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RESEARCH ARTICLE

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Optimal risk allocation in alliance infrastructure projects: A social preference perspective

Abstract The mechanism of risk allocation is designed to protect all stakeholders, and it is vital to project success. Qualitative and quantitative ways of optimizing risk allocation have been well documented in extant literature (e.g., allocation principles, models, and solutions), and the foci of existing research are usually the maximization of rational utility. Few research has focused on partners' social preferences affecting the output of risk allocation. This study presents a quantitative approach based on modeling alliance member (AM)'s inequity aversion (IA) to analyze risk-sharing arrangements in an alliance project. Fehr and Schmidt's inequity-aversion model is integrated into modeling partner's utility. This paper derives results for an alliance leader (AL)'s optimal risk-sharing ratio and AM's optimal risk-management effort simultaneously. The derivation is based on solving a restrained optimization problem using the conception and methods from Stackelberg game theory. Results show that an AM's IA significantly affects risk allocation between AL and AM. Specifically, envious preference is positively related to AL's optimal risk-sharing ratio, whereas guilty preference negatively affects AL's optimal risk-sharing ratio. These findings will be of interest to academics and practitioners involved in designing alliance negotiations.

Keywords public project, contract design, risk sharing, inequity aversion, governance

1 Introduction

Owing to its technological complexity and long duration, infrastructure projects are confronted with a high degree of integration between design, construction, consulting, supplying, and other operation partners (Love et al., 2010). Studies have shown that adversarial/uncooperative relationships between contractors often cause project failures (Ng et al., 2002; Ling et al., 2013). Consequently, selecting an alliance to deliver a complex infrastructure project is preferable (Kumaraswamy et al., 2005; Alderman and Ivory, 2007; Love et al., 2010). An alliance can provide a favorable working environment aiming to motivate partners cooperating and working toward the same goal to achieve project success (Love et al., 2010; Hosseinian and Carmichael, 2013a), and it is proven to be a preferred project delivery method for infrastructure projects (Hauck et al., 2004; Hosseinian and Carmichael, 2013b). Based on the fundamental principles of win–win, all corporations joining the alliance need to share any pain or gain during the project delivery period (Hosseinian and Carmichael, 2013b). In other words, the alliance members (AMs) need to share risks (Das and Kumar, 2011). According to Tang et al. (2020), the arrangement of risk allocation is specifically designed for adapting to the contingent disturbances. However, as legally independent commercial organizations, the priority for those alliance parties is to seek profit as much as possible (Frank et al., 2006). To a certain extent, the business nature of profit pursuit may contribute to sharing other's risk. Therefore, undertaking a re-examination of the mainstream thinking on risk allocation while dealing with alliance infrastructure projects is needed.

Inappropriate risk allocation would lead to possible extra costs, such as higher contingency and/or recovering fees for lower quality work (Hartman et al., 1997; Lam et al.,

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2007; Jin and Zhang, 2011; Nasirzadeh et al., 2014). Thus, discussion is ongoing as to the definition of optimal risk allocation both in theory (Yescombe, 2002; Winch, 2010) and practice (Casey and Bamford, 2014). Numbers of qualitative and quantitative methods are developed to analyze the problem of who should be responsible for risk and the amount of risk-sharing percentage (Jin and Zhang, 2011; Khazaeni et al., 2012; Alireza et al., 2014). However, mainstream thinking is strongly influenced by homo economicus theory (Nasirzadeh et al., 2014), and it is flawed in the sense that parties involving in delivering projects are rational and narrowly self-interested actors. The alliance partner with bounded rationality faces a social preference that considerably affects people's utility functions (Luttmer, 2005), under which people make the decision of effort or capital to control and manage risks.

According to studies in behavioral economics, people not only are concerned about their own payoff, but also compare with coworker's payoffs; whether the payoff distributions are fair will affect people's behavior (Rey-Biel, 2008). In other words, economic agents have a social preference for fairness and resistance to incidental inequalities (Rohde, 2010), the so-called "inequity aversion (IA)". This phenomenon has been demonstrated by many experiments such as ultimatum games (Forsythe et al., 1994), gift-exchange games (Clark et al., 2010), and trust games (Nicholas, 2012). Furthermore, the existence of IA is proven to constrain profit-seeking (Kahneman et al., 1986). Consequently, IA is necessary to be recognized when designing risk allocation strategy. However, no studies on project risk allocation based on modeling partners' IA have been published. Until recently, Meng et al. (2019) used an agent-based model using competitive and social preference to optimize the timeline negotiation. In this case, this paper focuses on alliance infrastructure projects where the alliance partner's decision/behavior is not undertaken rationally but rather in a bounded rational way. This paper mainly focuses on the relationship between alliance leader (AL) and AM, but it has applicability to other relationships. This IA-based risk allocation model aims to bridge the research gap between traditional risk management theory and modern behavior theory.

