j + \rho^G B
\]

which suggests that the firm still achieves the same optimal profit and effort level \( e^\ast \) as the other two cases for the first-best solutions. The difference lies in the design of \( r_j \) rewards to induce workers to exert effort at \( e^\ast \), while satisfying the implementable conditions.

**Lemma 12.** The reward policy \( r_j, \forall j = 1, \ldots, M \), that satisfies the following condition

\[
\sum_{j=1}^{M} C^j_{M-1}(\rho^I(e, M))^j(1 - \rho^I(e, M))^{M-j}r_j = \frac{\rho^G(e, M)}{M\rho^I(e, M)}, \tag{5.23}
\]

can induce pioneers to exert the first-best efforts under the symmetric equilibrium.

**Proof.** The first-best effort satisfies \( Mc'(e) = \rho^G(e, M) \), which generates the above equation when combined with Equation (5.22). \( \blacksquare \)

The above equation is the generalized condition to reward successful researchers. The individual reward policy is actually the special case when all \( r_j \) are equal, \( \forall j = 1, \ldots, M \). The following proposition suggests that the \( r_j \) reward policy has the same implementable conditions as that of the individual reward policy.

---

\(^1\)This profit is for the workers’ efforts at the symmetric equilibrium.
Proposition 11. The reward policy \( r_j, \forall j = 1, \ldots, M \), that satisfies the condition in Equation 5.23 under the symmetric equilibrium, can be implemented under the same condition as that of individual reward policy.

Proof. If we use the \( R_j \) to represent the term on the right hand side of Equation 5.23, we can essentially regard this as the individual reward policy.

Therefore, the reward policy \( r_j \) can implement the firm’s first-best solution if the symmetric equilibrium can be achieved. According to the condition in Equation 5.23, \( r_j \) can be designed to increase in \( j \), the number of successful pioneers. One example is to let \( r_j \) linearly increase in \( j \), i.e., \( r_j = jr_0 \), so the condition in Equation 5.23 can be rewritten as

\[
\sum_{j=1}^{M} jC_{M-1}^{j-1}(\rho^I(e, M))^j(1 - \rho^I(e, M))^{M-j}r_0 = \frac{\rho^G(e, M)}{M\rho^I(e, M)},
\]

or

\[
r_0 = \frac{\rho^G(e, M)}{M^2\rho^I(e, M)\rho^I(e, M)}.
\]

Eventually, the reward \( r_j, \forall j = 1, \ldots, M \), can be obtained as

\[
r_j = \frac{j}{M} \cdot \frac{(1 - \rho(e))^q(M)}{[1 - (1 - \rho(e))^{\frac{M}{M-1}}(1 - \rho(e))^{\frac{M}{M-1}}]} = \frac{j}{M} \cdot \frac{1 - \rho^G}{\rho^I(1 - \rho^I)}.
\]

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<th>asymmetric equilibrium</th>
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<td>exogenous</td>
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<tr>
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<td>endogenous</td>
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<tr>
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<td>endogenous</td>
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Table 5.4. A comparison of three reward policies

However, this alternative reward policy is not without disadvantages. Our prior discussions are all based on its symmetric equilibrium, but an asymmetric equilibrium is also possible under this policy. Table 5.4 compares the three reward policies from three perspectives. Each policy has its advantages and disadvantages to be
taken into account when adopted to assemble a research team for innovation and knowledge discovery. Overall, the alternative aggregate reward policy outperforms the other two in both implementing the firm’s first-best solution and embedding the synergy within the team. However, the possible asymmetric equilibria is the spin-off when this policy is adopted. Hence, the firm has to balance the overall tradeoffs when determining which reward policy to implement.

5.3.2 Heterogeneous pioneers with individual reward

In this subsection, the firm’s optimal decision is studied when heterogeneous knowledge pioneers are available on the labor market. The analysis in previous subsection suggests that the individual reward policy is more likely to be implemented for the firm’s first-best solution than the aggregate team reward policy under some conditions. In addition, the individual reward policy is relatively more tractable while giving similar insights. Therefore, the following analysis for optimal incentives focuses on the individual reward policy for heterogeneous pioneers.

Considering two types of pioneers who incur different costs and achieve different success rates for the same effort levels, the firm offers two contracts \((w_1, r_1)\) and \((w_2, r_2)\) to induce the self selection of these two types of pioneers and achieve the maximal profit.

For each type of worker \(i\), her total expected payoff is

\[
\pi_i = w_i - c_i(e_i) + \rho I^i(e_i, M)r_i, \forall i = 1, 2.
\]

The firm’s total payoff is

\[
\pi = -M\delta w_1 - M(1 - \delta)w_2 - M\delta \rho I^1(e_1, M)r_1 - M(1 - \delta)\rho I^2(e_2, M)r_2 + \rho G(e, M)B.
\]

The firm’s decision problem can be described as to maximize the expected profit \(\pi\) by determining the appropriate team size \(M\) and designing the contracts \(w_i, r_i\) for both types \(i = 1, 2\), which can be mathematically formulated as

\[
\max_{w_i, r_i, M} \pi, \quad (5.24)
\]
subject to

\[ e_i = \arg\max_{\tilde{e}_i} \{ \pi_i(\tilde{e}_i) | w_i, r_i \}, \quad (5.25) \]

\[ \pi_i \geq U_r, \quad (5.26) \]

\[ \pi_i(w_i, r_i) \geq \pi_i(w_j, r_j), \quad (5.27) \]

\[ w_i \geq 0, \quad (5.28) \]

where Constraint (5.27) is to ensure that both types of pioneers will voluntarily select the contract specially designed for them.

Before proceeding to the formal analysis of optimal contracts for two types of pioneers, we first introduce the following lemma, which helps to establish the results in the subsequent subsection.

**Lemma 13.** Given the same individual reward \( r \), the high type always achieves the better individual success rate than the low type does, i.e., \( \rho_1(e_1) > \rho_2(e_2) \).

**Proof.** Given the individual reward \( r \), each type chooses her best effort level as,

\[ c_i^*(e_i) = \rho_i^I(e_i, M)r = \rho_i'(e_i) \frac{q(M)}{M} (1 - \rho_i(e_i))^{q(M)/M-1} r. \]

Therefore, we have

\[ \frac{c_1^*(e_1)/\rho_1'(e_1)}{c_2^*(e_2)/\rho_2'(e_2)} = \left[ \frac{1 - \rho_1(e_1)}{1 - \rho_2(e_2)} \right]^{q(M)/M-1}. \]

1) If \( \rho_1(e_1) < \rho_2(e_2) \), then the RHS is greater than 1, which suggests that \( e_1 > e_2 \) from the LHS. This is contradictory to the assumption that \( \rho_1(e_1) < \rho_2(e_2) \).

2) If \( \rho_1(e_1) = \rho_2(e_2) \), then the RHS equals one, which suggests that \( e_1 > e_2 \) from the LHS. This is contradictory to the assumption that \( \rho_1(e_1) = \rho_2(e_2) \).

This lemma indicates that if two types of pioneers are different in their cost and success rate functions, the high type always achieves the higher success rate than the low type even though she may exert less effort, given that the same rewards are offered to both type upon success.
5.3.2.1 Optimal incentives for a given team size

We first treat the innovation team size $M$ as a given parameter and analyze the firm’s optimal wages and rewards to achieve the separating equilibrium between two types of pioneers. Two slack variables, $\alpha_1$ and $\alpha_2$ ($\alpha_1, \alpha_2 \geq 0$), are introduced into the IC constraints (5.26) and an individual’s payoff function is transformed into

$$
\pi_i = w_i - c_i(e_i) + \rho^I(e_i, M)r_i = U_r + \alpha_i, \forall i = 1, 2.
$$

Hence, an individual’s wage payment can be always described as

$$
w_i = c_i(e_i) + U_r - \rho^I(e_i, M)r_i + \alpha_i,
$$

and the firm’s profit can be simplified as

$$
\pi = -M\delta[c_1(e_1) + \alpha_1 + U_r] - M(1 - \delta)[c_2(e_2) + \alpha_2 + U_r] + \rho^G(e, M)B.
$$

By introducing Lagrangian multipliers $\gamma_i$ and $\mu_i$ for constraints (5.27) and (5.28), we get the Lagrangian function as shown in Appendix B.11, and we next explore all the possible cases for feasible solutions as follows.

(1) $\mu_1 = \mu_2 = \gamma_1 = \gamma_2 = 0$

In this case, both IR constraints are binding and since $\gamma_1 = \gamma_2 = 0$, the following inequalities have to be satisfied to achieve the self-selection between two types,

$$
c_1(e_1(r_2)) - \rho^I(e_1(r_2), M)r_2 > c_2(e_2(r_2)) - \rho^I(e_2(r_2), M)r_2,
$$

$$
c_2(e_2(r_1)) - \rho^I(e_2(r_1), M)r_1 > c_1(e_1(r_1)) - \rho^I(e_1(r_1), M)r_1.
$$

These two conditions can be written as

$$
w_1(e_1^*(r_2)) > w_2(e_2^*(r_2)),
$$

$$
w_2(e_2^*(r_1)) > w_1(e_1^*(r_1)),
$$

where $w_i(e_i^*(r_j))$ is the optimal objective value for each type $i$ given the reward $r_j$ ($i, j = 1, 2$). $w_i(e_i^*(r_j))$ is a decreasing function of $r_j$. 
Suppose both workers have an equal and positive reservation utility $U_r$, then $w_1(e_1^*(r))$ and $w_2(e_2^*(r))$ only intersect at $r = 0$, where $w_1(e_1^*(0)) = w_2(e_2^*(0)) = U_r$, as the point $(0, U_r)$ shown in Figure 5.8. Therefore, it is impossible for the firm to offer two rewards $r_1$ and $r_2$ to satisfy both inequalities above because for any contracts offered on both types’ indifference curves with utility of $U_r$, high type always prefers low type’s contract.

Figure 5.8. Workers’ indifference curves for a fixed team: two types

(2) $\mu_1, \mu_2 > 0$, $\gamma_1 = \gamma_2 = 0$

In this case, the positive wage payment constraints are binding for both types, i.e., $c_1(e_1(r_1)) - \rho^{i_1}(e_1(r_1), M)r_1 = c_2(e_2(r_2)) - \rho^{i_2}(e_2(r_2), M)r_2 = -U_r$. Therefore, the effort levels and rewards are

$$\tilde{r}_i = \frac{c'_i(\tilde{e}_i)}{\rho^{i_1}(\tilde{e}_i, M)},$$

$$U_r = \rho^{i_1}(\tilde{e}_i, M)\tilde{r}_i - c_i(\tilde{e}_i), \forall i = 1, 2.$$

As shown in Figure 5.8, the contracts $(0, \tilde{r}_1)$ and $(0, \tilde{r}_2)$ cannot separate high type from low type because of the same reason as previous case, i.e., high type always prefers $(0, \tilde{r}_2)$.

(3) $\mu_1 = 0$, $\mu_2 > 0$, $(\gamma_1 = \gamma_2 = 0; \gamma_1 > 0, \gamma_2 = 0, \text{or} \gamma_1 = 0, \gamma_2 > 0)$

This case can be ruled out because it is never possible to separate two types if low type’s wage payment is always zero.

(4) $\mu_2 = 0$, $\mu_1 > 0$, $(\gamma_1 = \gamma_2 = 0; \text{or} \gamma_1 = 0, \gamma_2 > 0)$
This case can also be ruled out because it is never possible to separate two types by designing contracts to make low type be indifferent and high type strictly prefer her contract.

(5) \( \mu_1 = \mu_2 = \gamma_1 = 0, \gamma_2 > 0 \)

This implies that low type worker is indifferent between \((w_1, r_1)\) and \((w_2, r_2)\), and high type worker strictly prefer \((w_1, r_1)\) over \((w_2, r_2)\). Additionally, in this case, \( \partial L / \partial \alpha_1 < 0 \), therefore, \( \alpha_1 = 0 \), which means that the individual rationality constraint is binding for high type worker. However, it is impossible to offer \((w_1, r_1)\) on high type’s indifference curve while making high type strictly prefer \((w_1, r_1)\) over \((w_2, r_2)\) unless that low type can accept an offer with lower utility than her reservation utility \(U_r\).

(6) \( \mu_1 = \mu_2 = \gamma_2 = 0, \gamma_1 > 0 \)

This implies that high type worker is indifferent between \((w_1, r_1)\) and \((w_2, r_2)\), and low type worker strictly prefer \((w_2, r_2)\) over \((w_1, r_1)\). Additionally, in this case, \( \partial L / \partial \alpha_2 < 0 \), therefore, \( \alpha_2 = 0 \), which means that the individual rationality constraint is binding for low type worker. Hence, the only possible offers are \((w_2, r_2)\) as in Figure 5.8 for low type and \((w_1, r_1)\) for high type on her indifference curve with utility \(U_r + \alpha_1\), where \( \alpha_1 \) is the difference between the utility of high type at \((w_1, r_1)\) and the utility of low type at \((w_2, r_2)\). If low type is induced to work, exerting effort \(e_2 > 0\), the firm will have to offer additional utility \(\alpha_1\) to high type. The indifference curve of high type is within the shaded area in Figure 5.8. Hence, the following proposition can be naturally elicited.

**Proposition 12.** The separating equilibrium between two types of pioneers can be achieved by offering two contracts \((w_1, r_1)\) and \((w_2, r_2)\) for low and high type when high type worker is indifferent between \((w_1, r_1)\) and \((w_2, r_2)\), and low type worker strictly prefer \((w_2, r_2)\) over \((w_1, r_1)\). In addition, the low type’s individual rationality constraint is always binding, i.e., low type always gets her reservation utility \(U_r\), and high type will get the additional utility \(\alpha_1\). The additional utility of high type decreases when more people belong to high type within the team.

The firm’s profit can be simplified as

\[
\pi = -M\delta[c_1(e_1) + \alpha_1 + U_r] - M(1 - \delta)[c_2(e_2) + U_r] + \rho G(e, M)B,
\]
where $e_2$ is related to $\alpha_1$ and in particular, $\partial e_2 / \partial \alpha_1 > 0$. Therefore, the derivative of the firm’s profit with respect to $\alpha_1$ is
\[
\frac{\partial \pi}{\partial \alpha_1} = -M \delta + [\rho_{e_2}^G B - M(1 - \delta)c'_2(e_2)] \frac{\partial e_2}{\partial \alpha_1}.
\]

For $\alpha_1$ to be positive, it must be that $\rho_{e_2}^G B > M(1 - \delta)c'_2(e_2)$, which implies that $e_2$ is always less than the low type’s first-best effort, the effort when the firm can differentiate workers’ types and observe their efforts.

From the definition of $\alpha_1$, for the offer of $(w_2, r_2)$, high type obtains additional utility $\alpha_1$ than low type, that is,
\[
w_2 - c_1(e_1(r_2)) + \rho^{l_1}(e_1(r_2), M)r_2 = w_2 - c_2(e_2(r_2)) + \rho^{l_2}(e_2(r_2), M)r_2 + \alpha_1,
\]
which indicates that
\[
\frac{\partial r_2}{\partial \alpha_1} = \frac{1}{\rho^{l_1}(e_1(r_2), M) - \rho^{l_2}(e_2(r_2), M)} > 0.
\]

In addition, from the equation $c'_2(e_2) = \rho^{l_2}(e_2, M)r_2$, $\partial e_2 / \partial r_2$ can be obtained. Therefore, $e_1$ and $\alpha_1$ can be solved to maximize the firm’s profit $\pi$. Given $e_1$ and $\alpha_1$, $w_1$ and $r_1$ can be obtained, hence, the high type’s contract. The low type’s contract will be determined accordingly as long as the high type’s contract is fixed.

Both type’s contracts changes with the proportion $\delta$. (1) When $\delta \to 1$, $\rho_{e_2}^G B \to 0$, therefore, $\partial \pi / \partial \alpha_1 \to -M < 0$ and $\alpha_1 \to 0$. $e_2$ and $\alpha_1$ decrease. The high type worker’s indifferent curve converges to the position of dotted line in Figure 5.8, and low type’s contract to $(\hat{w}_2, \hat{r}_2)$. (2) When $\delta \to 0$, $\rho_{e_2}^G B \to M(1 - \delta)c'_2(e_2)$ because $\partial e_2 / \partial \alpha_1 \neq 0$. Therefore, $e_2$ and $\alpha_1$ increase. The high type worker’s indifferent curve converges to the position with the indifference utility of $U_r$, high type’s contract to $(\hat{w}_1, \hat{r}_1)$, and low type’s contract to $(U_r, 0)$.

Finally, we have to check whether the separating equilibrium is implementable as to whether the wage payments for both types are positive. The following proposition suggests that the necessary conditions for positive wage payments are always satisfied.
Proposition 13. It is always necessarily true that both types’ wage payments are positive under the feasible separating equilibrium.

Proof. Since $\mu_1 = \mu_2 = 0$, both wage payments must be positive, that is,

$$\begin{align*}
c_1(e_1(r_1)) - \rho^{f_1}(e_1(r_1), M)r_1 + \alpha_1 + U_r &> 0, \\
c_2(e_2(r_2)) - \rho^{f_2}(e_2(r_2), M)r_2 + U_r &> 0.
\end{align*}$$

Hence, the necessary condition for both the firm’s profit and workers’ wage payments to be positive is

$$M\delta\rho^{f_1}(e_1(r_1), M)r_1 + M(1-\delta)\rho^{f_2}(e_2(r_2), M)r_2 < \rho^G(e_1(r_1), e_2(r_2), M)B,$$

where

$$\begin{align*}
r_1 &= \frac{1 - \rho^G}{1 - \rho^{f_1}B}, \\
r_2 &< \frac{1 - \rho^G}{1 - \rho^{f_2}B}.
\end{align*}$$

From the proof in Proposition 7, the following inequalities always hold,

$$\rho^G \geq M\delta \frac{\rho^{f_1}}{1 - \rho^{f_1}}$$

and

$$\frac{\rho^G}{1 - \rho^G} \geq M(1 - \delta) \frac{\rho^{f_2}}{1 - \rho^{f_2}}.$$

In addition,

$$\frac{\rho^G}{1 - \rho^G} = \frac{1 - (1 - \rho^G)(1 - \rho^{f_2})}{(1 - \rho^{f_1})(1 - \rho^{f_2})} > \frac{\rho^{f_1}}{1 - \rho^{f_1}} + \frac{\rho^{f_2}}{1 - \rho^{f_2}},$$

therefore,

$$\rho^G B > M\delta \frac{(1 - \rho^G)\rho^{f_1}}{1 - \rho^{f_1}}B + M(1 - \delta) \frac{(1 - \rho^G)\rho^{f_2}}{1 - \rho^{f_2}}B$$

$$> M\delta \rho^{f_1} r_1 + M(1 - \delta) \rho^{f_2} r_2. \quad \blacksquare$$

(7) $\mu_2 = 0, \mu_1 > 0, \gamma_2 = 0, \gamma_1 > 0$

In this case, the firm offers a contract $(0, r_1)$ for high type, where $\tilde{r}_1 < r_1 < \bar{r}_1$, and $(w_2, r_2)$ for low type as in previous case.
Since $\mu_1 > 0$ and $\mu_2 = 0$,
\[
\begin{align*}
    c_1(e_1(r_1)) - \rho^{j_1}(e_1(r_1), M)r_1 + \alpha_1 + U_r &= 0, \\
    c_2(e_2(r_2)) - \rho^{j_2}(e_2(r_2), M)r_2 + U_r &> 0.
\end{align*}
\]

The sufficient condition for $\mu_1 > 0$ is $\rho e_1^G B \geq M\delta c_1'(e_1)$ at the contract $(0, \tilde{r}_1)$, which implies that the firm’s optimal substitution rate for high type have no intersection with high type’s indifference curve.

In summary, only the last two cases, (6) and (7), are possible for a feasible separating equilibrium, where high type worker is indifferent between her contract and low type’s contract and low type worker strictly prefer her contract over high type’s contract. In some situations, the firm will not be able to offer a positive wage payment to the high type in order to achieve the separating equilibrium, which implies that the firm has to lose some profit by not being able to implement the positive wage payment on the high type pioneer.

5.3.2.2 Optimal team size

Following upon the analysis in previous subsection, we treat the team size as the decision variable and discuss the how to choose an optimal size of innovation team. First, we compare the optimal team size when all the pioneers belong to one type, either high or low type.