2 Literature review

2.1 Studies on social preference

Social preference in previous studies can be classified into two categories: Distributive and reciprocal ones. Distributive preferences mean that people care about the final distribution, which are related to consequences and outcomes (Konow, 2001). Reciprocal preferences mean that people reward or punish others according to the consequences (Croson and Konow, 2009). This research mainly focuses on the output of risk allocation; therefore, the distributive preference models are considered. To describe people's IA, fair process and social preference (FS) model and equity, reciprocity, and competition (ERC) model are developed. According to the FS model (Fehr and Schmidt, 1999), people's IA is based on the payoff gap between himself/herself and everyone else. Different from the FS model, the ERC model (Bolton and Ockenfels, 2000) proposed that people feel inequity by comparing the average income of all partners. However, the AL shares different types of risks with different AMs, and the AL needs to design a risk allocation strategy for each member in the alliance project. The risks shared between the AL and different AMs are heterogeneous. Thus, no average level of risk-sharing ratio is used in this study. Therefore, owing to its prominence and simplicity, the FS model is used in this paper to show the reduced form of IA, and the concrete description of the model is provided in the following sections.

2.2 Studies on risk allocation

The extant research on project risk allocation has been mainly concerned with three subjects, namely, allocation principle, affecting factor, and allocation method/model. As for risk allocation principles, ex-ante allocating ratios and listing each risk resources are mainstreams in the field (Karim, 2011; Chan et al., 2018; Jin et al., 2019). Abednego and Ogunlana (2006) and Chen and Hubbard (2012) inclined to identify the definition of "appropriate" risk allocation and the relationship among stakeholders. Risk control capability, agents' risk aversion, risk revenue, and cost-benefit calculation are usually treated as the affecting factors for allocating project risks (Chou and Pramudawardhani, 2015; Osei-Kyei and Chan, 2015; Kakati and Baruah, 2016). Risk allocation method/model in the construction and project management literature can be classified into two categories: Qualitative and quantitative (Khazaeni et al., 2012). Qualitative risk allocation methods contribute to the development of the risk allocation matrix deciding which party is best for taking responsibility for specific risk. Quantitative methods are developed to solve quantitative problems like how much percentage of risk is allocated to each party (Nasirzadeh et al., 2014). Kate and Patil (2020) proposed an expected monetary value method (EVM) for risk allocation, and the model was empirically validated in power transmission line projects. Similarly, Ameyaw and Chan (2016) and Shan et al. (2018), respectively, applied the fuzzy-set approach and artificial neural network (ANN) as an integral and separately into risk allocating/analyzing model using empirical evidence. Nasirzadeh et al. (2014) presented an integrated fuzzy-system dynamics approach to examine the relationship between project cost and risk-sharing ratio. Using concepts from principal-agent theory, Chang (2014) presented a risk allocation model based on contract incentive theory and pointed out the significant effect of incentives on a contractor's efficiency improvement potential for risk management.

In summary, recent studies have identified various factors that would affect the allocation of different risks between the project owner and contractor. The contractor's internal risk allocation mechanism was not considered, especially in mega infrastructure projects where the contractor usually is a coalition or an alliance consisted of different corporations. Moreover, the economic agents' bounded rationality (e.g., IA), which directly affects the risk management strategy, is not considered.

Therefore, this research aims to (1) investigate the optimal risk allocation strategy for AL under AM's different types of IA, (2) revise the effect of individual rationality (IR) level on the optimal risk-sharing ratio and risk-management effort, (3) identify how IR level affects utilities of AL and AM, and (4) select the allocation rules that are most suitable and beneficial for delivering alliance infrastructure projects. By voiding some risk allocation proposal that is able to induce alliance to poor performance, the optimal risk allocation model presented in this study improves ex-ante welfare. By integrating the FS model, this research attempts to derive a more realistic model of the optimal risk allocation between AM and AL. The derivation is based on solving optimization problems using Stackelberg game theory that provides an appropriate basis for solving the leader and followers sequential model.

3 Proposed risk allocation model

Fast-tracking is one of the most common project acceleration techniques for alliance infrastructure projects (Ballesteros-Pérez, 2017; Rasul et al., 2019). Under this circumstance, design, procurement, and construction can be overlapped to shorten the project timeline (Pishdad-Bozorgi et al., 2016). The AL assigns the work to the member, usually along with negotiations on timeline, benefit, and risk. The AM's working effort always depends on the negotiation clauses and their behavioral bias. This problem is a typical leader–follower problem in game theory research, especially the Stackelberg game, and the authors therefore performed the following models.

In this section, a risk allocation model between one leader corporation and one member corporation will be introduced in the context of alliance contracting. Notably, any corporation's decision (or behavior) depends on its maximum utility. In this case, the main tasks of building a risk allocation model are to analyze factors affecting agent's payoff and then to construct reasonable utility functions. The flowchart of the proposed model can be seen in Fig. 1. At the beginning of the construction period, the AL offers a risk allocation proposal to AM through the choice of risk-sharing ratio q. Under this allocation structure, the AM then will decide on the best risk control effort according to the utility function. Notably, the economic agent's IA is considered in modeling AM's utility.

3.1 Model formulation with no consideration of IA

The authors assume that the leader corporation in an infrastructure alliance is solely responsible for the decision of risk allocation, whereas the AMs determine their effort on risk management. The interactions between AL and AM represent a Stackelberg game with the sequence of events as given in (A1)–(A3).

(A1) AL determines and announces the ratio q that will share the risk which exists during AM's construction period.

(A2) AM determines the effort level e on risk management, and different effort levels lead to different investments and methods in controlling risk.

(A3) The construction period starts and the outcome of risk handling π is observed.

Here, AL's decision rests on maximizing the utility function, and AL also needs to consider AM's benefit, that is, AM's optimal effort toward the risk allocation proposal. Thus, the risk allocation between AL and AM is a constrained optimization problem. According to previous research on mathematical optimization methods, backward induction is recommended as the main solution to solve for

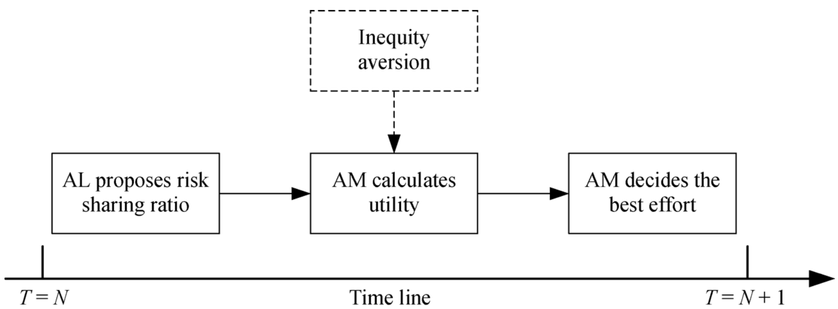

Fig. 1 Flowchart of risk allocation model.

the equilibrium decisions (Chu and You, 2014; Du et al., 2014; Xue et al., 2014). The solving process is as follows: (1) find AM's optimal effort $\hat{e}$ when achieving the maximum expected utility and (2) substitute $\hat{e}$ into AL's utility function and then solve optimal risk-sharing ratio by maximizing AL's expected utility.

After the risk-sharing perceptions of each party are put on, AM then selects an effort level e of risk management to meet the construction requirements. The selection of risk management efforts is AM's strategy to cope with AL's risk allocation proposal. During the construction period, the member corporation needs to deal with many different subtasks. Although AM will probably take different efforts on risk management to deal with these subtasks, the effort level e can still be applied in this study because the authors consider e as an overall evaluation of AM's efforts on the entire project. In addition, AM needs to pay $\chi(e)$ for the risk management effort, and the utility function can be seen (McAfee and McMillan, 1986; Laffont and Marimort, 2001):

$$\chi(e) = \frac{1}{2}me^2, \tag{1}$$

where m measures AM's cost on exerting efforts to control risk.

Referring to the output function commonly used in principal agent theory (Laffont and Marimort, 2001), the authors assume that the output of risk allocation, denoted as π, is a linear function of AM's effort level that is embodied in monetary units:

$$\pi = e + \varepsilon, \tag{2}$$

where ε is the random exogenous variable following a standard normal distribution, $\varepsilon \sim N(0, \sigma^2)$. Here, ε stands for information asymmetry between AL and AM that cannot be ignored in alliance contracting (Owen and Yawson, 2013).