**Proposition 14.** When all the workers are in the same type, the optimal team size of all the workers belong to high type $\geq$ that of all the workers belonging to low type, when

\[
\begin{align*}
    \frac{c_1(\hat{e}_1)}{-\ln(1 - \rho_1(\hat{e}_1))} &\geq \frac{c_2(\hat{e}_2)}{-\ln(1 - \rho_2(\hat{e}_2))}.
\end{align*}
\]

**Proof.** If M is not fixed, but a decision variable, the first order conditions of the firm’s profit show that

\[
\begin{align*}
    M\delta &= [\rho e_2^G B - M(1 - \delta)c_2'(e_2)] \frac{\partial e_2}{\partial \alpha_1}, \\
    \rho e_2^G B &= \delta[c_1(e_1) + \alpha_1] + (1 - \delta)c_2(e_2) + U_r,
\end{align*}
\]
\[ \rho^G_{e_1} B = M \delta c'_1(e_1), \]

which indicates that

\[
\frac{q'(M)M}{q(M)} = \frac{\rho'_1(e_1)}{c'_1(e_1)(1 - \rho_1(e_1))} \cdot \frac{\delta[c_1(e_1) + \alpha_1] + (1 - \delta)c_2(e_2) + U_r}{-\delta ln(1 - \rho_1(e_1)) - (1 - \delta)ln(1 - \rho_2(e_2))}.
\]

where the RHS decreases in \( \delta \) if

\[
\frac{c_1(e_1) + \alpha_1}{-\ln(1 - \rho_1(e_1))} < \frac{c_2(e_2)}{-\ln(1 - \rho_2(e_2))}.
\]

When \( \delta \to 1 \), all the workers tend to belong to high type, \( \alpha_1 \to 0 \), hence,

\[
\frac{q'(M)M}{q(M)} \to \frac{q'(M_1)M_1}{q(M_1)} = \frac{c_1(\hat{e}_1) + U_r}{c'_1(\hat{e}_1)} \cdot \frac{\rho'_1(\hat{e}_1)}{-(1 - \rho_1(\hat{e}_1))ln(1 - \rho_1(\hat{e}_1))},
\]

and when \( \delta \to 0 \), all the workers tend to belong to low type,

\[
\frac{q'(M)M}{q(M)} \to \frac{q'(M_2)M_2}{q(M_2)} = \frac{c_2(\hat{e}_2) + U_r}{c'_2(\hat{e}_2)} \cdot \frac{\rho'_2(\hat{e}_2)}{-(1 - \rho_2(\hat{e}_2))ln(1 - \rho_2(\hat{e}_2))},
\]

where \( \hat{e}_1 \) and \( \hat{e}_2 \) are the best effort levels for high or low type when all the workers belong to high or low type.

Therefore, \( M_1 \geq M_2 \), when

\[
\frac{c_1(\hat{e}_1)}{-\ln(1 - \rho_1(\hat{e}_1))} \leq \frac{c_2(\hat{e}_2)}{-\ln(1 - \rho_2(\hat{e}_2))}.
\]

The implication for the above inequality is whether it is better to hire one more high type or low type worker given the current team size. Because we know that, given the proportion \( \delta \),

\[
\frac{c_1(\hat{e}_1)}{-\ln(1 - \rho^G_{e_1}(\hat{e}_1))} \leq \frac{c_2(\hat{e}_2)}{-\ln(1 - \rho^G_{e_1}(\hat{e}_2))},
\]

is equivalent to

\[
\frac{c_1(\hat{e}_1)}{-(1 - \rho^G_{e_2})ln(1 - \rho_1(\hat{e}_1))} \leq \frac{c_2(\hat{e}_2)}{-(1 - \rho^G_{e_2})ln(1 - \rho_2(\hat{e}_2))}.\]
where, the team success rate elasticity of cost for type \( i \)

\[
\varepsilon(\hat{e}_i) = \frac{c_1(\hat{e}_i)}{-(1 - \rho^2)\ln(1 - \rho_1(\hat{e}_i))},
\]

is the ratio of marginal cost to the marginal team success rate when the firm hire
one more worker of type \( i \). Therefore, in the first best case, when \( \varepsilon(\hat{e}_1) > \varepsilon(\hat{e}_2) \),
it is cheaper to hire the low type, the firm will decrease the team size when more
workers belong to high type (when \( \delta \) increases). In contrast, when \( \varepsilon(\hat{e}_1) < \varepsilon(\hat{e}_2) \),
it is cheaper to hire the high type, the firm will increase the team size when more
workers belong to high type. When types are not differentiable and efforts not
observable, additional utility \( \alpha_1 \) has to be offered to high type to achieve separating
equilibrium between two types. Hence, \( \varepsilon(e_1) \) may be greater than, equal to, or less
than \( \varepsilon(e_2) \) when more workers belong to high type because the additional utility
\( \alpha_1 \) decreases in \( \delta \). The following proposition reveals the lower and upper bound
for an optimal team size by using the optimal team size for single type workers.

**Proposition 15.** The optimal team size \( M \) is: (1) \( M_1 \leq M \leq \bar{M} \) when \( \bar{M} \geq M_2 \);
(2) \( \bar{M} \leq M \leq M_1 \) when \( \bar{M} \leq M_2 \), where \( \bar{M} \) is the team size when \( \delta = \bar{\delta} \) such that

\[
\frac{c_1(e_1) + \alpha_1}{-\ln(1 - \rho_1(e_1))} = \frac{c_2(e_2)}{-\ln(1 - \rho_2(e_2))}.
\]

**Proof.** When

\[
\frac{c_1(\hat{e}_1)}{-\ln(1 - \rho_1(\hat{e}_1))} > \frac{c_2(\hat{e}_2)}{-\ln(1 - \rho_2(\hat{e}_2))},
\]

since \( e_1 > \hat{e}_1 \), \( e_2 < \hat{e}_2 \), and \( \alpha_1 > 0 \), when \( \delta \) increase from 0 to 1, it may first

\[
\frac{c_1(e_1) + \alpha_1}{-\ln(1 - \rho_1(e_1))} < \frac{c_2(e_2)}{-\ln(1 - \rho_2(e_2))},
\]

and then

\[
\frac{c_1(e_1) + \alpha_1}{-\ln(1 - \rho_1(e_1))} > \frac{c_2(e_2)}{-\ln(1 - \rho_2(e_2))}.
\]

Therefore, \( M \) may first increase from \( M_2 \) and then decrease to \( M_1 \), or \( M \) may
directly decrease from $M_2$ to $M_1$ as shown in Figure 5.9.

![Figure 5.9. M vs $\delta$: $M_2 > M_1$](image1)

![Figure 5.10. M vs $\delta$: $M_2 < M_1$](image2)

Similarly, when

$$\frac{c_1(\hat{e}_1)}{-\ln(1 - \rho_1(\hat{e}_1))} < \frac{c_2(\hat{e}_2)}{-\ln(1 - \rho_2(\hat{e}_2))},$$

$M$ may first decrease from $M_2$ and then increase to $M_1$, or $M$ may directly increase from $M_2$ to $M_1$ as shown in Figure 5.10.

The optimal team sizes when all the pioneers belong to either high or low type can be used as the approximate upper or lower bound for the firm to estimate the best team size.

### 5.4 Optimal Incentives for Knowledge Discovery and Diffusion

Given the detailed analysis on optimal incentives for knowledge discovery, we next investigate the optimal incentives when taking into account knowledge diffusion.

**Lemma 14.** The learning participation constraint is binding for the firm’s optimal decision.

**Proof.** For IWR policy, by rearranging the terms in profit function, we get

$$\pi = (N - M + \beta N)(x_L - w_p(x_L)) - \beta \sum_{j=1}^{M} j p_p^M r$$
\[-M w + \beta N \rho^G(E, M)(x_H - w_p(x_H)) - (x_L - w_p(x_L))\],

where \( w = c(e) - \beta(c_l - c_s) + \beta(w_p(x_H) - c_l) - \beta(1 - \rho^I(e, M))p_{\eta=0}^{M-1}[w_p(x_H) - w_p(x_L) - c_l] \). We assume there exists the optimal solution where the constraint (5.2) is not binding and let \( \tilde{w}_p(x_H) - \tilde{w}_p(x_L) = c_l + \sigma(\sigma > 0) \). We keep the other decision variables \( M \) and \( r \) unchanged and adjust the wage contracts to make Constraint (5.2) binding such that \( w_p(x_H) - w_p(x_L) = c_l \). Then,

\[ \pi(\tilde{w}_p) - \pi(w_p) = \beta M \sigma(1 - p_{\eta=0}^M) - \beta N(\sigma + c_l)(1 - p_{\eta=0}^M) < 0. \]

The above equation uses the property that both \( \tilde{w}_p(x_L) \) and \( w_p(x_L) \) equals zero when the firm maximizes its profit while satisfying knowledge executor’s IR constraint. Therefore, \( \pi(\tilde{w}_p) < \pi(w_p) \), which contradicts our assumption. 

The binding learning constraint implies that optimal solutions require that knowledge executors be indifferent in whether or not to learn new technologies to improve productivity because they get same expected payoffs under both options. Following Lemma 14, the wage payment for production can be obtained as \( w_p(x_L) = 0 \) and \( w_p(x_H) = c_l \), which indicates that the firm should offer knowledge executors their reservation utilities as the wage payment for production with old technology and reservation utility plus learning cost for production with adoption of new discovery.

### 5.4.1 Knowledge diffusion from independent knowledge pioneers

In this section, we consider that the firm hires independent knowledge pioneers who continuously engage in innovation in each period and will not return to production positions in the second period.

#### I. Only Learning Cost

If there is no sharing cost when successful pioneers disseminate their knowledge to other workers, since both IR constraints are binding as well, the firm’s profit can be reorganized as

\[ \pi = N(1 + \beta)(x_L - w_p(x_L)) - Mc(e) + \beta \rho^G(e, M)N(x_H - x_L - c_l(T)), \]
where \( N(1 + \beta)(x_L - w_p(x_L)) \) is the firm’s total payoff in two period without engaging in innovation and \( N(x_H - x_L - c_l(T)) \) is the total benefit of innovation for the second period, which is the same as \( B \) in §5.3. Therefore, if we define \( B \) as \( N(x_H - x_L - c_l(T)) \), we will get the same solution for team size \( M \) and reward \( r \).

In the other scenarios as aggregate reward policy, two types of researchers can be analyzed in the exactly same fashion as that in §5.3.

II. Both Sharing and Learning Costs

In this case, pioneers have to incur sharing costs \( c_s \) to diffuse their successful discoveries to knowledge executors. Hence, under the individual reward policy, a pioneer’s payoff is

\[
\pi_p = w - c(e) + \beta r^I(e, M)(r - c_s(T)),
\]

subject to the individual rationality constraint \( \pi_p \geq U_p \) and the discovery retention constraint \( r - c_s(T) \geq U_d \). Next proposition suggests that the solution to the optimal team size in §5.4.1 is a lower bound for that case when there exist both sharing and learning costs for knowledge diffusion.

**Proposition 16.** The firm will assemble a larger innovation team and induce pioneers to exert more efforts when there exist both sharing and learning costs during knowledge diffusion.

**Proof.** In this case, the firm’s payoff will be

\[
\pi = N(x_L - w_p(x_L)) - M w - M \beta \rho^I(e, M)r + \beta N \rho^G(e, M)(x_H - w_p(x_H)) \\
+ \beta N(1 - \rho^G(e, M))(x_L - w_p(x_L)) \\
= N(1 + \beta)(x_L - w_p(x_L)) - M(c(e) + \beta r^I(e, M)c_s(T)) \\
+ \beta \rho^G(e, M)N(x_H - x_L - c_l(T)),
\]

whose first order conditions yield

\[
M(c'(e) + \beta \rho^I(e, M)c_s(T)) = \rho^G(e, M)B,
\]
\[
c(e) + \beta \rho^I(e, M)c_s(T) + \beta M \rho^I_M(e, M)c_s(T) = \rho^G_M(e, M)B,
\]

where \( B \) is the benefit of innovation \( N(x_H - x_L - c_l(T)) \).
The first equation implies that the firm has to induce an effort level such that the marginal benefit for pioneers exerting efforts is greater than that of marginal cost for the case with no sharing cost, i.e., $\rho_e^G(e, M)B > M c'(e)$. Therefore, the effort level should increase when there exits sharing cost. Similarly, the second equation implies that the firm has to choose a team size such that the marginal benefit for the team size is greater than its marginal cost for the case with no sharing cost, i.e., $\rho^G_M(e, M)B > c(e)$, which is only true when the team size increases beyond the optimal $M^*$ with no sharing cost. ■

Notice that investment in IT can increase the IT level $T$ and reduce the second term on the LHS so that actual team size can converge to that without sharing cost. Therefore, there exists the tradeoff between IT investment and research team size when both sharing and learning are costly during the knowledge diffusion process, which will be discussed in detail in §5.4.3.

5.4.2 Knowledge diffusion from temporary knowledge pioneers

As our model formulation in §5.1 shows, if the firm just wants to temporarily assemble the innovation team from inside, $M$ workers will be assigned to innovation in the first period for research purpose and return to their routine production positions in the second period. In this case, knowledge pioneers have to incur learning costs to adopt potential discoveries as other knowledge executors do if they are unsuccessful in innovation.

**Proposition 17.** When the firm assembles the temporary innovation team, the optimal team size and effort level under the individual reward policy remain unchanged when $c_s(T) = c_l(T)$, increase when $c_s(T) > c_l(T)$, and decrease when $c_s(T) < c_l(T)$.

**Proof.** Under the individual reward policy, a knowledge pioneer’s payoff is

$$\pi_p = w - c(e) + \beta \rho^I(e, M)(r - c_s(T) + w_p(x_H)) + \beta (1 - \rho^I(e, M))[p_{\eta=0}^{M-1}w_p(x_L) + (1 - p_{\eta=0}^{M-1})(w_p(x_H) - c_l(T))],$$
Since the learning participation constraint is binding, the above payoff is
\[ \pi_r = w - c(e) + \beta \rho^I(e, M)(r - c_s(T) + c_l(T)), \]
where an individual’s effort level can be determined by
\[ \frac{c(e)}{\beta \rho^I_c(e, M)} = r - c_s(T) + c_l(T). \]

Accordingly, the firm’s payoff will be
\[ \pi = N(x_L - w_p(x_L)) - M w - M \beta \rho^I(e, M)r + \beta N \rho^G(e, M)(x_H - w_p(x_H)) + \beta N (1 - \rho^G(e, M))(x_L - w_p(x_L)) = N(1 + \beta)(x_L - w_p(x_L)) - M[c(e) + \beta \rho^I(e, M)(c_s(T) - c_l(T))] + \beta \rho^G(e, M) N (x_H - x_L - c_l(T)). \]

First order conditions:
\[ M[c(e) + \beta \rho^I_c(e, M)(c_s(T) - c_l(T))] = \rho^G_c(e, M)B, \]
\[ c(e) + \rho^I(e, M)(c_s(T) - c_l(T)) + \beta M \rho^I_M(e, M)(c_s(T) - c_l(T)) = \rho^G_M(e, M)B, \]
where \( B \) is the benefit of innovation \( N(x_H - x_L - c_l(T)). \)

Hence, the optimal \( M \) and \( e \) remain unchanged when \( c_s(T) = c_l(T), \) increase when \( c_s(T) > c_l(T), \) and decrease when \( c_s(T) < c_l(T). \)

The above proposition indicates how the optimal team size and effort level may change when temporary researchers have to return to production positions. These changes vary with workers’ sharing and learning cost of knowledge discovery. Investment in IT can increase the IT level \( T \) and reduce workers sharing and learning costs so that actually team size may converge to that case without sharing cost, which is discussed in its detail in the following subsection.

5.4.3 Impact of Information Technology
The impact of information technology on the optimal organizational decisions is investigated in this subsection. When the level of information systems increases,
costs of knowledge sharing and learning will be reduced. Based on this assumption, we study how this reduction of knowledge-transfer costs affects knowledge workers’ wage contracts, wage payments for knowledge innovation, and innovation effort in equilibrium. The following proposition first illustrates the influence of information technology on production workers’ wage payments.

**Proposition 18.** When the level $T$ of information systems utilized in knowledge transfer increases, knowledge workers’ production wage for a high output decreases.

**Proof.** When $T$ increases, $c_l$ decreases, consequently,

$$\frac{\partial w_p^*(x_H)}{\partial T} = \frac{\partial c_l}{\partial T} < 0.$$  

The learning participation constraint is binding and the reservation utility $U_e$ for production is zero, so the firm makes the contract so that a worker’s expected payoff in production by applying current technology equals $U_e$ and a worker’s expected payoff in production by applying new technology is reflected by the learning cost ($c_l = w_p(x_H)$). Therefore, when the firm makes investment in information technology to increase its level of information systems in knowledge transfer, it will be easier for workers to learn, resulting in a lower compensation for production with the new technology. However, a worker’s totaly expected payoff in two periods remains unchanged.

We next analyze the impact of information technology on other organizational decisions. Suppose that there exists such a level $\tilde{T}$ of information systems such that $c_s(\tilde{T}) = c_l(\tilde{T})$, then Table 5.5 summarizes how the solution to $M$ (when there exist both sharing and learning costs in knowledge diffusion) is related to the optimal solution $M^*$ in §5.4.1 as $T$ varies.

If the IT level happens to be $\tilde{T}$, then the increased payment for adoption of

<table>
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<tr>
<td>$T = \tilde{T}$</td>
<td>same solution to $M^*$</td>
<td></td>
</tr>
</tbody>
</table>

**Table 5.5.** The effect of $T$ on the team size
new discovery exactly compensates the sharing costs at this IT level, therefore, the firm assigns the optimal innovation team size as that when there is no sharing cost for knowledge diffusion. If the firm applies two information systems for learning and sharing, respectively, then the firm can always adjust the IT levels of these two systems separately to let the adoption cost equal the sharing cost.

If the actual IT level is lower or higher than $\tilde{T}$, then the optimal team size $M^*$ without sharing cost can be either a lower or an upper bound, which depends on how the sharing and learning costs change in the IT level $T$. As implied in Table 5.5, when the sharing cost decreases faster than the learning cost ([1] and [3]), investing more in IT to increase the IT level enables the firm to assemble a smaller innovation team. In contrast, when the learning cost decreases faster than the sharing cost ([2] and [4]), a higher IT level requires the firm to assemble a larger innovation team for knowledge discovery. Therefore, when the potential knowledge discovery is easier to be adopted than diffused, the firm does not have to invest so much in IT to maintain an innovation team of the same size.

5.5 Summary

The increasingly fierce competition has demanded companies to seek more cost-effective ways to engage in R&D. Investing appropriately in R&D and then internally disseminating knowledge discovery has become critical to maintain a sustainable development. This chapter helps us to understand how incentives affect organizational decisions on knowledge creation, retention, and diffusion within organizations and how information technologies influence these decisions by reducing knowledge-transfer costs. The analysis in this chapter provides valuable insights for managers to choose the best team size for knowledge discovery, determine appropriate level of rewards, and make proper IT investments to achieve optimal organizational profits.
Chapter 6

Knowledge Market Signalling in Firms

Applying knowledge market principles in facilitating knowledge sharing and learning has recently emerged as another effective knowledge management practice. Creating and maintaining a successful knowledge market requires the firm to allow the trade of distinctive knowledge, provide an exchange mechanism, keep up competition, and develop standards, protocols, and regulators for both knowledge buyers and sellers [53]. The idea of maintaining a knowledge market to manage internal knowledge assets is relatively new for business practice. However, among those that have fully adopted the concept, there are quite a few successful examples. Siemens Medical Solutions, a North Carolina based company, uses bonus points in combination with technological assistance to promote knowledge-sharing culture [25]. To support an environment amiable to knowledge sharing, the company built three web-based knowledge management tools to provide employees support in collecting and sharing useful information within the company. To motivate employees to take advantage of these three tools, the company offers employees bonus points each time they participate in knowledge sharing and learning activities. Bonus points can be used to purchase T-shirts and vacation packages. In this way, employees are incented to constantly apply knowledge-sharing tools in their daily works.

Despite the emerging importance of knowledge market and demonstrated success of business practices, the joint role of incentives and information systems for
internal knowledge markets is not well understood. This chapter addresses this gap by studying how internal knowledge markets benefit firms in enabling knowledge sharing and learning. Based on business practice, we model an internal knowledge market as a marketplace where knowledge providers can signal their knowledge and learners acquire the knowledge from providers. Specifically, we study how the firm can design the reward structures for workers participating in the internal knowledge market and what the influence of trust is on knowledge providers’ signalling decisions within the knowledge market. In addition, we investigate the necessary support of information systems for this internal knowledge market to improve knowledge providers’ trust.

The rest of the chapter is organized as follows. Next section presents the model of internal knowledge market. §6.2 details our analysis and discussion. §6.3 summarizes the chapter.

6.1 The Model of Internal Knowledge Market

In this section, we propose an analytical model to study how to induce knowledge diffusion through an incentive structure for sharing knowledge and learning. We first outline the setting of the internal knowledge market and then analyze the model of signals and threshold functions on the internal knowledge market.

6.1.1 Internal Knowledge Market

The pricing system of knowledge market within organizations consists of four critical components: 
\textit{reciprocity}, \textit{repute}, \textit{altruism}, and \textit{trust} [20]. In addition, knowledge within organization has the distinctive features: (1) knowledge is resalable; and (2) knowledge has no real price tag. Based on these unique properties of knowledge within organizations, the internal knowledge market is described as follows.

The internal knowledge market is considered as a marketplace where knowledge workers can post advertisements, or \textit{signals}, of their knowledge so that potential learners can judge the value of the knowledge from their own interests. Knowledge providers spend time and efforts in explicating their knowledge components and
condensing them into signals to be posted on the internal knowledge market. As mentioned above, workers may share their knowledge out of altruism, but in our model each individual is regarded as self-interested and participates in the knowledge market only by pursuing some benefits such as reciprocity, reputation, or monetary reward. If we assume that all the benefits, both tangible and intangible, of sharing knowledge can be represented as a single monetary reward offered by the firm, then the motivation for workers to signal and share knowledge on the internal knowledge market is simply to obtain the reward.

To protect knowledge providers’ property rights and ensure high-quality knowledge transfer, only those workers whose valuable knowledge is eventually acquired by learners and reported will be rewarded by the firm. In this way, the firm can track the knowledge flow from providers and recipients, inhibiting the recipients to resell the knowledge. However, in some circumstances, learners will not voluntarily report their learning to the firm. For instance, a worker may not be willing to admit learning from her subordinates for fear of losing her reputation and authority among subordinates. In addition, when there exists competition among knowledge workers, workers may intentionally not report their learning from other workers. Therefore, the trust of voluntary learning report from potential knowledge recipients is critical in the development and functioning of the internal knowledge market. Without the necessary trust, knowledge providers will not have the motivation to send signals and share their knowledge on the market. We discuss how the firm can improve this trust by designing appropriate reward structures and investing in IT in this chapter.

6.1.2 Knowledge Signalling and Threshold Functions

Suppose that each worker \( i \) in the firm has certain knowledge \( k_i \) which is unique and may be valuable to other workers. Individual’s knowledge level is not observable, but a probability distribution \( \Theta(k) \) about workers’ knowledge level is known to the firm and all the workers. A worker \( i \) makes effort \( e_i \) in documenting her knowledge so that it can be acquired by other workers from the internal knowledge market. In addition, to attract the attention of other workers, a label has to be made and attached on the knowledge \( k_i \) to describe its content. A label \( s_i \) is regarded as the
Table 6.1. Summary of Notation: the model of knowledge market signalling

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>$\alpha(k_j)$</td>
<td>signal active threshold function</td>
</tr>
<tr>
<td>$\beta(k_j)$</td>
<td>signal expiring threshold function</td>
</tr>
<tr>
<td>$B$</td>
<td>benefit of knowledge transfer</td>
</tr>
<tr>
<td>$c_i(s_i, k_i)$</td>
<td>cost of signalling for worker $i$</td>
</tr>
<tr>
<td>$k_i$</td>
<td>worker $i$’s knowledge level</td>
</tr>
<tr>
<td>$k_{\alpha j}$</td>
<td>worker $j$’s active threshold knowledge level</td>
</tr>
<tr>
<td>$k_{\beta j}$</td>
<td>worker $j$’s expiring threshold knowledge level</td>
</tr>
<tr>
<td>$k_{l j}$</td>
<td>worker $j$’s learning inhibition threshold knowledge level</td>
</tr>
<tr>
<td>$L(k_j)$</td>
<td>learning inhibition cost function</td>
</tr>
<tr>
<td>$p(s_i, k_j)$</td>
<td>p.d.f. of worker $j$ learning $k_i$ given the signal $s_i$</td>
</tr>
<tr>
<td>$P(s_i, k_j)$</td>
<td>probability of worker $j$ learning $k_i$ given the signal $s_i$</td>
</tr>
<tr>
<td>$r_l$</td>
<td>learning reward</td>
</tr>
<tr>
<td>$r_s$</td>
<td>sharing reward</td>
</tr>
<tr>
<td>$s_i$</td>
<td>worker $i$’s signal of her knowledge $k_i$</td>
</tr>
<tr>
<td>$\theta(k_i)$</td>
<td>p.d.f. of worker $i$’s knowledge level</td>
</tr>
<tr>
<td>$V(q_2)$</td>
<td>IT investment with $q_2$ probability of monitoring learning</td>
</tr>
<tr>
<td>$w_i$</td>
<td>participation reward for signalling</td>
</tr>
</tbody>
</table>

signal of the value of knowledge $k_i$. Different workers have different valuations on knowledge $k_i$ based on their own knowledge levels.

When a signal $s_i$ of knowledge $k_i$ is observed on the market place, the following possibilities arise: 1) Signal strength is too weak and the knowledge $k_i$ represented by it cannot be evaluated; 2) Signal strength is too strong so that people know the value of $k_i$ directly without having to acquire it; 3) Signal strength is appropriate and people learn knowledge $k_i$, find it valuable, and report learning; and 4) Signal strength is appropriate and people learn knowledge $k_i$, find it not useful, and will not report learning.

Therefore, knowledge sharing will be rewarded only when it is valuable to other workers. Workers with knowledge of low quality will be inhibited to signal on the knowledge market, whereas workers with knowledge of high quality will be induced to signal by the firm’s sharing reward. The following function is used to denote the probability of learning knowledge $k_i$ by worker $j$ with knowledge level $k_j$ given the signal of $k_i$ as $s_i$,

$$P(k_j, s_i) = \int_0^{s_i} p(k_j, s) ds,$$
where \( p(k_j, s) \) is the probability density function of worker \( j \) learning knowledge \( k_i \), given its signal as \( s \),

\[
p(k_j, s) = \begin{cases} 
0 & s < \alpha(k_j), \\
\gamma(k_j, s) & \alpha(k_j) \leq s \leq \beta(k_j), \\
0 & s > \beta(k_j).
\end{cases}
\]

\( \gamma(k_j, s) \) represents the relationship between \( k_j \) and \( s \). \( \alpha(k_j) \) is regarded as the signal active threshold function and \( \beta(k_j) \) as the signal expiring threshold function for worker \( j \). When worker \( j \) has a higher knowledge level \( k_j \), both \( \alpha(k_j) \) and \( \beta(k_j) \) shifts to the right on the \( x \) axis. However, the rate for this shift increases for \( \alpha(k_j) \) but decreases for \( \beta(k_j) \), which implies that if worker \( j \) has a higher knowledge level, worker \( i \) needs to send a stronger signal \( s \) to arouse her interest to learn \( k_i \).

Our construction of these two threshold functions stems from the effectiveness of advertising as well as the nature of knowledge as experience good. Because the value of knowledge can only be judged after its acquisition, a potential knowledge user will only determine whether or not to acquire the knowledge from its advertisement, the signal. The knowledge signal in our model is represented as the partial disclosure of the knowledge, for instance, a list of bullets describing the facts, information, and usefulness contained in the knowledge body (which can be a collection of documents). The strength of knowledge signal results in different actions from potential knowledge users. If the knowledge signal is too weak, or only a small portion of the knowledge is displayed, knowledge users cannot appropriately assess the value of the knowledge; therefore, the knowledge being signalled will not be acquired. In contrast, if the knowledge signal is too strong, or the majority of the knowledge is disclosed, knowledge users can judge its value from learning the signal without acquiring the entire knowledge body. We assume that if a knowledge user can learn from the signal, she will not bother to report this learning to the firm which is costly and requires additional time and effort. Therefore, knowledge providers will not know how many users have actually acquired the knowledge, or signal, in this case because it will not be reported. Hence, knowledge providers refrain from sending out too strong signals. Only when the signal strength is appropriate, i.e., between the two threshold functions, can knowl-
edge providers expect to have their knowledge acquired and learning reported. In this case, potential knowledge users have to contact the providers for knowledge acquisition, so there will exist evidence for the knowledge transfer from providers to users.

Based on the varieties of threshold functions $\alpha(k_j)$ and $\beta(k_j)$, three types of knowledge workers may be differentiated as follows.

**Knowledge Connoisseur**: knowledge experts in their fields with high signal active threshold function and signal expiring threshold function.

**Knowledge Public**: general knowledge workers with relative low signal active threshold function and high signal expiring threshold function.

**Knowledge Superficialist**: knowledge workers with relative low signal active threshold function and signal expiring threshold function.

In this paper, the uniform distribution is considered as shown in Figure 6.1,

$$p(k_j, s) = \begin{cases} 
0 & s < \alpha(k_j), \\
1/k_j & \alpha(k_j) \leq s \leq \beta(k_j), \\
0 & s > \beta(k_j), 
\end{cases}$$

where $\alpha(k_j)$ convexly and $\beta(k_j)$ concavely increases in $k_j$.

![Figure 6.1](image.png)

**Figure 6.1.** The probability density function of uniform distribution

Then, the probability of worker $j$ learning knowledge $k_i$ given the signal as $s_i$.
is

\[ p_{ij} = P(k_j, s_i) = \begin{cases} 
0 & 0 < s_i < \alpha(k_j), \\
\frac{s_i - \alpha(k_j)}{k_j} & \alpha(k_j) \leq s_i \leq \beta(k_j), \\
\frac{\beta(k_j) - \alpha(k_j)}{k_j} & s_i > \beta(k_j).
\end{cases} \]

A knowledge worker’s total payoff is her expected reward less the cost of signalling on the knowledge market and the firm’s total payoff is the expected benefit of knowledge transfer less the total expected reward given knowledge providers’ signalling strategy. In terms of rewards, three types are considered and analyzed during the knowledge transfer processes.

**Participation reward** \( w_i \): a worker gets the reward \( w_i \) by signalling her knowledge \( k_i \).

**Sharing reward** \( r_s \): a worker gets the reward \( r_s \) by sharing her knowledge with other workers.

**Learning reward** \( r_l \): a worker gets the reward \( r_l \) by learning knowledge from other workers.

### 6.2 Analysis and Discussion

The optimal design of reward structures is shown in this section. We analyze a potential knowledge provider’s best signalling strategy and the firm’s optimal designs of rewards with or without trust. The trust referred here is a knowledge provider’s belief that learners will always report their learning to the firm when they acquire the knowledge so that the provider may obtain the benefit, the sharing reward, from the firm.

#### 6.2.1 Signalling with Trust

When a knowledge provider is assured with complete trust from her potential learners, she will signal her knowledge level based on the rewards provided by the firm. We first show individual’s best signal function for given rewards and then discuss the firm’s optimal design of reward structures.
6.2.1.1 Individual’s signal function

For a specific worker \( j \) with knowledge level \( k_j \), worker \( i \) will send out her signal \( s_i \) to maximize her payoff of \( P(k_j, s_i)r_s - c_i(k_i, s_i) \), expecting her knowledge will be learned from worker \( j \). With the representation of uniform distribution for \( P(k_j, s_i) \), the first order condition shows that

\[
\frac{r_s}{k_j} = \frac{\partial c_i(k_i, s_i^*)}{\partial s_i},
\]

which indicates that the optimal \( s_i^* \) increases in \( k_i \) but decreases in \( k_j \). If the recipient \( j \) of the signal \( s_i \) has a higher knowledge level, the probability for \( j \) to learn knowledge \( k_j \) after receiving the signal \( s_i \) will be lower; therefore, the optimal signal \( s_i \) decreases as well.

![Cost and benefit](image)

**Figure 6.2.** Worker \( i \)'s best signal \( s_i^* \) for a worker with knowledge \( k_j \)

Figure 6.2 intuitively demonstrates the cost and benefit of worker \( i \)'s signal for a potential recipient with knowledge level \( k_j \). As \( k_j \) increases, the straight line becomes flatter, resulting in less net benefit for signalling. When \( k_j \) keeps increasing to the position of the dashed line in the figure, there will be no net benefit for signalling. Therefore, worker \( i \) will not signal on the market if the recipient has a knowledge level \( k_j > \hat{k}_j \), where

\[
\frac{s_i^*(\hat{k}_j) - \alpha(\hat{k}_j)}{\hat{k}_j} = c_i(k_i, s_i^*(\hat{k}_j)).
\]

In addition, \( s_i^* \) has to be in the range between two signal threshold functions
\( \alpha(k_j) \) and \( \beta(k_j) \). Otherwise, worker \( i \) will take different actions for signalling \( s_i \), either sending no signal or sending the signal at the expiring threshold function \( \beta(k_j) \), that is,

\[
s_i = \begin{cases} 
0 & s_i^* < \alpha(k_j), \\
s_i^* & \alpha(k_j) \leq s_i^* \leq \beta(k_j), \\
\beta(k_j) & s_i^* > \beta(k_j). 
\end{cases}
\]

**Signal function**

![Diagram](image)

**Figure 6.3.** Threshold effects on worker’s choice of best signal

If the best signal \( s_i^* \) is so weak that it is less than the active threshold function \( \alpha(k_j) \), worker \( j \) will not have enough interest to learn \( k_i \). So worker \( i \) should not send any signals. If the best signal \( s_i^* \) is so strong that is greater than the expiring threshold function \( \beta(k_j) \), worker \( j \) will not learn \( k_j \) because she has obtained enough knowledge from the signal. Therefore, worker \( i \) should decrease the signal strength to \( \beta(k_j) \). However, for the actual signal to stay at \( \beta(k_j) \) when \( s_i^* > \beta(k_j) \), the net benefit for signalling has to be positive, which requires the sufficient condition \( \beta(k_j) \geq \tilde{s}_i(k_i, k_j) \). This condition will be satisfied if \( k_j^\beta < \tilde{k}_j^\beta \), or if the intersection \( A \) between curves \( s_i^* \) and \( \tilde{s}_i \) is below the curve \( \beta(k_j) \) as demonstrated in Figure 6.3, i.e., \( \beta(\tilde{k}_j) \geq s_i^*(k_i, \tilde{k}_j) = \tilde{s}_i(k_i, \tilde{k}_j) \). From Figure 6.2,

\[
\tilde{s}_i = \frac{k_i}{r_s} \cdot c_i(k_i, \tilde{s}_i) + \alpha(k_j).
\]  

(6.2)
Therefore, if the following condition holds,

$$\beta(\hat{k}_j) - \alpha(\hat{k}_j) \geq \frac{c_i(k_i, s_i^*(\hat{k}_j))}{\partial c_i/\partial s_i^*},$$  \hspace{1cm} (6.3)$$

worker $i$ will always send $\beta(k_j)$ when $s_i^* > \beta(k_j)$.

To explore the effect of active threshold $\alpha(k_j)$, we compare the threshold knowledge level $k_{j}^{\alpha}$, where $s_i^*(k_i, k_{j}^{\alpha}) = \alpha(k_{j}^{\alpha})$, with $\hat{k}_j$. Equation (6.2) indicates that $\tilde{s}_i$ is always greater than $\alpha(k_j)$. Therefore, $\hat{k}_j$ is always less than $k_{j}^{\alpha}$, which implies that worker $i$ will not signal even for some $s_i^*$ that is greater than the active threshold level $\alpha(k_j)$.

![Figure 6.4. Worker $i$’s signal function for worker $j$ as a knowledge public](image)

In summary, if the condition in Equation (6.3) holds, worker $i$ will be able to identify two threshold knowledge levels $\hat{k}_j$ and $k_{j}^{\alpha}$ for signalling, where $s_i^*(k_i, k_{j}^{\alpha}) = \beta(k_{j}^{\alpha})$. Combined with her belief of worker $j$’s distribution $\theta(k_j)$ of knowledge level $k_j$, worker $j$ will have a strategy of sending her signal $s_i$ as summarized in the following lemma.

**Lemma 15.** Under the condition in Equation (6.3), worker $i$’s optimal signalling strategy is

$$s_i = \begin{cases} 
\beta(k_j) & 0 \leq k_j < k_{j}^{\alpha}, \\
 s_i^* & k_{j}^{\alpha} \leq k_j \leq \hat{k}_j, \\
0 & \hat{k}_j < k_j,
\end{cases}$$
and the expected probability of her knowledge to be learned by worker $j$ is

$$E_{k_i}[P(k_j, s_i)] = \int_0^{k^\beta_j} \frac{\beta(k_j) - \alpha(k_j)}{k_j} \theta(k_j) dk_j + \int_{k^\beta_j}^k s^*_i - \alpha(k_j) \theta(k_j) dk_j, \quad (6.4)$$

which is represented by the shaded area in Figure 6.4.

Figure 6.4 demonstrates worker $i$’s signal function for worker $j$ as a knowledge public. The similar signal functions for a knowledge connoisseur and knowledge superficialist are shown in Figure 6.5, respectively. As we can see from the figures, when worker $i$’s knowledge level increases, her signal curve $s^*_i(k_i, k_j)$ increases and shifts to the left in the figures. However, the overall expected probability $P(k_j, s_j)$ for her knowledge to be learned may not increase, depending on the type of recipients. Typically, if the signal recipient is a general knowledge public as that in Figure 6.4, the expected probability $P(k_j, s_j)$ will increase if worker $i$ has a higher knowledge level $k_i$, whereas $P(k_j, s_j)$ may decrease if worker $i$ is dealing with a knowledge connoisseur or a knowledge superficialist in Figure 6.5.

### 6.2.1.2 Design of reward structures

Next, we analyze the firm’s optimal design of reward structures. The firm may choose to offer a participation reward except for the necessary sharing reward to induce the best signalling effect from individual providers. These two cases are analyzed in the follows.

A. Only sharing reward
For the given sharing reward $r_s$, knowledge providers will always get positive expected payoffs by engaging in knowledge transfer activities based on their best signalling strategy. Therefore, if knowledge providers participate in signalling and sharing activities on the knowledge market in addition to their routine tasks, they may not care about the total benefit of signalling as long as it is non-negative. Hence, the firm does not offer the participation reward $w_i$ and worker $i$’s expected payoff is

$$\pi_i = \int_{0}^{k_j} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j + \int_{k_j}^{\hat{k}_j} \left[ s_i^* - \frac{\alpha(k_j)}{k_j} r_s - c_i(k_i, s_i^*) \right] \theta(k_j) dk_j.$$

**Lemma 16.** The optimal reward $r_s^*$ can be solved from

$$r_s^* = B - \frac{E_{k_i}E_{k_j}[P(k_j, s_i)]}{\partial E_{k_i}E_{k_j}[P(k_j, s_i)]}.$$

**Proof.** Please see Appendix C.1. □

In this case, the firm just chooses a sharing reward $r_s$ to maximize the organizational expected net benefit of knowledge transfer without having to worry about individual’s rationality constraint. This design of reward structure is applicable to the organization culture where knowledge sharing and learning environment have already been established and regarded as the natural behavior and necessary component of workers’ routine jobs.

**Example:**

We let the cost function $c_i(k_i, s_i)$ of sending signal $s_i$ to be $\frac{\delta s_i^2}{2k_i}$, then the optimal $s_i^*$ is $\frac{r_{k_i}}{\delta k_i}$. For simplicity and tractability, we assume that $\alpha(k_j)$ and $\beta(k_j)$ are linear functions of $k_j$ as $\alpha k_j$ and $\beta k_j$, where the parameters $\alpha$ and $\beta$ can be empirically obtained from one’s prior experience within the organization. Accordingly, the following threshold knowledge levels for worker $j$ can be obtained,

$$k_j^\beta = \sqrt{\frac{r_s k_i}{\beta \delta}}$$

and

$$\hat{k}_j = \sqrt{\frac{r_s k_i}{2\alpha \delta}}.$$
and the condition in Equation (6.3) requires that $\beta \geq 2\alpha$. Hence, worker $i$’s signal function can be shown as,

$$
\begin{align*}
    s^*_i &= \begin{cases} 
        \beta k_j & 0 \leq k_j < \sqrt{\frac{r_s k_i}{\beta^2}}, \\
        \sqrt{\frac{r_s k_i}{\beta^2}} \leq k_j \leq \sqrt{\frac{r_s k_i}{2\alpha^2}}, \\
        0 & \sqrt{\frac{r_s k_i}{2\alpha^2}} < k_j,
    \end{cases}
\end{align*}
$$

and her expected payoff for sending signal is

$$
\pi_i = \int_0^{\sqrt{\frac{r_s k_i}{2\alpha^2}}} \left[ \frac{(\beta - \alpha)k_j}{k_j} \cdot r_s - \frac{\delta}{2k_i}(\beta k_j)^2 \right] \theta(k_j)dk_j \\
    + \int_{\sqrt{\frac{r_s k_i}{2\alpha^2}}}^{\frac{r_s k_i}{\delta k_j}} \left[ \frac{r_s k_i}{\delta k_j} - \frac{\alpha k_j}{k_j} \cdot r_s - \frac{\delta}{2k_i}(\frac{r_s k_i}{\delta k_j})^2 \right] \theta(k_j)dk_j.
$$

If we assume a uniform distribution for $\theta(k_j)$ in $[0, 1]$, then the expected payoff of worker $i$ can be solved as

$$
\pi_i = \sqrt{\frac{k_i r_s^3}{\delta}} \left( \frac{4}{3} \sqrt{\beta} - \sqrt{2\alpha} \right) .
$$

The firm’s expected payoff is

$$
\pi = \int_{k_i} \int_{k_j} P(k_j, s_i) (B - r_s) \theta(k_j) \theta(k_i) dk_j dk_i,
$$

which can be represented as follows, if we use the same uniform distribution for worker $i$’s knowledge level $k_i$ between 0 and 1,

$$
\pi = \int_0^{1} \sqrt{\frac{k_i r_s}{\delta}} \left( 2\sqrt{\beta} - \frac{3}{\sqrt{2}} \sqrt{\alpha} \right) (B - r_s) \theta(k_i) dk_i.
$$

\footnote{This implies that the gap between two thresholds should be large enough, $\beta \geq 2\alpha$, for the signalling functions to be continuous.}
Hence, the optimal reward $r^*_s = \frac{B^2}{3}$, and the optimal profit is

$$\pi^* = \frac{2}{27} \sqrt{\frac{6B}{\delta}} (2\sqrt{2\beta} - 3\sqrt{\alpha})B.$$ 

### B. Participation and sharing rewards

If workers have a high reservation utility for participating in knowledge sharing and learning, the firm will have to offer additional participation reward $w_i$ to induce workers’ participation in the knowledge market. Then, worker $i$’s expected payoff is

$$\pi_i = \int_0^{k_j} w_i \theta(k_j) \, dk_j + \int_0^{k_j} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) \, dk_j$$

$$+ \int_{k_j^\delta}^{k_j} \left[ s_i^* - \frac{\alpha(k_j)}{k_j} r_s - c_i(k_i, s_i^*) \right] \theta(k_j) \, dk_j.$$ 

However, when the learner worker $j$’s knowledge level is greater than $\hat{k}_j$, she will still send out a *fake signal* in order to get the participation reward while the signalling cost can be neglected. Hence, worker $i$’s total payoff is

$$\pi_i = w_i + \int_0^{k_j} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) \, dk_j$$

$$+ \int_{k_j^\delta}^{k_j} \left[ s_i^* - \frac{\alpha(k_j)}{k_j} r_s - c_i(k_i, s_i^*) \right] \theta(k_j) \, dk_j,$$

where $s_i^*$ can be determined in the same way as that in previous case.

Given the expected probability $P(k_j, s_i)$ from worker $i$’s signalling, the firm maximizes its expected payoff

$$\pi = \int_{k_j} \{ E_{k_j}[P(k_j, s_i)](B - r_s) - w_i \} \theta(k_j) \, dk_i,$$

by choosing a best sharing reward $r$ and participation reward $w_i$.

**Lemma 17.** The firm should offer the optimal participation reward as $w_i = U_0$

\footnote{In general, the optimal $r_s$ is a function of $\beta$ and $\alpha$. However, as we assume the linear threshold functions, the optimal $r_s$ here is only related to the transfer benefit $B$.}
and the sharing reward as $r^*_s$ where

$$r^*_s = \arg\max_{r_s} \left\{ \int_{k_i} E_{k_j}[P(k_j, s_i)B - \hat{c}_i(s_i, k_i)]\theta(k_i)dk_i - U_0 \right\},$$

in which

$$\hat{c}_i(s_i, k_i) = c_i(k_i, s_i) - \frac{\partial c_i(s_i, k_i)}{\partial k_i} \cdot \frac{1 - \Theta(k_i)}{\theta(k_i)},$$

and $s_i$ is a signal function of sharing reward $r_s$ that chosen by individual, i.e., $s_i = s^*_i(r_s, k_i, k_j)$.

**Proof.** Please see Appendix C.2.

Because worker $i$’s knowledge level is unobservable, the firm has to incur the total cost $\hat{c}_i(s_i, k_i)$ which is higher than $c_i(k_i, s_i)$, when satisfying the individual-rationality constraint. This cost structure is similar to that in [51], where the inferred production cost $\hat{c}_i(s_i, k_i)$ includes the actual production cost $c_i(k_i, s_i)$ and the additional cost (second term) because of the unobservable knowledge levels of knowledge providers. For the given optimal participation reward $w_i$ and sharing $r_s$, a knowledge provider’s expected payoff increases with her knowledge level. Compared with the reward structure in previous subsection, this two-tariff reward design can be applied to the initial stage of knowledge management practice to establish a knowledge-embracing culture [54].

Notice that the reward $r_s$ can be regarded as the mixed strategy with respect to a knowledge provider’s knowledge level $k_i$, i.e., $r_s = r_s(k_i)$. We next investigate whether this mixed strategy of sharing reward is incentive-compatible for knowledge providers.

**Example:**

By using the same linear format for both threshold functions, we get the total inferred cost as

$$\hat{c}_i(s_i, k_i) = \frac{\delta s^2_i(1 + k_i)}{2k^2_i},$$
and firm’s profit as
\[ \pi = \int_0^1 \frac{k_i r_s}{\delta} \left(3\sqrt{2\alpha} - 4\sqrt{\beta}\right) \cdot \frac{r_s + k_i(r - 3B)}{6k_i} \cdot \theta(k_i) dk_i - U_0, \]
whose first order condition with respect to \( r_s \) yields that \( r_s = \frac{B}{4} \) and the optimal profit is
\[ \pi^* = \frac{B}{9} \sqrt{\frac{B}{\delta}} (4\sqrt{\beta} - 3\sqrt{2\alpha}) B - U_0. \]

Obviously, in order to take into account the individual rationality constraints, the optimal sharing reward \( r_s \) is lowered and the firm’s total expected payoff decreases as well.

If we regard the sharing reward as the mixed strategy, the point-wise maximization shows that the optimal sharing reward is \( r_s = B k_i / (1 + k_i) \).

### 6.2.2 Signalling without Trust

Without trust, a knowledge provider will behave differently in signalling. If workers do not believe that learning will be reported, they will not signal at all on the knowledge market when the firm does not offer participation reward because there is no chance for them to get any reward. When the firm offers participation reward as well as sharing reward, a knowledge provider will send out the signal \( \tilde{s}_i \) to maximize her payoff, \( \pi_i = w_i - c_i(\tilde{s}_i, k_i) \), where \( \tilde{s}_i \) is just the fake signal barely enough for the firm to observe. In this case, a worker’s purpose for signalling is to obtain the participation reward, assuming that the participation reward exceeds her reservation utility. If the provider has to exert costly efforts to obtain the participation reward, she will not even bother to signal at all.

Therefore, the firm has to resort to various options to increase workers’ trust. The effects and tradeoffs of two methods, IT investment and learning reward, on workers’ signalling strategy and the firm’s optimal design of reward structures are discussed in this section.
**6.2.2.1 A priori or a posteriori learning report**

The firm may request learners to report their learning before or after they acquire the knowledge from providers, i.e., reporting learning can be either *a priori* or *a posteriori* with respect to the actual knowledge acquisition. The comparison of these two learning report policies are summarized in Table 6.2.

<table>
<thead>
<tr>
<th>Learning report</th>
<th><em>a priori</em></th>
<th><em>a posteriori</em></th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative effect</td>
<td>deter learning</td>
<td>deter signalling</td>
</tr>
<tr>
<td>Alleviation</td>
<td>remove learning barriers</td>
<td>increase belief of learning report</td>
</tr>
<tr>
<td>Methods</td>
<td>offer learning reward</td>
<td>1) improve ability of monitoring learning by IT investment; 2) offer learning reward</td>
</tr>
</tbody>
</table>

**Table 6.2. Learning report policy: *a priori* vs. *a posteriori***

If the firm requires learners to report learning *a priori*, then knowledge providers will get rewards before they share knowledge with learners. However, this *a priori* learning report policy can deter learning because workers may not be willing to disclose their learning in some situations. For instance, when a worker is in a more important position than a potential knowledge provider, she may eventually give up the learning opportunity even though the knowledge is valuable to her because to disclose her learning from the provider may seem unacceptable in her position. Therefore, *a priori* learning report policy decreases the learning probability by affecting learners’ threshold functions, which in turn influences knowledge providers’ signalling strategy and eventually decreases the success probability of knowledge transfer on the market. In order to remove workers’ learning barriers, the firm may offer learning rewards to encourage learning.

In contrast, the firm may require learners to report learning *a posteriori*. In this chapter, we focus on the *a posteriori* policy, analyzing its effects and proposing different methods to alleviate them. Similar to the *a priori* policy, when there exist conflicts of interests among different types of workers, learners may not report their actual learning to the firm even if they have acquired the knowledge from providers. Therefore, if knowledge providers believe that other workers will not report learning, they will not be willing to signal on the knowledge market. The firm has two options to resolve this problem and improve knowledge providers’
trust: 1) increase IT investment to acquire the ability of monitoring learning and
2) offer learning reward so that learners will voluntarily report their learning.
Next, we investigate the effects of learning reward and IT investment on trust
improvement under the *a posteriori* learning report policy.

### 6.2.2.2 The effects of learning reward and IT investment

There may exist various conflicts among knowledge workers, which inhibits the *a posteriori* voluntary learning reports. In this regard, we consider that, to report
her learning, a worker has to overcome an additional cost which is defined as the
*learning inhibition cost* (LIC) $L(k_j)$, a function of one’s knowledge level $k_j$. Therefore, if a learner is offered a learning reward which is large enough to compensate
her learning inhibition cost, she will be willing to report her learning voluntarily.

![Learning inhibition cost (LIC) functions](image)

**Figure 6.6.** Learning inhibition cost (LIC) functions

Two types of knowledge workers are differentiated with respect to their LIC functions. A *humble* knowledge worker (decreasing LIC function in Figure 6.6)
will be more willing to learn and not ashamed of reporting her learning when she
becomes more knowledgeable, whereas an *arrogant* knowledge worker (increasing
LIC function in Figure 6.6) will incur a higher learning inhibition cost and be
more reluctant to learn when she is more knowledgeable. Therefore, the expected
probability that learning will be reported is $q_1 = \int_0^{k_j^l} \theta(k_j)dk_j$ for an arrogant
knowledge worker and $q_1 = \int_{k_j^l}^1 \theta(k_j)dk_j$ for a humble knowledge worker, where $k_j^l = L^{-1}(r_l)$ is the *learning inhibition threshold knowledge level* given the learning
reward as $r_l$. 

In addition to offering a learning reward, the firm can improve its ability in monitoring learning through IT investment so that knowledge providers will be assured of the sharing rewards whenever their knowledge is acquired on the market. IT investments may have different success rates in monitoring learning for knowledge with different natures. In Figure 6.7, two types of knowledge, explicit or implicit, are differentiated in terms of the necessary IT investment $V(q_2)$ required to reach certain ability $q_2$ to monitor learning. As Figure 6.7 shows, if the knowledge signalled is explicit, the IT investment will convexly increase in the probability of monitoring its learning; in contrast, if the knowledge is implicit, the IT investment will concavely increase in the probability of monitoring its learning. The difference between explicit and implicit knowledge indicates that it is more expensive to achieve the same monitoring ability for implicit than explicit knowledge.

These two methods, IT investment and learning reward, have different effects, threshold effect or strength effect, on knowledge providers’ signal functions.

**Threshold effect:** the learning reward $r_l$ introduces a new threshold $k^i_j$ for worker $i$; when the LIC function increases in $k_j$, worker $i$ has the belief that $q_1 = 1$, $\forall k_j \in [0, k^i_j]$ and $q_1 = 0$ otherwise; when the LIC function decreases in $k_j$, worker $i$ has the belief that $q_1 = 1$, $\forall k_j \in [k^i_j, 1]$ and $q_1 = 0$ otherwise. Figure 6.6 demonstrates the threshold effect of learning rewards for different LIC functions when the resulting $k^i_j$ is between $k^0_j$ and $\hat{k}_j$. When worker $i$ believes that $q_1 = 0$, she will not signal at all, which modifies her signal function with complete trust by cutting off the right or left part at the threshold $k^i_j$. When the firm increase
the learning reward $r_i$, the learning inhibition threshold knowledge level will move in the direction of arrows in Figure 6.8, increasing the probability of learning.

**Strength effect:** the IT investment $V(q_2)$ lets worker $i$ believe that the probability of learning to be monitored is $q_2$ for all possible $k_j$. Therefore, compared with that of complete trust, the signal function is still similar, but the strength of signal $s_i^*(k_j, k_i)$ is lowered and $\tilde{s}_i(k_j, k_i)$ increased, varying with different IT investment $V(q_2)$. The threshold knowledge levels $k_j^\beta$ and $\hat{k}_j$ move accordingly for the signal $s_i^*(k_j, k_i)$ with various IT investment.

Applied independently, either method may only partially recover a knowledge provider’s signal function to its complete form with trust. Therefore, it may be better for the firm to simultaneously apply both methods to maximally increase the efficacy of signals. With the application of both methods, both the threshold and strength effects will exist and the overall probability for a knowledge provider
to believe that learning will be reported/monitored is
\[
q = \begin{cases} 
1 & 0 \leq k_j \leq k_j^1, \\
q_2 & k_j > k_j^1,
\end{cases}
\]
and the total expected cost incurred by the firm will be
\[
C = V(q_2) + \int_{k_i} E_{k_j}[P(s_i, k_j)]r_1\theta(k_i)dk_i,
\]
where \(E_{k_j}[P(s_i, k_j)]\) is the probability of worker \(i\)’s knowledge to be learned by worker \(j\) based on the revised signal function like those in Figure 6.10. Overall, the firm has to balance the tradeoffs between the IT cost and learning rewards to choose the more cost-effective method to improve the ability of monitoring learning.

![Figure 6.10. Effects of learning rewards and IT support on signal functions](image)

For different types of knowledge recipients, nature of knowledge, and LIC functions, these two methods may achieve different efficacies (Table 6.3). In general, IT investment is more effective in monitoring the learning of explicit knowledge, while learning reward works more effectively in increasing the rate of learning report from implicit knowledge. For knowledge superficialist, a knowledge provider will have a long stretched signal function, so monitoring learning by increasing IT investment will work well, whereas a signal function for knowledge connoisseurs is high and narrow, so learning reward will be more effective. Finally, an arrogant worker with a high learning inhibition cost finds a small amount of learning reward insufficient, so it is better to monitor learning with IT support; in contrast,
learning reward will perform well for a humble worker to report her learning. We further discuss this in next section.

<table>
<thead>
<tr>
<th>Recipient type</th>
<th>IT investment</th>
<th>Learning reward</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge nature</td>
<td>Knowledge Superficialist</td>
<td>Knowledge Connoisseur</td>
</tr>
<tr>
<td>LIC function</td>
<td>Explicit knowledge</td>
<td>Implicit knowledge</td>
</tr>
<tr>
<td></td>
<td>Arrogant worker</td>
<td>Humble worker</td>
</tr>
</tbody>
</table>

Table 6.3. IT investment vs. learning reward: the more effective method

6.2.2.3 Design of reward structures

Similar to the case with complete trust, the firm can choose whether or not to offer a participation reward in different situations. In addition, the firm has to deal with different types of knowledge recipients, arrogant or humble, when specifying the optimal reward structures.

A. Only sharing reward

We first consider the case when the firm designs the sharing reward $r_s$ without considering knowledge providers’ individual-rationality constraints. As Figure 6.10 demonstrates, for knowledge recipients being either arrogant or humble, the impacts of learning rewards and IT support on building up trust are different. Therefore, the design of sharing rewards is also different. Next, the sharing reward dealing with an arrogant recipient is analyzed.

1. Increasing LIC function—Arrogant Recipient

When only the sharing reward $r_s$ is offered and the LIC function is increasing, there exist five possible cases, as shown in Figure 6.10 part (a), for the revised individual’s signal functions with the offering of learning reward and support of information technology. By offering a learning reward $r_l$ to arrogant recipients, the firm induces those recipients with knowledge levels lower than $k_j^l = L^{-1}(r_l)$ to report their potential learning. However, this threshold knowledge level $k_j^l$ may locate in different areas with respect to other threshold knowledge levels such as $k_j^{AV}$, $k_j^3$, $\hat{k}_j$, and $\hat{k}_j^V$. Therefore, the following five cases can be enumerated, which corresponds to different expected payoff and learning probability for a knowledge provider.
Case I: When $0 \leq k_j^l < k_j^b$, where $k_j^b$ is the expiring threshold knowledge level determined by $s_i^V$, an individual provider’s expected payoff is

$$
\pi_i = \int_0^{k_j^b} \left[ \beta(k_j) - \alpha(k_j) \frac{r_s}{k_j} - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j 
+ \int_{k_j^b}^{k_j^V} \left[ s_i^V - \alpha(k_j) \frac{q_2 r_s - c_i(k_i, s_i^V)}{k_j} \right] \theta(k_j) dk_j,
$$

in which $s_i^V$ is the modified signal strength based on the belief $q_2$ by

$$
q_2 r_s \frac{k_j}{k_j^b} = \frac{\partial c_i(k_i, s_i^V)}{\partial s_i}.
$$

Case II: When $k_j^b \leq k_j^l < k_j^\hat{b}$, an individual provider’s expected payoff is

$$
\pi_i = \int_0^{k_j^b} \left[ \beta(k_j) - \alpha(k_j) \frac{r_s}{k_j} - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j 
+ \int_{k_j^b}^{k_j^l} \left[ s_i^V - \alpha(k_j) \frac{q_2 r_s - c_i(k_i, s_i^V)}{k_j} \right] \theta(k_j) dk_j.
$$

Case III: When $k_j^b \leq k_j^l < \hat{k}_j^V$, as shown in part (a) of Figure 6.10, an individual provider’s expected payoff is

$$
\pi_i = \int_0^{k_j^b} \left[ \beta(k_j) - \alpha(k_j) \frac{r_s}{k_j} - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j 
+ \int_{k_j^b}^{k_j^l} \left[ s_i^* - \alpha(k_j) \frac{r_s - c_i(k_i, s_i^*)}{k_j} \right] \theta(k_j) dk_j 
+ \int_{k_j^l}^{\hat{k}_j^V} \left[ s_i^V - \alpha(k_j) \frac{q_2 r_s - c_i(k_i, s_i^V)}{k_j} \right] \theta(k_j) dk_j,
$$

where $s_i^*$ is still the same as that with complete trust.

Case IV: When $\hat{k}_j^V \leq k_j^l < \hat{k}_j$, an individual provider’s expected payoff is

$$
\pi_i = \int_0^{k_j^b} \left[ \beta(k_j) - \alpha(k_j) \frac{r_s}{k_j} - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j 
+ \int_{k_j^b}^{\hat{k}_j^V} \left[ s_i^V - \alpha(k_j) \frac{q_2 r_s - c_i(k_i, s_i^V)}{k_j} \right] \theta(k_j) dk_j.
$$
+ \int_{k_j}^{k_j} \left[ s_i^* - \frac{\alpha(k_j)}{k_j} r_s - c_i(k_i, s_i^*) \right] \theta(k_j)dk_j.

Case V: When \( k_j^l \geq \hat{k}_j \), an individual provider’s expected payoff is

\[
\pi_i = \int_0^{\hat{k}_j} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j)dk_j \\
+ \int_{\hat{k}_j}^{k_j} \left[ s_i^* - \frac{\alpha(k_j)}{k_j} r_s - c_i(k_i, s_i^*) \right] \theta(k_j)dk_j.
\]

We denote \( P^I, P^{II}, P^{III}, P^{IV}, \) and \( P^V \) as the probabilities of learning in each case. Since worker \( i \)'s knowledge level is not observable, the firm can only maximize its expected payoff based on these five cases, i.e., the firm’s decision problem is now formulated as

\[
\max_{r_s, r_1, q_2} \pi = \int_{k_i}^{1} E_{k_j} P^V \cdot (B - r_s - r_1) \cdot p(\hat{k}_i \leq k_i < 1) \cdot \theta(k_i)dk_i \\
+ \int_{\hat{k}_i}^{k_i} E_{k_j} P^{IV} \cdot (B - r_s - r_1) \cdot p(\hat{k}_i^V \leq k_i < \hat{k}_i) \cdot \theta(k_i)dk_i \\
+ \int_{k_i}^{\hat{k}_i} E_{k_j} P^{III} \cdot (B - r_s - r_1) \cdot p(k_i^\beta \leq k_i < \hat{k}_i^V) \cdot \theta(k_i)dk_i \\
+ \int_{k_i^\beta}^{\hat{k}_i^V} E_{k_j} P^{II} \cdot (B - r_s - r_1) \cdot p(k_i^{\alpha V} \leq k_i \leq k_i^\beta) \cdot \theta(k_i)dk_i \\
+ \int_{0}^{k_i^{\alpha V}} E_{k_j} P^{I} \cdot (B - r_s - r_1) \cdot p(k_i < k_i^{\alpha V}) \cdot \theta(k_i)dk_i - V(q_2),
\]

in which \( \hat{k}_i, \hat{k}_i^V, k_i^\beta, k_i^{\alpha V} \) are worker \( i \)'s threshold knowledge levels where \( \hat{k}_j(\hat{k}_i) = \hat{k}_j^V(\hat{k}_i^V) = k_i^\beta(\hat{k}_i^\beta) = k_i^{\alpha V}(\hat{k}_i^{\alpha V}) = k_j^l = L^{-1}(r_1) \).

Because the variability of the above five cases depends on the unobservable knowledge level \( k_i \) of a knowledge provider, the firm will infer the probability of each case by determining the possible threshold knowledge levels for a knowledge provider and choose an appropriate reward structure to maximize the expected payoff. Essentially, when the firm offers a learning reward so high that \( k_j^l \geq \hat{k}_j \) (Case V), or the knowledge provider’s knowledge level is so low that all her recipients’ knowledge levels \( \hat{k}_j \) are below \( k_j^l \), then the learning reward will work
perfectly well to induce all the knowledge recipients from providers to report their learning, i.e., the signalling function remains unchanged. For this case, the IT support is not necessary to improve the trust. As the learning reward decreases or a knowledge provider’s knowledge level increases, it is not enough to induce all the recipients to report their learning (Case IV, III, II, and I). Only part of the recipients with relatively low knowledge levels \(k_j < k_j^l\) will be willing to do so. For these cases, the firm has to employ necessary information technologies to monitor learning (by choosing the \(q_2\)) to enhance the trust, improving the total expected knowledge transfer probability. Overall, it can be inferred that the necessity of IT support increases with the reduction of learning rewards, or the knowledge level of a knowledge provider. A more knowledgeable provider indicates the higher knowledge levels of her potential recipients, who, if belonging to the arrogant type, requires stronger incentives to be induced to report learning. Hence, the necessary IT support to monitor learning might be a better alternative for improving providers’ trust.

2. Decreasing LIC function—Humble Recipient

As shown in Figure 6.10 part (b), the effects of learning reward and IT support are different on humble recipients. Here also five different possible cases exist as follows for individual’s signal functions.

**Case I:** When \(0 \leq k_j^l < k_j^\beta V\), an individual provider’s expected payoff is

\[
\pi_i = \int_0^{k_j^\beta V} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j
+ \int_{k_j^l}^{k_j^\beta V} \left[ s_i^V - \frac{\alpha(k_j)}{k_j} r_s - c_i(k_i, s_i^V) \right] \theta(k_j) dk_j,
\]

**Case II:** When \(k_j^\beta V \leq k_j^l < k_j^\beta\), an individual provider’s expected payoff is

\[
\pi_i = \int_0^{k_j^\beta V} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j
+ \int_{k_j^\beta V}^{k_j^l} \left[ s_i^V - \frac{\alpha(k_j)}{k_j} q_2 r_s - c_i(k_i, s_i^V) \right] \theta(k_j) dk_j
+ \int_{k_j^l}^{k_j^\beta} \left[ \frac{\beta(k_j)}{k_j} - \frac{\alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j
\]
\[ + \int_{k_j^\beta}^{\hat{k}_j} \left[ \frac{s_i^* - \alpha(k_j)}{k_j} q_{2r_s} - c_i(k_i, s_i^*) \right] \theta(k_j) dk_j. \]

**Case III:** When \( k_j^\beta \leq k_j^l < \hat{k}_j^V \), as shown in part (b) of Figure 6.10, an individual provider's expected payoff is

\[
\pi_i = \int_0^{k_j^\beta} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j \\
+ \int_{k_j^\beta}^{k_j^l} \left[ \frac{s_i^V - \alpha(k_j)}{k_j} q_{2r_s} - c_i(k_i, s_i^V) \right] \theta(k_j) dk_j \\
+ \int_{k_j^l}^{\hat{k}_j^V} \left[ \frac{s_i^* - \alpha(k_j)}{k_j} q_{2r_s} - c_i(k_i, s_i^*) \right] \theta(k_j) dk_j.
\]

**Case IV:** When \( \hat{k}_j^V \leq k_j^l < \hat{k}_j \), an individual provider's expected payoff is

\[
\pi_i = \int_0^{k_j^\beta} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j \\
+ \int_{k_j^\beta}^{\hat{k}_j^V} \left[ \frac{s_i^V - \alpha(k_j)}{k_j} q_{2r_s} - c_i(k_i, s_i^V) \right] \theta(k_j) dk_j \\
+ \int_{k_j^l}^{\hat{k}_j^V} \left[ \frac{s_i^* - \alpha(k_j)}{k_j} q_{2r_s} - c_i(k_i, s_i^*) \right] \theta(k_j) dk_j.
\]

**Case V:** When \( k_j^l \geq \hat{k}_j \), an individual provider's expected payoff is

\[
\pi_i = \int_0^{k_j^\beta} \left[ \frac{\beta(k_j) - \alpha(k_j)}{k_j} r_s - c_i(k_i, \beta(k_j)) \right] \theta(k_j) dk_j \\
+ \int_{k_j^\beta}^{\hat{k}_j^V} \left[ \frac{s_i^V - \alpha(k_j)}{k_j} q_{2r_s} - c_i(k_i, s_i^V) \right] \theta(k_j) dk_j.
\]

Similar to that with decreasing LIC function, the firm does not know a knowledge provider \( i \)'s knowledge level and maximizes its expected payoff based on the above five possible scenarios. However, the interpretation for each case is different. When a knowledge provider’s knowledge level is relative low, her potential knowledge recipients’ knowledge level will also be low, which implies a very high learning inhibition cost for humble recipients. For this scenario (Case V), offering learning
rewards does not work at all to induce any knowledge recipients to report their learning. Therefore, IT support is indispensable to monitor recipients’ learning to enhance a knowledge provider’s trust. When a knowledge provider’s knowledge level increases (Case IV, III, II, and I), her potential knowledge recipients increases, too. Therefore, part of the recipients with relative higher knowledge levels will be induced to report their learning. For other recipients who are not covered by the learning reward, IT support is still necessary to monitor their learning so that the knowledge provider will have the trust for signalling.

![Figure 6.11. IT support and learning reward for trust improvement](image)

By comparing the necessary conditions of learning incentive rewards and IT support for the firm’s optimal decision, we summarize in the following proposition the appropriate application of IT support and leaning rewards to enhance knowledge providers’ trust.

**Proposition 19.** *In order to improve knowledge providers’ trust for signalling, the firm needs to provider strong IT support for signalling from less knowledgeable providers to humble recipients or from more knowledgeable providers to arrogant recipients and strong incentives of learning rewards for signalling from less knowledgeable providers to arrogant recipients or from more knowledgeable providers to humble recipients.*

Figure 6.11 graphically exhibits the above proposition with a three-dimensional
representation, in which $x$ axis is a knowledge provider’s knowledge level, $y$ axis denotes the type of a knowledge recipient with a higher $y$ value corresponding to the humble type, and $z$ axis symbolizes the strength of IT support or incentive rewards for learning with a higher $z$ value for stronger IT support and weaker incentives. $A$, $B$, $C$, and $D$ four positions represent the four cases described in Proposition 19. A knowledge provider has a high knowledge level at $C$ and $D$ and a low knowledge level at $A$ and $B$. $A$ and $C$ correspond to an arrogant knowledge recipient and $B$ and $D$ a humble recipient. Finally, $B$ and $C$ require stronger IT support and $A$ and $D$ stronger incentives for learning. The hyperplane $ABC$ and $BCD$ can be regarded as the appropriate combinatorial application of IT support and incentives to improve the knowledge providers’ trust for signalling, given various types of knowledge providers and recipients.

B. Participation and sharing rewards

Next, we analyze the scenario when individual knowledge providers have to be provided by a reservation utility for participation in signalling. Similar to the reward structure with complete trust, the firm offers both participation and sharing rewards for knowledge providers and its expected payoff is,

$$\pi = \int_{k_i}^{1} E_{k_j} P^V \cdot (B - r_s - r_l) \cdot p(\hat{k}_i \leq k_i < 1) \cdot \theta(k_i) dk_i$$

$$+ \int_{k_i^V}^{k_i} E_{k_j} P^{IV} \cdot (B - r_s - r_l) \cdot p(\hat{k}_i^V \leq k_i < \hat{k}_i) \cdot \theta(k_i) dk_i$$

$$+ \int_{k_i^V} E_{k_j} P^{III} \cdot (B - r_s - r_l) \cdot p(k_i^V \leq k_i < \hat{k}_i^V) \cdot \theta(k_i) dk_i$$

$$+ \int_{k_i^{\beta V}}^{k_i^V} E_{k_j} P^{II} \cdot (B - r_s - r_l) \cdot p(k_i^{\beta V} \leq k_i < k_i^{\beta V}) \cdot \theta(k_i) dk_i$$

$$+ \int_{0}^{k_i^{\beta V}} E_{k_j} P^I \cdot (B - r_s - r_l) \cdot p(k_i < k_i^{\beta V}) \cdot \theta(k_i) dk_i - \int_{k_i} w_i \theta(k_i) dk_i - V(q_2).$$

While maximizing its expected payoff by providing rewards ($r_s$, $r_l$, and $w_i$) and investing in IT ($V(q_2)$), the firm has to ensure that individual-rationality constraints are satisfied, i.e., $\pi_i \geq U_0$. Except for the decision for sharing and participation rewards $r_s$ and $w_i$, the firm has to make additional decisions on the learning reward $r_l$ and IT level $q_2$. Essentially, the optimal $r_l$ and $q_2$ can
be chosen by balancing the tradeoff between the benefits and costs of restoring
the knowledge provider’s signalling function, which is similar to the analysis in
Figure 6.11. The costs and benefits vary with the firm’s optimal reward structures
and IT investment, i.e., the optimal solution to $r_s$, $r_l$, and $q_2$. When $q_2$ is very
large, the modified signalling function will be very close to the one with complete
trust no matter where $k^j$ is located. When $q_2$ converges to 1, the second and
fourth terms in the firm’s payoff tend to be zero (case II and IV will disappear)
and the entire expected payoff converge to that with complete trust, which will
cost the firm less in incentives. However, a high monitoring ability of $q_2$ may entail
a large amount of IT investment, so the firm has to balance the tradeoff between
the reduction of incentive cost and the increase of IT investment. The following
proposition illustrates the optimal reward structure and IT level for the firm.

**Lemma 18.** The firm should offer the optimal participation reward as $w_i = U_0$
and the sharing, learning rewards and IT level as $r^*_s$, $r^*_l$, and $q^*_2$ where

$$\{r^*_s, r^*_l, q^*_2\} \in \arg\max_{r_s, r_l, q_2} \left\{ \sum_{i=1}^{V} \int_{k_i} E_k P^i \cdot [B - r_l - \hat{c}_i(s_i, k_i)] \cdot p_i \cdot \theta(k_i) dk_i - U_0 \right\},$$

in which $p_i$ is the probability for $k_i$ to be in case $i \in \{I, II, III, IV, V\}$,

$$\hat{c}_i(s_i, k_i) = c_i(k_i, s_i) - \frac{\partial c_i(s_i, k_i)}{\partial k_i} \cdot \frac{1 - \Theta(k_i)}{\theta(k_i)},$$

and $s_i$ is a signal function of sharing reward $r_s$ that chosen by individual, i.e.,
$s_i = s^*_i(r_s, k_i, k_j)$.

**Proof.** Please see Appendix C.3.

Here, the cost $\hat{c}_i(s_i, k_i)$ bears the same interpretation as that in Lemma 17.
Even though an individual provider’s revised signalling function may belong to one
of five cases described above, her expected payoff still increases with her knowledge
level. Therefore, the individual-rationality constraint is satisfied as long as the firm
offers a participation reward as $w_i = U_0$ for all knowledge providers. The higher a
knowledge provider’s knowledge level, the more the additional utility she will get.
6.2.3 Discussion: Quality and Quantity of Knowledge Signalled

Based on the analysis and discussion of previous two subsections, we finally investigate the tradeoffs between quality and quantity of knowledge being signalled on the internal knowledge market.

The trust that has been previously illustrated stems from a knowledge provider’s asymmetric information of her recipients’ valuations of her knowledge. The implication of the trust is two-fold: first, a knowledge provider trusts that her knowledge is valuable to potential recipients; and second, she trusts that her recipients will report their learning to the firm after knowledge acquisition if they find her knowledge valuable. Therefore, the first level of trust is not only about the recipients but also related to the providers themselves and the second level of trust results from the first one. In Section 6.2.1, knowledge providers are assumed to have both levels of trust (or those who do not have this level of trust will not signal on the market) and in Section 6.2.2, they lack the second level of trust, so the firm has to employ necessary incentives or IT support to improve this level of trust. However, while the second level of trust is enhanced, the learning from recipients who do not value the acquired knowledge will be reported or monitored. Therefore, those knowledge providers who originally are not confident about the value of their knowledge will start to signal on the internal knowledge market, which increases the total quantity but decreases the quality of signalling. In this argument, we implicitly assume that knowledge providers are explicitly aware of the value of their knowledge to other workers. However, in most cases, knowledge providers are not completely confident about the value of their knowledge as perceived by other workers, which will be the focus of analysis in this section.

In stead of assuming that providers either have or not have the first level of trust, we consider it as a probability \( \gamma(k_i) \) that varies with a knowledge provider’s knowledge level \( k_i \). If \( \gamma(k_i) \) is a function that increases in a knowledge provider’s knowledge level, i.e., the higher a knowledge provider’s knowledge level, the more trust she will have, then it essentially modifies a knowledge provider’s signal function by reducing \( s_i^* \) and increasing \( \tilde{s}_i \), which only changes the scale of the signal.
function because Equation (6.1) is now

\[ \frac{r_s}{k_j} = \frac{1}{\gamma(k_i)} \cdot \frac{\partial c_i(k_i, s_i^*)}{\partial s_i}. \]

However, if \( \gamma(k_i) \) is not a continuous function, for instance \( \gamma(k_i) = 1 \), when \( k_i \geq \hat{k}_i \), and \( \gamma(k_i) = 0 \), when \( k_j < \hat{k}_i \), then only those knowledge providers with knowledge levels higher than \( \hat{k}_i \) will signal on the market, whereas others with low knowledge levels will not signal at all.

### 6.3 Summary

Devising and maintaining an efficient internal knowledge market may effectively facilitate knowledge sharing and learning within organizations. Appropriate reward structures and necessary IT support provide sufficient trust for knowledge providers to signal on the market and share their knowledge. This chapter investigates the optimal organizational designs of reward structures and investment of IT for supporting the necessary trust on the internal knowledge market and their effects on an individual knowledge provider’s signalling strategy. This study provides valuable guidelines for managers to maintain a successful and efficient internal knowledge market.
Managerial Insights and Conclusions

Prior research in knowledge management focuses either on managerial or technical perspectives, independently. On the one hand, various studies investigate the knowledge management strategies and influential factors for knowledge diffusion. On the other hand, research is abundant in the construction and mechanisms of knowledge management systems. However, the impact of information systems on the degree of knowledge sharing and learning, the function of incentives within knowledge-transfer processes, and the complementarity between managerial incentives and knowledge management systems are not well understood. Our research addresses this gap by studying the joint role of incentives and information systems in knowledge management.

In three related essays, we study the role of managerial incentives, the impact of knowledge management systems, and their relationship in different knowledge-management contexts. In the first essay, these three issues are analyzed within a knowledge-sharing team context, the second essay explores these issues in knowledge creation, retention, and diffusion context within organizations, and the last essay embeds these issues in the internal knowledge market. We next discuss the managerial insights and future extensions for each study.

7.1 Knowledge Sharing and Learning

The first model studies the impact of IT investment and incentives on knowledge transfer in organizations. Extending team incentive models, we incorporate both
incentive structures for rewarding knowledge sharing and learning and the influence of information technologies.

Our first study contributes to the literature in many ways. First of all, we study a combined moral hazard and adverse selection problem in a team implementing knowledge management practices. Our model is more general than those in [51] and [19] and we explicitly embed incentive issues in knowledge-transfer context. Secondly, knowledge sharing is studied by [11], [12], and [19] in the context of research joint venture by assuming that knowledge sharing and learning are costless and can be achieved through a (either Blackwell ordered or general) precision function. We distinguish our research by explicitly constructing the costs for sharing and learning and allowing flexible knowledge sharing and learning decisions among workers. Finally, our study makes another major contribution by considering IT as the enabler of knowledge sharing and learning and investigating its relationship with incentives.

The first study provides valuable guidance for effectively managing knowledge assets within organizations. First, incentives are necessary not only to induce workers to exert best efforts, but also to achieve the desirable knowledge management properties such as knowledge-sharing(learning) alignment, full knowledge transfer, and truthful reporting of knowledge levels. Managers can compensate knowledge workers for their participation in the knowledge management system by allocating rewards in linear proportion to the sharing and learning amount captured by the knowledge server. Second, information technologies have great impact on knowledge sharing and learning within a team. Investment in IT reduces knowledge workers’ sharing and learning costs, increasing the sharing and learning amount within the team. Beyond certain level of information systems, each knowledge worker will share her knowledge completely such that all knowledge workers can reach their highest knowledge levels, facilitating the high-performance team. In addition, there exists a level of information systems where the firm achieves its optimal profit. Finally, two knowledge-transfer policies, mandatory learning and voluntary learning, should be appropriately employed in conjunction with the incentive rewards for knowledge sharing and learning in different situations. When the optimal level of information systems is higher enough to enable complete-knowledge enable-
ment, managers can use voluntary learning policy. In constrast, when the optimal level of information systems is not sufficient to achieve complete-knowledge enablement, mandatory learning policies should be adopted to ensure that knowledge workers’ sharing and learning decisions are aligned with that of the organization.

Our results are readily extended to the scenarios of multi-dimensional knowledge levels, multiple agents, and multiple periods. Given the importance of information technology in knowledge management and the role of incentives, our research provides valuable guidance for practicing managers to choose appropriate level of investments in information technology to facilitate knowledge transfer, and design incentive systems that reward and induce knowledge sharing and learning while taking into account the level of IT investments.

7.2 Knowledge Creation, Retention, and Diffusion

The increasingly competitive market has forced companies to seek more cost-effective ways to engage in R&D. The recent trend in outsourcing R&D clearly indicates that companies are constantly searching for the best business strategy to not only save the costs but also improve the quality of R&D. Investing appropriately in R&D and then internally disseminating knowledge discovery has become critical to sustain a competitive edge and profitability.

To derive important managerial insights about how to create, retain, and diffuse knowledge discoveries within firms, our second model analyzes the knowledge discovery and diffusion processes in which a firm selects part of knowledge workers to participate in knowledge innovation in the first period and uses incentives to induce successful pioneers to share their discoveries in the second period to improve the productivity of all the workers. Our analysis provides valuable guidance for managers in managing knowledge assets as discussed below.

First, effectively disseminating internal knowledge discoveries from R&D is essential for firms to improve their productivity and overall performance. Appropriate incentives (for instance, wage payments) can be designed to motivate knowledge workers to absorb and employ the new knowledge discoveries to improve their pro-
ductivity. Consequently, managers can properly apply reward policies to induce workers’ best efforts in knowledge innovation, enhancing the success rate of knowledge discovery.

Second, synergy is indispensable for a firm to assemble an innovation team and engage in knowledge discovery, achieving the first-best effort levels among knowledge pioneers. Without the necessary synergy, the firm will not be able to offer a positive wage payment in order to engage in innovation and only the second-best solution is attainable. In other words, the firm cannot achieve the same profit by engaging in innovation as that with the presence of team synergy. Knowledge pioneers will not be offered a wage payment and only successful ones get the reward.

Third, successful knowledge pioneers can be rewarded either individually or collectively, which are equivalent and achieve the same symmetric equilibrium with the necessary synergy as long as all pioneers collaborate as one group. (If under the AWR policy, sub-groups do not collaborate, some asymmetric equilibria may exist, which are inferior to the symmetric equilibrium for the firm.) However, the individual reward policy can be implemented to achieve the first-best solution, whereas the aggregate reward policy cannot. Nevertheless, the aggregate reward policy is not totally disadvantageous. The synergy under the IWR policy is exogenous to the team, in some sense, because only successful pioneers get the reward and, therefore, pioneers may not be willing to collaborate with others, generating synergy. In contrast, under the AWR policy, pioneers will get the reward as long as the team succeeds, so they will voluntarily collaborate with others.

Fourth, the investment in R&D and routine production should be carefully balanced to maintain innovativeness and profitability. While rewarding knowledge pioneers to achieve the maximal success rate for knowledge discovery, managers also need to choose suitable team size for knowledge innovation. Our results demonstrate the tradeoffs between the team size and rewards for knowledge innovation, which helps to assign appropriate team size to knowledge innovation under both the IWR and AWR policies. Essentially, managers have to consider the team success rate elasticity of cost for type when choosing the optimal team size, i.e., the managers must make clear which type of pioneers is less expensive when contributing to the team success rate.
Finally, managers need to make proper IT investments to support internal knowledge diffusion. Information technologies have been widely used in the effective management of knowledge assets by facilitating knowledge sharing and learning among workers. Because it is easier for knowledge workers to learn new discoveries when the level of information systems increases, managers can reduce the wage payment for knowledge workers in production by investing more in IT. However, managers should appropriately adjust the incentive rewards for knowledge innovation team to balance the tradeoff between incentives and IT investments, maximizing the firm's profit.

The second study helps us to understand how incentives affect organizational decisions on creating, retaining, and diffusing knowledge discoveries and how information technologies influence these by reducing knowledge-transfer costs. Future research will study the uncertainty of innovation benefit with potential knowledge discovery and investigate the impacts of information technology accordingly in more complete detail. In conclusion, this study provides valuable insights for managers to choose the best team size for knowledge discovery, determine appropriate level of rewards, and make proper IT investments to achieve optimal organizational profits.

7.3 Knowledge Market

Maintaining an efficient internal knowledge market may effectively facilitate knowledge sharing and learning within organizations. Appropriate reward structures and necessary IT support provide sufficient trust for knowledge providers to signal on the market and share their knowledge. The third model makes contribution in analyzing the optimal organizational designs of reward structures and investment of IT for supporting the necessary trust on the internal knowledge market and their effects on an individual knowledge provider's signalling strategy.

First of all, trust is the indispensable element for the existence and success of the internal knowledge market. Without sufficient trust in reporting from her potential recipients, a knowledge provider would not truly signal and share her knowledge at all. Therefore, developing an organizational culture where trust can be ensured is paramount for implementing knowledge markets. If a firm is fortunate
enough to already have such a culture, not only can the internal knowledge market be efficient and effective but also the firm can save a lot of costs in running the market.

Second, remedies are available to improve the trust in the knowledge market. Two treatments, learning rewards and IT support, and their effects are discussed in the paper. Offering learning rewards has the threshold effect on knowledge providers’ trust whereas IT support the strength effect. The former improves provider’s belief only to certain threshold level and the latter increases the overall belief but with lower strength. Hence, neither method is perfect and the firm has to apply both methods while balancing the tradeoff between the benefits and costs.

Third, different knowledge recipients entail different reward structures as well as different methods for improving trust. A knowledge recipient can be a knowledge connoisseur, knowledge public, or knowledge superficialist. Generally, for recipients in knowledge public group, the firm only has to offer sharing rewards for knowledge providers, whereas for recipients in either knowledge connoisseur or superficialist groups, the firm may have to offer additional participation reward to induce providers’ signals on the knowledge market. In addition, the focus to improve trust will be different for different types of recipients, nature of knowledge, and learning inhibition cost functions, as shown in Table 6.3.

Finally, improving trust may not always be efficient for the knowledge market from another perspective, the quality of the knowledge being signalled. While enhancing the chance of leaning being reported/monitored, the probability of signalling from workers with low-quality knowledge is also increased. Therefore, the firm has to deal with another tradeoff when applying different methods to enhance the trust on the internal knowledge market.

In conclusion, the third study provides valuable guidelines for managers to maintain a successful and efficient internal knowledge market. Future research can be extended along the following two lines. First, the model focuses on the signalling behaviors on the knowledge providers’ side, while regarding many characteristics of the potential knowledge recipients as known, for instance, the signalling active and expiring threshold functions and the learning inhibition cost functions. Future research may extend this framework and analyze the interactions between the providers and recipients. Second, our model assumes that all knowledge workers are
similar in terms of their abilities in sending signals and participating in knowledge transfer processes. The firm cannot observe their knowledge levels, but knows the common distribution of their knowledge levels. Workers may differ in their actual knowledge levels and adopt different signaling functions with respect to their own knowledge levels. However, since the firm offers the sharing and participation rewards by maximizing its expected profit, each knowledge worker gets the same sharing and participation rewards. In this regard, our model is still applicable for the heterogeneous workers as long as they share the same distribution of knowledge levels. However, to further analyze the influence of this heterogeneity, the future extension may consider types of knowledge workers with different distribution of knowledge levels; hence, the firm has to offer a menu of rewards to screen different workers.
A.1 Proof of Lemma 1

Proof. Since in optimality, VL policy ensures that the sharing amount equals learning amount, i.e., $k_s = k_l$, which is the same as that under ML policy. Therefore, these two policies have the same optimal profits.

A.2 Proof of Lemma 2

Proof. This can be shown by contradiction. Suppose the optimal solution requires that low-knowledge worker to share. However, since the high-knowledge worker will not learn from low-knowledge worker, we can construct a similar solution by letting $(k_2^*) = 0$ and lower the payment to the low-knowledge worker, which will increase the firm’s final profit. The second part of the lemma can be established by the same logic.
A.3 Proof of Lemma 3

Proof. We define the rule for worker’s efficiency levels and amount of sharing and learning as

\[
(e_1^*, e_2^*, (k_1^*)^*, (k_2^*)^*) = \arg\max_{(e_1, e_2, k_1^*, k_2^*)} \{ E[x] - I(T) - \sum_{i=1}^2 \gamma(e_i, k_i^*) - \theta(k_1^*, k_1^*) - \delta(k_2^*, k_2^*) \},
\]

where

\[
\gamma(e_i, k_i^*) = C_i(e_i, k_i^*) - \frac{\partial C_i(e_i, k_i^*)}{\partial k_i} \left( 1 - G(k_i) \right),
\]

\[
\theta(k_1^*, k_1^*) = C_1^s(k_1^*, k_1^*, T) - \frac{\partial C_1^s(k_1^*, k_1^*, T)}{\partial k_1} \left( 1 - G(k_1) \right) \frac{g(k_1)}{g(k_1)},
\]

\[
\delta(k_2^*, k_1^*) = C_2^l(k_2^*, k_1^*, T) - \frac{\partial C_2^l(k_2^*, k_1^*, T)}{\partial k_2} \left( 1 - G(k_2) \right) \frac{g(k_2)}{g(k_2)}.
\]

Since worker 1 chooses \( e_1^*, \tau_1(= k_1^*, k_1^* = 0) \), and \( k_1^* \) and worker 2 chooses \( e_2^*, \tau_2(= k_2^*, k_2^* = 0) \) optimally, the Envelope Theorem indicates that

\[
\frac{dE_x[\pi_1]}{dk_1} = \frac{dE_xE_2[\pi_1]}{dk_1} = \frac{\partial E_xE_2[\pi_1]}{\partial k_1} \bigg|_{\tau_1 = k_1^*, k_2^* = 0} = - \frac{\partial C_1(e_1, k_1^*)}{\partial k_1} - \frac{\partial C_1^s(k_1^*, k_1^*, T)}{\partial k_1} \geq 0,
\]

\[
\frac{dE_x[\pi_2]}{dk_2} = \frac{dE_xE_1[\pi_2]}{dk_2} = \frac{\partial E_xE_1[\pi_2]}{\partial k_2} \bigg|_{\tau_1 = k_2^*, k_2^* = 0} = - \frac{\partial C_2(e_2, k_2^* + k_2^*)}{\partial k_2} - \frac{\partial C_2^l(k_2^*, k_2^*, T)}{\partial k_2} \geq 0.
\]

Hence, the individual rationality constraints can be reduced to

\[
E_xE_{-i}[\pi_i] |_{k_i = 0} = 0, \forall i = 1, 2.
\]

Therefore, the firm’s expected profit is

\[
E\{x - I(T) - \sum_{i=1}^2 [s_i(x, \tau) + R_s(k_i^*, \tau_i) + R_l(k_i^*, \tau_i)]\}
\]
The linear contract for high-knowledge worker is

\[ s_1^{VL}(x, k) + R_s^{VL}(k_s, k_1) = \lambda_1^{VL}(x - E_x[x^*]) + \rho_1^{VL}(k_s - k_s^*) + C_1(e_1, k_1) \]  

(A.6)

Therefore, \((e_1^*, e_2^*, (k_1^*)^*, (k_2^*)^*)\) pointwise maximize the firm’s expected profit.  

\[ E_x E_{-i}[\pi_i]|_{k_i=0} = 0. \]

The third equation uses integration by parts and the fourth equation sets

\[ E_x E_{-i}[\pi_i]|_{k_i=0} = 0. \]
\[ +C_s^1(k_s^*, k_1) - \int_0^{k_1} \left[ \frac{\partial C_1^*(e_1^*(t, k_2), t)}{\partial t} + \frac{\partial C_1^*(k_s^*(t, k_2), t)}{\partial t} \right] dt, \]

and the linear contract for low-knowledge worker is

\[ s_2^{VL}(x, k) + R_l^{VL}(k_l, k_2) = \lambda_2^{VL}(x - E_x[x^*]) + \rho_2^{VL}(k_1 - k_1^*) + C_2(e_2^*, k_2 + k_1^*) \quad \text{(A.7)} \]

\[ +C_2^l(k_1^*, k_2) - \int_0^{k_2} \left[ \frac{\partial C_2^l(e_2^*(t, k_1), t)}{\partial t} + \frac{\partial C_2^l(k_1^*(t, k_l), t)}{\partial t} \right] dt, \]

where,

\[ \lambda_1^{VL}(k_1, k_2) = \left. \frac{\partial C_1(e_1, k_1)}{\partial e_1} \right|_{(e_1^*, e_2^*, k_s^*)}, \quad \text{(A.8)} \]

\[ \lambda_2^{VL}(k_1, k_2) = \left. \frac{\partial C_2(e_2, k_2 + k_1^*)}{\partial e_2} \right|_{(e_1^*, e_2^*, k_l^*)}, \quad \text{(A.9)} \]

\[ \rho_1^{VL} = \left[ \frac{\partial C_2^l(k_1^*, k_s^*)}{\partial k_s} - \frac{\lambda_1^{VL}}{\lambda_2^{VL}} \frac{\partial C_2^l(e_2^*, k_2^*)}{\partial e_2} \frac{\partial e_2}{\partial k_s} \right]_{(e_1^*, e_2^*, k_s^*, k_l^*)}, \quad \text{and} \quad \text{(A.10)} \]

\[ \rho_2^{VL} = \left[ \frac{\partial C_2(e_2, k_2 + k_1^*)}{\partial k_1} + \frac{\partial C_2^l(k_2, k_1)}{\partial k_1} - \frac{\lambda_2^{VL}}{\lambda_1^{VL}} \frac{\partial C_1(e_1^*, k_1)}{\partial e_1} \frac{\partial e_1}{\partial k_1} \right]_{(e_1^*, e_2^*, k_1^*)}. \quad \text{(A.11)} \]

### A.5 Technical Details of Linear Contract for ML Policy

The linear contract for high-knowledge worker is

\[ s_1^{ML}(x, k) + R_s^{ML}(k_s, k_i) = \lambda_1^{ML}(x - E_x[x^*]) + \rho_1^{ML}(k_s^* - k_1^*) + C_1(e_1^*, k_1) \quad \text{(A.12)} \]

\[ +C_1^s(k_s^*, k_1) - \int_0^{k_1} \left[ \frac{\partial C_1(e_1^*(t, k_2), t)}{\partial t} + \frac{\partial C_1^s(k_s^*(t, k_2), t)}{\partial t} \right] dt \]

and the linear contract for low-knowledge worker is

\[ s_2^{ML}(x, k) = \lambda_2^{ML}(x - E_x[x^*]) + C_2(e_2^*, k_2 + k_1^*) \quad \text{(A.13)} \]


\[ C_2^l(k_1^*, k_2) = \int_0^{k_2} \left[ \frac{\partial C_2(e_2^*(t, k_1), t)}{\partial t} + \frac{\partial C_2^l(k_1^*(t, k_1), t)}{\partial t} \right] dt, \]

where,

\[ \lambda_{1ML}(k_1, k_2) = \frac{\partial C_1(e_1, k_1)}{\partial e_1} \bigg|_{(e_1^*, e_2^*, k_1^*)}, \tag{A.14} \]

\[ \lambda_{2ML}(k_1, k_2) = \frac{\partial C_2(e_2, k_2 + k_1^*)}{\partial e_2} \bigg|_{(e_1^*, e_2^*, k_1^*)}, \quad \text{and} \tag{A.15} \]

\[ \rho_{1ML} = \left[ \frac{\partial C_1^s(k_1, k_s)}{\partial k_s} - \frac{\lambda_{1ML} \partial C_2(e_2, k_2^*)}{\lambda_{2ML} \partial e_2} \right] \bigg|_{(e_1^*, e_2^*, k_1^*, k_s^*)}. \tag{A.16} \]

### A.6 Proof of Conditions for VL Linear Contracts

**Proof.** The high-knowledge worker maximizes her profit by reporting the knowledge level of \( \tau_1 \) and choosing \( e_1 \) and \( \hat{k}_s \) accordingly, expecting the low-knowledge worker to report her true knowledge level and acting optimally according to her reported knowledge level \( \tau_1 \) and amount of sharing \( \hat{k}_s \). Acting optimally, the low-knowledge worker wants to learn \( k_s^*(\tau_1, k_2) \) amount of knowledge. However, since the high-knowledge worker actually share \( \hat{k}_s \), the actual learning amount by the low-knowledge worker may vary correspondingly. The profit for a high-knowledge worker with knowledge level \( k_1 \) reporting \( \tau_1 \), contributing \( e_1 \), and sharing \( \hat{k}_s \) is

\[
E[\pi_1(k_1, \tau_1, e_1)] = \lambda_1(\tau_1, k_2)(E_x[x(\tau_1, k_2, \hat{k}_s)]) - E_x[x(\tau_1, k_2, k_s^* (\tau_1, k_2))])
+ \rho_1(\tau_1, k_2)(\hat{k}_s - k_s^*(\tau_1, k_2)) + C_1(e_1^*(\tau_1, k_2), \tau_1)
- C_1(e_1, k_1) + C_1^*(k_s^*(\tau_1, k_2), \tau_1) - C_1^*(\hat{k}_s, k_1)
- \int_0^{\tau_1} \left[ \frac{\partial C_1^*(t, k_2)}{\partial t} + \frac{\partial C_2^*(k_1^*(t, k_1), t)}{\partial t} \right] dt.
\]

The first order conditions with respect to \( e_1 \) and \( \hat{k}_s \) are

\[
\frac{\partial E[\pi_1]}{\partial e_1} = \lambda_1(\tau_1, k_2) \frac{\partial E_x[x(\tau_1, k_2, \hat{k}_s)]}{\partial e_1} - \frac{\partial C_1(e_1, k_1)}{\partial e_1},
\]

\[
\frac{\partial E[\pi_1]}{\partial \hat{k}_s} = \rho_1(\tau_1, k_2) + C_1(e_1^*(\tau_1, k_2), \tau_1) - C_1(e_1, k_1) + C_1^*(\hat{k}_s, k_1) - \int_0^{\tau_1} \left[ \frac{\partial C_1^*(t, k_2)}{\partial t} + \frac{\partial C_2^*(k_1^*(t, k_1), t)}{\partial t} \right] dt.
\]
\[
\frac{\partial E[\pi_1]}{\partial k_s} = \lambda_1(\tau_1, k_2) \frac{\partial E_x[x(e_1, e_2^*(\tau_1, k_2, \hat{k}_s))]}{\partial e_2} \frac{\partial e_2}{\partial k_s} + \rho_1(\tau_1, k_2) - \frac{\partial C_1(\hat{k}_s, k_1)}{\partial k_s}.
\]

The second order conditions with respect to \(e_1\) and \(\hat{k}_s\) are

\[
\frac{\partial^2 E[\pi_1]}{\partial e_1^2} = \lambda_1(\tau_1, k_2) \frac{\partial^2 E_x[x(e_1, e_2^*(\tau_1, k_2, \hat{k}_s))]}{\partial e_1^2} - \frac{\partial^2 C_1(e_1, k_1)}{\partial e_1^2} < 0,
\]

\[
\frac{\partial^2 E[\pi_1]}{\partial k_s^2} = \lambda_1(\tau_1, k_2) \left\{ \left. \frac{\partial E_x[x(e_1, e_2^*(\tau_1, k_2, \hat{k}_s))]}{\partial e_2} \right| \frac{\partial e_2}{\partial k_s} \right. + \left. \frac{\partial^2 E_x[x(e_1, e_2^*(\tau_1, k_2, \hat{k}_s))]}{\partial e_2^2} \right\} \left( \frac{\partial e_2}{\partial k_s} \right)^2 - \frac{\partial^2 C_1(\hat{k}_s, k_1)}{\partial k_s^2} < 0, \text{ if } \frac{\partial^2 e_2}{\partial k_s^2} \leq 0.
\]

We know that

\[
\frac{\partial^2 e_2}{\partial k_s^2} = \frac{\partial^2 e_2}{\partial \tau_1^2} - \frac{\partial^2 e_2}{\partial \tau_1 \partial k_s} \right)^2 \leq 0, \text{ if } \frac{\partial^2 e_2}{\partial \tau_1^2} \leq 0, \frac{\partial^2 k_s}{\partial \tau_1^2} \geq 0, \frac{\partial e_2}{\partial \tau_1} \geq 0, \frac{\partial \hat{k}_s}{\partial \tau_1} \geq 0.
\]

If there is no complementarity between \(e_1\) and \(e_2\), then the Hessian matrix of \(E[\pi_1]\) is always negative semidefinite. If there is complementarity between \(e_1\) and \(e_2\), the Hessian matrix of \(E[\pi_1]\) is always negative semidefinite if

\[
\left( \frac{\partial^2 E_x[x]}{\partial e_2 \partial e_1} \right)^2 \leq \frac{\partial^2 E_x[x]}{\partial e_2^2} \frac{\partial^2 E_x[x]}{\partial e_1^2}.
\]

Since

\[
\frac{\partial \lambda_1(\tau_1, k_2)}{\partial \tau_1} = \frac{\partial^2 C_1 \frac{\partial E_x[x]}{\partial \tau_1 \partial e_1}}{\partial \tau_1} - \frac{\partial C_1 \frac{\partial^2 E_x[x]}{\partial e_1^2} \partial e_2}{\partial \tau_1} + \frac{\partial^2 E_x[x]}{\partial e_2^2} \frac{\partial^2 E_x[x]}{\partial e_1 \partial \tau_1},
\]

\[
\frac{\partial e_1}{\partial \tau_1} = \frac{\partial \lambda_1(\tau_1, k_2)}{\partial \tau_1} \left( \frac{\partial E_x[x]}{\partial e_1} \right)^2 + \frac{\partial C_1 \frac{\partial^2 E_x[x]}{\partial e_2^2}}{\partial e_2 \partial \tau_1} \frac{\partial^2 E_x[x]}{\partial e_1 \partial \tau_1} > 0,
\]

if

\[
\frac{\partial \lambda_1}{\partial \tau_1} \geq 0, \frac{\partial e_2}{\partial \tau_1} \geq 0, \frac{\partial \hat{k}_s}{\partial \tau_1} \geq 0.
\]
To prove that $\tau^*_1 = k_1$, it is equivalent to prove

$$E_x[\pi_1(\tau_1, k_1, e_1, \hat{k}_s)] \leq E_x[\pi_1(k_1, k_1, e^*_1, k^*_s)],$$

which is implied by

$$\left. \frac{\partial E_x[\pi_1(\tau_1, k_1, e_1, \hat{k}_s)]}{\partial \tau_1} \right|_{\tau_1 = k_1} = 0 \quad \text{(A.17)}$$

and

$$\left. \frac{\partial^2 E_x[\pi_1(\tau_1, k_1, e_1, \hat{k}_s)]}{\partial \tau_1 \partial k_1} \right|_{\tau_1 = k_1} \geq 0. \quad \text{(A.18)}$$

Since

$$\frac{\partial E_x[\pi_1(\tau_1, k_1, e_1, \hat{k}_s)]}{\partial k_1} = - \frac{\partial C_1(e_1, k_1)}{\partial k_1} - \frac{\partial C^*_1(k_1, \hat{k}_s)}{\partial k_1},$$

it follows that

$$\left. \frac{\partial^2 E_x[\pi_1(\tau_1, k_1, e_1, \hat{k}_s)]}{\partial k_1 \partial \tau_1} \right|_{\tau_1 = k_1} = - \frac{\partial^2 C_1(e_1, k_1)}{\partial k_1 \partial e_1} \frac{\partial e_1}{\partial \tau_1} - \frac{\partial^2 C^*_1(k_1, \hat{k}_s)}{\partial k_1 \partial \hat{k}_s} \frac{\partial \hat{k}_s}{\partial \tau_1} \geq 0,$$

if $\frac{\partial e_1}{\partial \tau_1} \geq 0$, $\frac{\partial \hat{k}_s}{\partial \tau_1} \geq 0$,

which proves the condition (A.18).

In addition, we know that

$$\frac{dE_x[\pi_1(k_1, k_1, e^*_1, k^*_s)]}{dk_1} = - \frac{\partial C_1(e^*_1, k_1)}{\partial k_1} - \frac{\partial C^*_1(k^*_1, k_1)}{\partial k_1}$$

and

$$\left. \frac{\partial E_x[\pi_1(\tau_1, k_1, e_1, \hat{k}_s)]}{\partial k_1} \right|_{\tau_1 = k_1} = - \frac{\partial C_1(e^*_1, k_1)}{\partial k_1} - \frac{\partial C^*_1(k^*_1, k^*_s)}{\partial k_1}.$$

Hence,

$$\left. \frac{\partial E_x[\pi_1(\tau_1, k_1, e_1, \hat{k}_s)]}{\partial k_1} \right|_{\tau_1 = k_1} = \frac{dE_x[\pi_1(k_1, k_1, e^*_1, k^*_s)]}{dk_1},$$

which implies condition (A.17).
Next we prove the case for the low-knowledge worker. The low-knowledge worker maximizes her profit by reporting the knowledge level of $\tau_2$ and choosing $e_2$ and $\hat{k}_l$ accordingly, expecting the high-knowledge worker to report her true knowledge level and acting optimally according to her reported knowledge level $\tau_2$ and amount of learning $\hat{k}_l$. The profit for a low-knowledge worker with knowledge level $k_2$ reporting $\tau_2$, contributing $e_2$, and learning $\hat{k}_l$ is

$$E[\pi_2(k_2, \tau_2, e_2)] = \lambda_2(\tau_2, k_1)(E_x[x(e_2, e_1^*(\tau_2, k_1, \hat{k}_l))] - E_x[x(e^*(\tau_2, k_1, k_1^*(\tau_2, k_1)))]$$

$$+ \rho_2(\tau_2, k_1)(\hat{k}_l - k_1^*(\tau_2, k_1)) + C_2(e_2^*(\tau_2, k_1), \tau_2 + k_1^*(\tau_2, k_1))$$

$$- C_2(e_2, k_2 + k_1) + C_2(k_1^*(\tau_2, k_1), \tau_2) - C_2^l(k_1, k_2)$$

$$- \int_0^{\tau_2} \left[ \frac{\partial C_2^l(e_2^*(t, k_1), t)}{\partial t} + \frac{\partial C_2^l(k_1^*(t, k_1), t)}{\partial t} \right] dt.$$

Notice that $k_l < \hat{k}_l$ when the low-knowledge worker under-reports her knowledge level, i.e., $\tau_2 < k_2$. This is because $\hat{k}_l$ contains knowledge already known by the low-knowledge worker when $\tau_2 < k_2$. Hence, $k_l = \hat{k}_l + \tau_2 - k_2$. The low-knowledge worker can pretend to have learnt $\hat{k}_l$ while the actual learning amount is just $k_l$. On the other hand, when $\tau_2 > k_2$, $k_l$ will be zero because in this case, there is a gap between $k_2$ and $\hat{k}_l$. Therefore, the low-knowledge worker will not be able to learn with the existence of this gap according to our assumption.

The first order conditions with respect to $e_2$ and $\hat{k}_l$ are

$$\frac{\partial E[\pi_2]}{\partial e_2} = \lambda_2(\tau_2, k_1) \frac{\partial E_x[x(e_2, e_1^*(\tau_2, k_1, \hat{k}_l))]}{\partial e_2} - \frac{\partial C_2(e_2, k_2 + k_1)}{\partial e_2},$$

$$\frac{\partial E[\pi_2]}{\partial \hat{k}_l} = \rho_2(\tau_2, k_1) - \frac{\partial C_2(e_2, k_2 + k_1)}{\partial k_l} - \frac{\partial C_2^l(k_1, k_1)}{\partial k_l}$$

$$+ \lambda_2 \frac{\partial E_x[x(e_2, e_1^*(\tau_1, k_2, \hat{k}_l))]}{\partial e_1}.$$

The second order conditions with respect to $e_2$ and $\hat{k}_l$ are

$$\frac{\partial^2 E[\pi_2]}{\partial e_2^2} = \lambda_2(\tau_2, k_1) \frac{\partial^2 E_x[x(e_2, e_1^*(\tau_2, k_1, \hat{k}_l))]}{\partial e_2^2} - \frac{\partial^2 C_2(e_2, k_2 + k_1)}{\partial e_2^2} < 0,$$

$$\frac{\partial^2 E[\pi_2]}{\partial k_l^2} = - \frac{\partial^2 C_2(e_2, k_2 + k_1)}{\partial k_l^2} - \frac{\partial^2 C_2^l(k_1, k_1)}{\partial k_l^2} + \lambda_2 \left\{ \frac{\partial^2 E_x[x(e_2, e_1^*(\tau_2, k_1, \hat{k}_l))]}{\partial e_2^2} \left( \frac{\partial e_1}{\partial k_l} \right)^2 \right\}.$$
+ \frac{\partial E[x(e_2, e_1^*(\tau_2, k_1))] \partial^2 e_1}{\partial k_i^2}) < 0, \quad \text{if} \quad \frac{\partial^2 e_1}{\partial k_i^2} \leq 0.

If there is no complementarity between $e_1$ and $e_2$, then the Hessian matrix of $E[\pi_2]$ is always negative semidefinite. If there is complementarity between $e_1$ and $e_2$, the Hessian matrix of $E[\pi_1]$ is always negative semidefinite if

$$
\left(\frac{\partial^2 E[x]}{\partial e_2 \partial e_1}\right)^2 \leq \frac{\partial^2 E[x]}{\partial e_2^2} \frac{\partial^2 E[x]}{\partial e_1^2} \quad \text{and} \quad \left(\frac{\partial^2 C_2}{\partial e_2 \partial k_i}\right)^2 \leq \frac{\partial^2 C_2}{\partial e_2^2} \frac{\partial^2 C_2}{\partial k_i^2}.
$$

If

$$
\frac{\partial^2 e_1}{\partial \tau_2^2} \geq 0, \quad \frac{\partial^2 k_i}{\partial \tau_2^2} \leq 0, \quad \frac{\partial e_1}{\partial \tau_2} \geq 0, \quad \frac{\partial k_i}{\partial \tau_2} \leq 0,
$$

then

$$
\frac{\partial e_1}{\partial k_i} \leq 0 \quad \text{and} \quad \frac{\partial^2 e_1}{\partial k_i^2} = \frac{\partial^2 e_1}{\partial k_i^2} \left(\frac{\partial k_i}{\partial \tau_2}\right)^2 \leq 0.
$$

In addition, we know that

$$
\frac{\partial^3 C_2}{\partial e_2 \partial e_1 \partial e_2} = \frac{\partial^3 C_2}{\partial e_2^3} \left(\frac{\partial e_1}{\partial k_i}\right)^2 \left(\frac{\partial k_i}{\partial \tau_2}\right)^2 \geq 0,
$$

if

$$
\frac{\partial \lambda_2}{\partial \tau_2} \geq 0, \quad \frac{\partial e_1}{\partial \tau_2} \geq 0, \quad \frac{\partial k_i}{\partial \tau_2} \geq 0.
$$

Similarly, we want to show that $\tau_2^* = k_2$ with the same approach.
Since
\[\frac{\partial E_x[\pi_2(\tau_2, k_2, e_2)]}{\partial k_2}\bigg|_{\tau_2 = k_2} = -\frac{\partial C_2(e_2', k_2 + k_1^*)}{\partial k_2} - \frac{\partial C'_2(k_2, k_1^*)}{\partial k_2}\]
and
\[\frac{dE_x[\pi_2(k_2, k_2, e_2^*)]}{dk_2} = -\frac{\partial C_2(e_2', k_2 + k_1^*)}{\partial k_2} - \frac{\partial C'_2(k_1^*, k_2)}{\partial k_2},\]
it follows that
\[\frac{\partial E_x[\pi_2(\tau_2, k_2, e_2)]}{\partial k_2}\bigg|_{\tau_2 = k_2} = \frac{dE_x[\pi_2(k_2, k_2, e_2^*)]}{dk_2}.
\]
In addition, we know that
\[\frac{\partial^2 E_x[\pi_2(\tau_2, k_2, e_2)]}{\partial k_2 \partial \tau_2} = -\frac{\partial^2 C_2(e_2, k_2 + k_1)}{\partial k_2 \partial e_2} \frac{\partial e_2}{\partial \tau_2} - \frac{\partial^2 C_2(e_2, k_2 + k_1)}{\partial k_2^2} \frac{\partial k_1}{\partial \tau_2},\]
\[\frac{\partial^2 C'_2(k_2, k_1)}{\partial k_2 \partial k_1} \frac{\partial k_1}{\partial \tau_2} \geq 0, \text{ if } \frac{\partial e_2}{\partial \tau_2} \geq 0, \frac{\partial k_1}{\partial \tau_2} \leq 0, \frac{\partial k_1}{\partial \tau_2} \geq 0.
\]
Combining the above conditions of \(k_1\), we know that if
\[\frac{\partial k_1}{\partial \tau_2} = 0,
\]
then the low-knowledge worker will truthfully report her knowledge level.

Since \(k_1 = \hat{k}_1 + \tau_2 - k_2\), it follows that
\[\frac{\partial k_1}{\partial \tau_2} = \frac{\partial \hat{k}_1}{\partial \tau_2} + 1, \text{ or } \frac{\partial \hat{k}_1}{\partial \tau_2} = -1. \]

**A.7 Proof of Conditions for ML Linear Contracts**

*Proof.* For the high-knowledge worker, we can still prove and get the same conditions as those under VL policy.

Next we prove the case for the low-knowledge worker. The profit for a low-knowledge worker with knowledge level \(k_2\) reporting \(\tau_2\), contributing \(e_2\) is
\[E[\pi_2(k_2, \tau_2, e_2)] = \lambda_2(\tau_2, k_1)(E_x[x(e_2, e_1^*(\tau_2, k_1))] - E_x[x(e^*(\tau_2, k_1, k_1^*(\tau_2, k_1)))]).\]
\[ + C_2(e_2^*(\tau_2, k_1), \tau_2 + k_1^*(\tau_2, k_1)) - C_2(e_2, k_2 + k_1) \\
+ C^l_2(k_2^*(\tau_2, k_1), \tau_2) - C^l_2(k_2^*, k_2) \\
- \int_{\tau_2}^{2} \left[ \frac{\partial C_2(e_2^*(t, k_1), t)}{\partial t} + \frac{\partial C^l_2(k_2^*(t, k_1), t)}{\partial t} \right] dt. \]

The first order condition with respect to \(e_2\) is

\[ \frac{\partial E[\pi_2]}{\partial e_2} = \lambda_2(\tau_2, k_1) \frac{\partial E_x[x(e_2, e_1^*(\tau_2, k_1))]}{\partial e_2} - \frac{\partial C_2(e_2, k_2 + k_1)}{\partial e_2}. \]

The second order condition with respect to \(e_2\) is

\[ \frac{\partial^2 E[\pi_2]}{\partial e_2^2} = \lambda_2(\tau_2, k_1) \frac{\partial^2 E_x[x(e_2, e_1^*(\tau_2, k_1))]}{\partial e_2^2} - \frac{\partial^2 C_2(e_2, k_2 + k_1)}{\partial e_2^2} < 0. \]

\[ \frac{\partial e_2}{\partial \tau_2} = \frac{\partial \lambda_2}{\partial \tau_2} \frac{\partial E_x[x]}{\partial k_2} + \lambda_2 \frac{\partial^2 E_x[x]}{\partial e_2 \partial \tau_2} - \lambda_2 \frac{\partial^2 E_x[x]}{\partial e_2^2} \]

\[ \int_{\tau_2}^{2} \left[ \frac{\partial C_2(e_2^*(t, k_1), t)}{\partial t} + \frac{\partial C^l_2(k_2^*(t, k_1), t)}{\partial t} \right] dt. \]

To show that \(\tau_2^* = k_2\), we use the same logic as before.

Since

\[ \frac{\partial E_x[\pi_2(\tau_2, k_2, e_2)]}{\partial k_2} \bigg|_{\tau_2 = k_2} = \frac{\partial C_2(e_2^*, k_2 + k_1^*)}{\partial k_2} - \frac{\partial C^l_2(k_2^*, k_2)}{\partial k_2} \]

and

\[ \frac{d E_x[\pi_2(k_2, k_2, e_2^*)]}{dk_2} = \frac{\partial C_2(e_2^*, k_2 + k_1^*)}{\partial k_2} - \frac{\partial C^l_2(k_2^*, k_2)}{\partial k_2}, \]

it follows that

\[ \frac{\partial E_x[\pi_2(\tau_2, k_2, e_2)]}{\partial k_2} \bigg|_{\tau_2 = k_2} = \frac{d E_x[\pi_2(k_2, k_2, e_2^*)]}{dk_2}. \]
Because

\[
\frac{\partial E_x[\tau_2(\tau_2, k_2, e_2)]}{\partial k_2} = -\frac{\partial C_2(e_2, k_2 + k_1)}{\partial k_2} - \frac{\partial C_2'(k_2, k_s)}{\partial k_2},
\]

we know that

\[
\frac{\partial^2 E_x[\tau_2(\tau_2, k_2, e_2)]}{\partial k_2 \partial \tau_2} = -\frac{\partial^2 C_2(e_2, k_2 + k_1)}{\partial k_2 \partial e_2} - \frac{\partial^2 C_2(e_2, k_2 + k_1)}{\partial k_2^2} \frac{\partial k_i}{\partial \tau_2} - \frac{\partial^2 C_2'(k_2, k_s)}{\partial k_2 \partial k_s^*} \frac{\partial k_s^*}{\partial \tau_2} \geq 0, \text{ if } \frac{\partial e_2}{\partial \tau_2} \geq 0, \frac{\partial k_i}{\partial \tau_2} \leq 0, \frac{\partial k_s^*}{\partial \tau_2} \leq 0.
\]

Since learning is mandatory, a test will be conducted by the firm to verify whether the low-knowledge worker has enhanced her knowledge level to a fixed one (for example, \(\hat{\alpha}k_1\)) after learning. In this way, \(\frac{\partial k_i}{\partial \tau_2}\) is always zero.

\[\boxed{}\]

A.8 Proof of Proposition 2

Proof. For the high knowledge worker under VL policy,

\[
\frac{\partial \rho_1(\tau_1, k_2)}{\partial \tau_1} = \frac{\partial^2 C_1'(\hat{k}_s, k_1)}{\partial \hat{k}_s^2} \frac{\partial \hat{k}_s}{\partial \tau_1} - \frac{\partial \lambda_1}{\partial \tau_1} \frac{\partial E_x[x]}{\partial e_2} \frac{\partial e_2}{\partial k_s} - \frac{\partial^2 E_x[x]}{\partial e_2^2} \frac{\partial e_2}{\partial k_s^2} \frac{\partial k_s}{\partial \tau_1} = \lambda_1 \frac{\partial^2 E_x[x]}{\partial e_2^2} \frac{\partial e_2}{\partial k_s^2} \frac{\partial k_s}{\partial \tau_1},
\]

therefore,

\[
\frac{\partial k_s}{\partial \tau_1} = \frac{\partial \rho_1(\tau_1, k_2)}{\partial \tau_1} + \frac{\partial \lambda_1}{\partial \tau_1} \frac{\partial E_x[x]}{\partial e_2} \frac{\partial e_2}{\partial k_s} + \lambda_1 \frac{\partial^2 E_x[x]}{\partial e_2^2} \frac{\partial e_2}{\partial k_s^2} \frac{\partial k_s}{\partial \tau_1} \geq 0, \text{ if } \frac{\partial \rho_1(\tau_1, k_2)}{\partial \tau_1} \geq 0.
\]

For the low knowledge worker under VL policy,

\[
\frac{\partial \rho_2(\tau_2, k_1)}{\partial \tau_2} = \frac{\partial^2 C_2(e_2, k_2 + k_1)}{\partial \tau_2} + \frac{\partial^2 C_2'(k_2, k_2)}{\partial \tau_2} = \lambda_2 \frac{\partial^2 E_x[x]}{\partial e_2^2} \frac{\partial e_2}{\partial k_s} \frac{\partial k_s}{\partial \tau_2} - \frac{\partial \lambda_2}{\partial \tau_2} \frac{\partial E_x[x]}{\partial e_2} \frac{\partial e_2}{\partial k_s} \frac{\partial k_s}{\partial \tau_2} - \frac{\partial^2 E_x[x]}{\partial e_2^2} \frac{\partial e_2}{\partial k_s} \frac{\partial k_s}{\partial \tau_2} \frac{\partial k_s}{\partial \tau_2} \frac{\partial k_s}{\partial \tau_2}.
\]
we know that
\[
\frac{\partial \hat{k}_l}{\partial \tau_2} = \frac{\partial \rho_2(\tau_2, k_1)}{\partial \tau_2} + \frac{\partial \lambda_2 \partial E_x [x]}{\partial e_1} \frac{\partial e_1}{\partial \hat{k}_l} + \lambda_2 \frac{\partial^2 E_x [x]}{\partial e_1 \partial e_2} \frac{\partial e_2}{\partial \hat{k}_l} - \lambda_2 \frac{\partial^2 E_x [x]}{\partial e_1} \frac{\partial^2 e_1}{\partial \hat{k}_l^2} - \frac{\partial^2 C_2}{\partial \hat{k}_l^2} \leq 0,
\]
if
\[
\frac{\partial \rho_2(\tau_2, k_1)}{\partial \tau_2} \leq 0.
\]

Similar conditions can be shown for workers under ML policy.

\section{A.9 Proof of Proposition 3}

Proof. The first order condition of the firm’s expected profit (from Lemma A.3) with respect to \( T \) indicates that
\[
\frac{\partial^2 \rho^s_1(k^s_1, k_1, T)}{\partial k_1 \partial T} \cdot \frac{1 - G(k_1)}{g(k_1)} - \frac{\partial^2 C^l_2(k^l_2, k_2, T)}{\partial k_2 \partial T} \cdot \frac{1 - G(k_2)}{g(k_2)} + \frac{\partial I(T)}{\partial T} = \frac{\partial C^s_1(k^s_1, k_1, T)}{\partial T} - \frac{\partial C^l_2(k^l_2, k_2, T)}{\partial T}.
\]

According to our assumption, \( \frac{\partial^2 \rho^s_1(k^s_1, k_1, T)}{\partial k_1 \partial T} < 0 \) and \( \frac{\partial^2 C^l_2(k^l_2, k_2, T)}{\partial k_2 \partial T} > 0 \), which implies that the decreasing rate of the sharing cost with respect to one’s knowledge level is a convexly decreasing function of \( T \). Hence, the LHS part of above equation is an increasing function of \( T \) and RHS part is a decreasing function of \( T \). The second order condition with respect to \( T \) is always negative. Therefore, an optimal level \( T^* \) of information systems exists, or
\[
T^* = \arg\max_T \{ E[x] - I(T) - \sum_{i=1}^2 \gamma(e_i, k'_i) - \theta(k^s_1, k_1) - \delta(k^l_2, k_2) \}. \tag{A.19}
\]

\section{A.10 Proof of Proposition 4}

Proof. The first order conditions for Equation (A.1) yield
\[
\frac{\partial E[x]}{\partial e_1} = \frac{\partial E[\gamma(e_1, k_1)]}{\partial e_1} \quad \text{and} \quad \frac{\partial E[x]}{\partial e_2} = \frac{\partial E[\gamma(e_2, k_2 + k_i)]}{\partial e_2}.
\]
The first order condition with respect to $k_s$ is

\[
\frac{\partial E[x]}{\partial e_1} \frac{\partial e_1}{\partial k_s} + \frac{\partial e_2}{\partial k_s} = \frac{\partial E[\gamma(e_1, k_1)]}{\partial e_1} \frac{\partial e_1}{\partial k_s} + \frac{\partial E[\gamma(e_2, k_2 + k_l)]}{\partial e_2} \frac{\partial e_2}{\partial k_s} + \frac{\partial E[\gamma(e_2, k_2 + qk_s)]}{\partial k_s} + \frac{\partial E[\theta(k_1, k_s)]}{\partial k_s} + \frac{\partial E[\delta(k_2, qk_s)]}{\partial k_s}.
\]

Therefore, $k_s^* = k_1^*$ can be solved from

\[
\frac{\partial E[\gamma(e_2, k_2 + k_s)]}{\partial k_s} + \frac{\partial E[\theta(k_1, k_s)]}{\partial k_s} + \frac{\partial E[\delta(k_2, k_s)]}{\partial k_s} = 0.
\]

Remember that $C_s^i(\cdot)$ and $C_i^l(\cdot)$ are decreasing functions of $T$. Therefore, when $T$ increases, $\delta(\cdot)$ and $\theta(\cdot)$ decreases. Hence, there exists one $T^C$ where $k_s = k_l = k_1 - k_2$, i.e., complete-knowledge enablement is achieved.

## A.11 Numerical Example

We suppose that the expected output $E[x] = 1 - (1 - e_1 - e_2)^2$ and that knowledge level of each worker is uniformly distributed between 0 and 1, i.e., $k_i \sim U[0, 1]$. In addition, we let $C_1(e_1, k_1) = \beta_1 e_1^2(a - k_1)$, $C_2(e_2, k_2) = \beta_2 e_2^2(a - k_2 - k_1)$, $C_s(k_1, k_s) = \sigma k_s^2(b - k_1)/T$, and $C_i(k_2, k_s) = \omega(k_i)^2(d - k_2)/T$. Therefore, the expected profits of the firm and each worker are

\[
\pi = E[x - s_1(x, \tau_1) - s_2(x, \tau_2) - R_s(k_s, k_1) - R_i(k_1, k_2)],
\]

\[
\pi_1 = E[s_1(x, \tau)] - \beta_1 e_1^2(a - k_1) - \sigma k_s^2(b - k_1)/T + R_s(k_s, k_1),
\]

\[
\pi_2 = E[s_2(x, \tau)] - \beta_2 e_2^2(a - k_2 - k_1) - \omega k_s^2(d - k_2)/T + R_i(k_1, k_2).
\]

According to the definition in Equation (A.2), $\gamma(e_1, k_1) = \beta_1 e_1^2(a - k_1) + \beta_1 e_1^2(1 - k_1)$, $\gamma(e_2, k_2) = \beta_2 e_2^2(a - k_2 - k_s) + \beta_2 e_2^2(1 - k_2)$, $\theta(k_1^*, k_1) = \sigma k_s^2(b - k_1)/T + \sigma k_s^2(1 - k_1)/T$, $\delta(k_1^*, k_2) = \omega(k_2^*)^2(d - k_2)/T + \omega(k_s)^2(1 - k_2)/T$.

In addition, we let $k_s = \alpha k_1 - k_2$. Therefore, the optimal effort levels and sharing amount can be derived from Equation (3). We let $\beta_1 = \beta_2 = 1$, $a = b = d = 1$, $\theta = \omega = 0.8$, $k_1 = 0.9$, and $k_2 = 0.4$ in Figure 4.2.
Appendix B

Proofs and Technical Details of Chapter 5

B.1 Proof of Lemma 6

Proof. The first order conditions of the firm’s payoff with respect to $e$ and $M$ indicate that

\begin{align*}
Mc'(e) &= \rho'_c(e, M)B \\
c(e) + U_r &= \rho'_M(e, M)B.
\end{align*}

and the second order conditions are,

\begin{align*}
\frac{\partial^2 \pi}{\partial e^2} &= -Mc''(e) + \rho''(e)M(1 - \rho(e))^{M-1}B - [\rho'(e)]^2M(M - 1)(1 - \rho(e))^{M-2}B < 0, \\
\frac{\partial^2 \pi}{\partial M^2} &= -(1 - \rho(e))^M[\ln(1 - \rho(e))]^2B < 0, \\
\frac{\partial^2 \pi}{\partial e \partial M} &= -c'(e) + [\rho'(e)(1 - \rho(e))^{M-1} + \rho'(e)M(1 - \rho(e))^{M-1}\ln(1 - \rho(e))]B \\
&= \rho'(e)M(1 - \rho(e))^{M-1}B\ln(1 - \rho(e)).
\end{align*}

Hence, the sufficient condition for the Hessian matrix to be negative definite is

\[\rho''(e)(1 - \rho(e)) + [\rho'(e)]^2 \leq 0,\]
at the optimal effort level $e^\ast$. ■

B.2 Proof of Proposition 5

Proof. The firm’s optimal profit with $(e^\ast, M^\ast)$ is

$$\pi^\ast = [\rho^G - M\rho^G_M]B,$$

which is positive if $M\rho^G_M \leq \rho^G$.

The optimal wage payment with $(e^\ast, M^\ast)$ is

$$w^\ast = c(e) + U_r - \rho(e)r$$

$$= [\rho^G - \frac{\rho(e)(1 - \rho^G)}{1 - \rho(e)}]B$$

which is positive if $\rho^G_{M} \geq \rho(e)(1 - \rho^G)\frac{1}{1 - \rho(e)}$.

Hence, to achieve both the positive profit and wage payment, it must be that

$$M\frac{\rho(e)(1 - \rho^G)}{1 - \rho(e)} \leq M\rho^G_M \leq \rho^G,$$

which is

$$\frac{M\rho(e)}{-(1 - \rho(e))\ln(1 - \rho^G)} \leq 1 \leq \frac{\rho^G}{-(1 - \rho^G)\ln(1 - \rho^G)}.$$

These two conditions can never be satisfied at the same time because

$$\frac{M\rho(e)}{-(1 - \rho(e))\ln(1 - \rho^G)} \geq 1, \forall e^\ast, M^\ast.$$

Hence, the firm has to bind the wage payment condition, i.e., the reward and optimal effort level can be determined from

$$r = \frac{c'(e)}{\rho'(e)}$$

$$U_r = \frac{\rho(e)}{\rho'(e)}c'(e) - c(e).$$
B.3 Proof of Lemma 7

Proof. Treating the effort level $e$ and team size $M$ as decision variables, we get the first order conditions as

\[
\frac{\partial \pi}{\partial e} = -Mc'(e) + \rho'(e)q(M)(1 - \rho(e))^{q(M)-1}B = 0,
\]
\[
\frac{\partial \pi}{\partial M} = -c(e) - U_r - q'(M)(1 - \rho(e))^{q(M)}ln(1 - \rho(e))B = 0,
\]

and the second order derivatives are

\[
\frac{\partial^2 \pi}{\partial e^2} = -Mc''(e) + \rho''(e)q(M)(1 - \rho(e))^{q(M)-1}B
\]
\[-[\rho'(e)]^2 q(M)(q(M) - 1)(1 - \rho(e))^{q(M)-2}B < 0,
\]
\[
\frac{\partial^2 \pi}{\partial M^2} = -q''(M)(1 - \rho(e))^{q(M)}ln(1 - \rho(e))B
\]
\[-[q'(M)]^2(1 - \rho(e))^{q(M)}[ln(1 - \rho(e))]^2B < 0,
\]
\[
\frac{\partial^2 \pi}{\partial e \partial M} = -c'(e) + [\rho'(e)q'(M)(1 - \rho(e))^{q(M)-1}
\]
\[+ \rho'(e)q'(M)(1 - \rho(e))^{q(M)-1}ln(1 - \rho(e))]B
\]
\[= - \frac{q(M)}{M} \rho'(e)(1 - \rho(e))^{q(M)-1}B + [\rho'(e)q'(M)(1 - \rho(e))^{q(M)-1}
\]
\[+ \rho'(e)q'(M)(1 - \rho(e))^{q(M)-1}ln(1 - \rho(e))]B.
\]

At the stationary point $(e^*, M^*)$,

\[
\frac{\partial^2 \pi}{\partial e \partial M} \geq 0 \quad \text{iff} \quad \frac{q(M)}{M} \geq q'(M)[1 + q(M)ln(1 - \rho(e))]. \tag{B.1}
\]

If the equality holds, then there is no complementarity between the effort level $e$ and team size $M$, the Hessian matrix is always negative definite. If the equality does not hold, then to ensure the Hessian matrix is negative definite, it must be that

\[
\frac{\partial \pi}{\partial e} \cdot \frac{\partial \pi}{\partial M} > \left[ \frac{\partial^2 \pi}{\partial e \partial M} \right]^2,
\]
which has the sufficient condition as $\rho''(e)(1 - \rho(e)) + [\rho'(e)]^2 \leq 0$ and

$$-q'(M)q(M)ln(1 - \rho(e)) \geq \left| q'(M)[1 + q(M)ln(1 - \rho(e))] - \frac{q(M)}{M} \right|. \quad \blacksquare$$

### B.4 Proof of Lemma 8

**Proof.** The firm achieves the optimal profit as

$$\pi^* = \left[ \rho^G(e, M) - M\rho_M^G(e, M) \right] B$$

$$= \left[ 1 - (1 - \rho(e))^{q(M)} + Mq'(M)ln(1 - \rho(e))(1 - \rho(e))^{q(M)} \right] B.$$

Therefore, $\pi^* \geq 0$ if and only if

$$-Mq'(M)ln(1 - \rho(e))(1 - \rho(e))^{q(M)} \leq 1 - (1 - \rho(e))^{q(M)}.$$ 

which is

$$\frac{q'(M)M}{q(M)} \leq \frac{\rho^G}{-(1 - \rho^G)ln(1 - \rho^G)}. \quad \blacksquare$$

### B.5 Proof of Lemma 9

**Proof.** Optimal wage:

$$w = c(e) + U_r - \rho'(e, M)r$$

$$\begin{align*}
= & \rho_M^G(e, M)B - \rho'(e, M)\frac{(1 - \rho(e))^{q(M)}}{(1 - \rho(e))^{\frac{q(M)}{M}}} B \\
= & -q'(M)ln(1 - \rho(e))(1 - \rho(e))^{q(M)}B - \left[ 1 - (1 - \rho(e))^{\frac{q(M)}{M}} \right] \left[ 1 - (1 - \rho(e))^{\frac{q(M)}{M}} \right] B.
\end{align*}$$

For the wage to be positive, it must be that

$$-q'(M)ln(1 - \rho(e)) \geq \left[ 1 - (1 - \rho(e))^{\frac{q(M)}{M}} \right] \frac{1}{(1 - \rho(e))^{\frac{q(M)}{M}}}. $$
which is

\[
\frac{q'(M)M}{q(M)} \geq \frac{M\rho^I}{-(1 - \rho^I)ln(1 - \rho^G)}.
\]

**B.6 Proof of Proposition 6**

*Proof.* For the firm’s profit to be positive, it must be that \(\rho^G(e, M) \geq M\rho_M^G(e, M)\), which is

\[
\frac{1 - (1 - \rho(e))^{q(M)}}{(1 - \rho(e))^{q(M)}} \geq Mq(M)ln(1 - \rho(e)) \text{ or } \frac{1 - (1 - \rho(e))^{q(M)}}{ln(1 - \rho(e))^{q(M)}} \geq \frac{Mq'(M)}{q(M)},
\]

which suggests that the team elasticity of synergy should be less than a function of team success rate, i.e.,

\[
\frac{Mq'(M)}{q(M)} \leq \frac{\rho^G}{-(1 - \rho^G)ln(1 - \rho^G)}.
\]

When there exists positive complementarity between \(e\) and \(M\), from the condition in Inequality (5.19),

\[
\frac{Mq'(M)}{q(M)} \geq \frac{1}{1 + ln(1 - \rho^G)} > 0.
\]

When \(1 + ln(1 - \rho^G) > 0\), it is always true that

\[
\frac{1}{1 + ln(1 - \rho^G)} > \frac{\rho^G}{-(1 - \rho^G)ln(1 - \rho^G)},
\]

which indicates that the profit will never be positive when there exists positive complementarity between \(e\) and \(M\).
B.7 Proof of Proposition 7

Proof. When there exists negative complementarity between $e$ and $M$, if $1 + \ln(1 - \rho^G) > 0$,

$$1 \leq \frac{Mq'(M)}{q(M)} < \frac{1}{1 + \ln(1 - \rho^G)},$$

and if $1 + \ln(1 - \rho^G) \leq 0$,

$$\frac{1}{1 + \ln(1 - \rho^G)} < 1 \leq \frac{Mq'(M)}{q(M)}.$$

Hence, to ensure a positive firm’s profit and wage payment, it must be that

$$1 \leq \frac{\rho^G}{-(1 - \rho^G)\ln(1 - \rho^G)},$$

and

$$1 \leq \frac{M\rho^I}{-(1 - \rho^I)\ln(1 - \rho^G)}.$$

We define

$$f(M) = \frac{M\rho^I}{(1 - \rho^I)} = \frac{1 - \frac{\sqrt{1 - \rho^G}}{\rho^G}}{\sqrt{1 - \rho^G}} M,$$

hence,

$$f(1) = \frac{\rho^G}{(1 - \rho^G)} \text{ and } \frac{\partial f(M)}{\partial M} = -1 + \frac{M + \ln(1 - \rho^G)}{M^{\frac{3}{2}} \sqrt{1 - \rho^G}}.$$

In addition,

$$\frac{\partial^2 f(M)}{\partial M^2} = \frac{[\ln(1 - \rho^G)]^2}{M^3 \sqrt{1 - \rho^G}} > 0,$$

$$\lim_{M \to \infty} \frac{\partial f(M)}{\partial M} = 0,$$

therefore,

$$\frac{\partial f(M)}{\partial M} < 0,$$
and we can claim that
\[
\frac{\rho^G}{(1 - \rho^G)\ln(1 - \rho^G)} \geq \frac{M\rho^I}{(1 - \rho^I)\ln(1 - \rho^I)}, \forall M \in \{1, 2, \ldots\}.
\]

In addition,
\[
\frac{M\rho^I}{(1 - \rho^I)\ln(1 - \rho^I)} \geq 1, \forall M \in \{1, 2, \ldots\}, \rho^G, \rho^I.
\]

which implies that when there exists such solution \((e^*, M^*)\) that satisfy the positive conditions for both the profit and wage payment, then there must exist negative complementarity between \(e^*\) and \(M^*\). □

### B.8 Proof of Proposition 8

**Proof.** In this case, the firm has to bind the wage payment constraint, i.e.,
\[
c(e) - \rho^I(e, M)r + U_r = 0,
\]

and the following inequality must hold
\[
\frac{\partial \pi}{\partial e} = -Mc'(e) + \rho^G(e, M)B > 0.
\]

Since \(c'(e) = \rho^I(e, M)r\), the above inequality is
\[
\rho^G(e, M)B > M[c(e) + U_r] \frac{\rho^I(e, M)}{\rho^I(e, M)}.
\]

From the first-order condition of the firm’s profit with respect to team size \(M\), we know that \(c(e) + U_r = \rho^G_M(e, M)B\). Therefore,
\[
\frac{\rho^G(e, M)}{\rho^G_M(e, M)} > M\frac{\rho^I(e, M)}{\rho^I(e, M)}
\]

which is
\[
-q'(M)\ln(1 - \rho(e)) < [1 - (1 - \rho(e))^{q(M)}] \frac{M}{(1 - \rho(e))^{q(M)}},
\]

or
\[
\frac{Mq'(M)}{q(M)} < \frac{M\rho^l}{-(1-\rho^l)\ln(1-\rho^G)}. \]

**B.9 Proof of Lemma 10**

*Proof.* The optimal wage under the symmetric equilibrium of AWR policy is

\[
w = c(e) + U_r - \rho^G(e, M)B = \rho_M^G(e, M)B - \rho^G(e, M)B = -q'(M)\ln(1 - \rho(e))(1 - \rho(e))^q(M)B - [1 - (1 - \rho(e))^q(M)]B.
\]

For the wage to be positive, it must be that

\[
-q'(M)\ln(1 - \rho(e)) \geq [1 - (1 - \rho(e))^q(M)] \frac{1}{(1 - \rho(e))^q(M)},
\]

which is equivalent to

\[
\frac{q'(M)M}{q(M)} \geq \frac{M\rho^G}{-(1-\rho^G)\ln(1-\rho^G)}. \]

(B.2)

**B.10 Proof of Lemma 11**

*Proof.* For the firm’s profit to be positive, it must be that \(\rho^G(e, M) \geq M\rho^G_M(e, M)\), which is

\[
\frac{1 - (1 - \rho(e))^q(M)}{(1 - \rho(e))^q(M)} \geq \frac{1}{-ln(1 - \rho(e))^q(M)} \geq \frac{Mq'(M)ln(1 - \rho(e))}{q(M)},
\]

which is

\[
\frac{q'(M)M}{q(M)} \leq \frac{\rho^G}{-(1-\rho^G)\ln(1-\rho^G)}. \]

B.11 Technical Details of Lagrangian Functions for Two Types

By introducing Lagrangian multipliers $\gamma_i$ and $\mu_i$ for constraints (5.27) and (5.28), we get

$$L = -M \delta [c_1(e_1(r_1)) + \alpha_1 + U_r] - M(1 - \delta) [c_2(e_2(r_2)) + \alpha_2 + U_r]$$

$$+ \gamma_1 [c_1(e_1(r_2)) - \rho^{I_1}(e_1(r_2), M)r_2 + \alpha_1 - c_2(e_2(r_2)) + \rho^{I_2}(e_2(r_2), M)r_2 - \alpha_2]$$

$$+ \gamma_2 [c_2(e_2(r_1)) - \rho^{I_2}(e_2(r_1), M)r_1 + \alpha_2 - c_1(e_1(r_1)) + \rho^{I_1}(e_1(r_1), M)r_1 - \alpha_1]$$

$$+ \mu_1 [c_1(e_1(r_1)) + U_r - \rho^{I_1}(e_1(r_1), M)r_1 + \alpha_1] + \mu_2 [c_2(e_2(r_2)) + U_r$$

$$+ \rho^G(e_1(r_1), e_2(r_2), M)B - \rho^{I_2}(e_2(r_2), M)r_2 + \alpha_2].$$

First, if we consider $M$ as a parameter, then the necessary K.K.T. conditions are

$$\frac{\partial L}{\partial r_1} = [\rho^G_{c_1} B - M \delta c'_1(e_1)] \frac{\partial e_1}{\partial r_1} + \gamma_1 \rho^{I_1}(e_1(r_1), M) - \gamma_2 \rho^{I_2}(e_2(r_1), M) - \mu_1 \rho^{I_1}(e_1(r_1), M) = 0,$$

$$\frac{\partial L}{\partial r_2} = [\rho^G_{c_2} B - M(1 - \delta) c'_2(e_2)] \frac{\partial e_2}{\partial r_2} + \gamma_2 \rho^{I_2}(e_2(r_2), M) - \gamma_1 \rho^{I_1}(e_1(r_2), M) - \mu_2 \rho^{I_2}(e_2(r_2), M) = 0,$$

$$\gamma_1 [c_1(e_1(r_2)) - \rho^{I_1}(e_1(r_2), M)r_2 + \alpha_1 - c_2(e_2(r_2)) + \rho^{I_2}(e_2(r_2), M)r_2 - \alpha_2] = 0,$$

$$\gamma_2 [c_2(e_2(r_1)) - \rho^{I_2}(e_2(r_1), M)r_1 + \alpha_2 - c_1(e_1(r_1)) + \rho^{I_1}(e_1(r_1), M)r_1 - \alpha_1] = 0,$$

$$\mu_1 [c_1(e_1(r_1)) - \rho^{I_1}(e_1(r_1), M)r_1 + \alpha_1 + U_r] = 0,$$

$$\mu_2 [c_2(e_2(r_2)) - \rho^{I_2}(e_2(r_2), M)r_2 + \alpha_2 + U_r] = 0,$$

$$c_1(e_1(r_2)) - \rho^{I_1}(e_1(r_2), M)r_2 + \alpha_1 - c_2(e_2(r_2)) + \rho^{I_2}(e_2(r_2), M)r_2 - \alpha_2 \geq 0,$$

$$c_2(e_2(r_1)) - \rho^{I_2}(e_2(r_1), M)r_1 + \alpha_2 - c_1(e_1(r_1)) + \rho^{I_1}(e_1(r_1), M)r_1 - \alpha_1 \geq 0,$$

$$c_1(e_1(r_1)) - \rho^{I_1}(e_1(r_1), M)r_1 + \alpha_1 + U_r \geq 0,$$

$$c_2(e_2(r_2)) - \rho^{I_2}(e_2(r_2), M)r_2 + \alpha_2 + U_r \geq 0,$$

$$\gamma_1, \gamma_2, \mu_1, \mu_2 \geq 0.$$
In addition,

\[
\frac{\partial L}{\partial \alpha_1} = -M\delta + \gamma_1 - \gamma_2 + \mu_1,
\]

\[
\frac{\partial L}{\partial \alpha_2} = -M(1 - \delta) + \gamma_2 - \gamma_1 + \mu_2.
\]
C.1 Proof of Lemma 16

Proof. Given the expected probability $E_{k_j}[P(k_j, s_i)]$ of knowledge $k_j$ to be learned from worker $i$’s signalling strategy (Equation (6.4)), the firm maximizes its expected payoff

$$\pi = \int_{k_i} E_{k_j}[P(k_j, s_i)](B - r_s)\theta(k_i)dk_i,$$

by choosing a best sharing reward $r_s$. 

C.2 Proof of Lemma 17

Proof. Worker $i$’s individual rationality constraint indicates that

$$\pi_i = w_i + E_{k_j}[P(k_j, s_i)r_s - c_i(k_i, s_i)] \geq U_0,$$

for which the Envelope theorem suggests that,

$$\frac{d\pi_i}{dk_i} = -\frac{E_{k_j}\partial c_i(s_i, k_i)}{\partial k_i} \geq 0,$$
which implies that the individual-rationality constraints can be reduced into

$$\pi_i|_{k_i=0} = U_0.$$  

Since when worker $i$’s knowledge $k_i = 0$, her payoff $\pi_i = w_i$, therefore, the firm should offer the participation reward as $w_i = U_0$.

Alternatively, the firm’s expected profit can be rewritten as

$$\pi = \int_{k_i} \left\{ E_{k_j}[P(k_j, s_i)](B - r_s) - w_i \right\} \theta(k_i)dk_i$$

$$= \int_{k_i} E_{k_j}[P(k_j, s_i)B - c_i(k_i, s_i)]\theta(k_i)dk_i - \int_{k_i} \pi_i\theta(k_i)dk_i$$

$$= \int_{k_i} E_{k_j}[P(k_j, s_i)B - c_i(k_i, s_i)]\theta(k_i)dk_i + \int_0^1 \pi_i d(1 - \Theta(k_i))$$

$$= \int_{k_i} E_{k_j}[P(k_j, s_i)B - c_i(k_i, s_i)]\theta(k_i)dk_i + [\pi_i(1 - \Theta(k_i))]_0^1 - \int_0^1 \frac{d\pi_i}{dk_i}(1 - \Theta(k_i))dk_i$$

$$= \int_{k_i} E_{k_j}[P(k_j, s_i)B - c_i(k_i, s_i)]\theta(k_i)dk_i - \int_0^1 \frac{E_{k_j} \partial c_i(s_i, k_i)}{\partial k_i} \cdot \frac{\pi_i}{\theta(k_i)} \cdot (1 - \Theta(k_i))dk_i - U_0$$

$$= \int_{k_i} E_{k_j} \left\{ P(k_j, s_i)B - \left[ c_i(k_i, s_i) - \frac{\partial c_i(s_i, k_i)}{\partial k_i} \cdot \frac{\pi_i}{\theta(k_i)} \cdot \frac{1 - \Theta(k_i)}{\theta(k_i)} \right] \right\} \theta(k_i)dk_i - U_0.$$  

Therefore, the firm maximizes $\pi$ by choosing the optimal $r_s$.  

C.3 Proof of Lemma 18

Proof. Even though an individual provider’s signalling function may belong to one of five cases, the Envelope theorem still suggests that,

$$\frac{d\pi_i}{dk_i} = -\frac{E_{k_j} \partial c_i(s_i, k_i)}{\partial k_i} \geq 0,$$

which implies that the individual-rationality constraints can be reduced into

$$\pi_i|_{k_i=0} = U_0.$$  

Since when worker $i$’s knowledge $k_i = 0$, her payoff $\pi_i = w_i$. Therefore, the firm should still offer the participation reward as $w_i = U_0$. 
Following the similar procedure as the above process, we can rewrite the firm’s payoff function as

$$\pi = \sum_{i=1}^{V} \int_{k_i} E_{k_j} P^i \cdot [B - r_l - w_i] \cdot p_i \cdot \theta(k_i) dk_i - U_0$$

$$= \sum_{i=1}^{V} \int_{k_i} E_{k_j} P^i \cdot [B - r_l - \hat{c}_i(s_i, k_i)] \cdot p_i \cdot \theta(k_i) dk_i - U_0$$

Therefore, the firm maximizes \( \pi \) by choosing the optimal \( r_s, r_l, \) and \( q_2 \).
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Vita
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Zuopeng Zhang was born in the northwestern China and grew up in Shanghai. His academic aspiration can be traced back to his grandma’s uncle, a famous poet, painter, calligrapher, antique connoisseur, and the Minister of Traffic and Communication in 1920s who founded the modern Shanghai Jiaotong University and was elected as its first president in 1921. In 1996, Zuopeng received the Bachelor of Engineering degree in Automobile Engineering from Tongji University. In 1999, he received the Master of Economics degree in International Trade and Economics from Shanghai University of Finance and Economics. In 2000, he enrolled in the Ph. D. program in Management Science and Information Systems at the Pennsylvania State University. Since 2000, he has been employed in the Management Science and Information Systems Department at The Pennsylvania State University as a teaching/research assistant.

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