Theoretically, the precise information of an agent's effort cannot be observed by other parties (Bamberg et al., 1987). Thus, AL cannot easily objectively monitor AM's effort level of risk management. However, AM is obligated to inform AL about the final settlement. Therefore, π is an observable value to AL. According to agent theory, to stimulate agent's effort, the owner needs to provide an adjustable contract (Laffont and Marimort, 2001). Thus, AL offers an incentive contract/negotiation (because the relationship type between AL and AM is diverse, formal and informal patterns are applied in practice) with a controllable parameter to AM.

Equation (3) proposed by Scherer (1964) and Chang (2014) describes the payment structure in the incentive contract/negotiation offered by the AL. Under this structure, AM receives payment P depending on a fixed-target fee and the sharing of cost overruns. The fixed construction fee Φ offered from AL is not involved with π, and it does not only rely on the average cost for the specific type of risk in the construction industry. Furthermore, the risk-sharing ratio q is the moderate variable that represents AL's risk allocation strategy. If $q = 0$, then AL does not want to share AM's construction risk. Then, the payment structure is similar to a fixed-price contract. By contrast, if $q = 1$, the leader corporation in the alliance will be responsible for all of the risks incurred on the project delivery.

$$P = \Phi + q(\pi - \Phi). \tag{3}$$

AL's purpose of risk sharing is to incentive AM's effort for risk control. According to Carvalho and Rabechini Junior (2015), the output of high-quality risk management is beneficial to achieve project success, in terms of decreasing factors such as cost overrun. In this case, the output of risk allocation can be seen as AL's payoff. Therefore, the gain of AL can be calculated as Eq. (2), and AL's pain is calculated as Eq. (3), then combining Eqs. (2) and (3) can obtain the utility function of AL (U_{AL}):

$$U_{\mathrm{AL}} = \pi - P = (1-q)(\pi - \Phi). \tag{4}$$

In previous studies, the risk preference of the contractor is not defined clearly, and different studies start with different hypotheses. Early scholars considered the contractor's risk preference uncertain (Clark Brown, 1986; 1987). In some studies later, the contractor is supposed to have a concave utility function reflecting loathing to risk taking, also known as risk aversion (Chapman and Ward, 1994; Tseng and Yeh, 2014; Xu and Wang, 2014). By contrast, some other researches posited that the contractor has a neutral attitude toward project risk (Chiles and McMackin, 1996; Laux, 2001; Hosseinian and Carmichael, 2013b). The main purpose of this research is to revise the effect of an agent's IA on risk allocation. In this case, the authors assume that AL and AM are risk-neutral in the proposed model for better focusing on the main topic. According to the expected utility hypothesis,

$$E_{\mathrm{AL}}(q) = (1-q)[E(\pi) - \Phi] = (1-q)(e - \Phi), \tag{5}$$

where $E_{\mathrm{AL}}(q)$ is AL's expected utility arising from risk sharing with AM. Similarly, combining Eqs. (1) and (3), the utility function of AM (U_{AM}) can be seen in Eq. (6):

$$U_{\mathrm{AM}} = P - \chi(e) = \Phi + q(\pi - \Phi) - \frac{1}{2}me^2. \tag{6}$$

AM's expected utility arising from risk allocation, $E_{\mathrm{AM}}(e)$, can be elicited as:

$$E_{\mathrm{AM}}(e) = \Phi + q(e - \Phi) - \frac{1}{2}me^2. \tag{7}$$

As mentioned previously, when AL pursues the maximum utility, a constraint arises that AM also obtains the maximum utility, also known as the incentive compatibility (IC) constraint. In the traditional restrained optimization research, another constraint arises, namely, the individual rationality (IR) constraint, which needs to be solved. However, once an alliance contract is signed, any of the partners involved in this contract generally does not quit this alliance unless this corporation wants to undertake the penalty. Thus, the authors assume AM will accept any risk-sharing ratio proposed by AL.

$$\underset{q,e}{\text{Max}}(1-q)(e-\Phi), \tag{8a}$$

$$s.t. \quad e \in \arg\max\left\{\Phi + q(e-\Phi) - \frac{1}{2}me^2\right\}. \tag{8b}$$

Equation (8a) stands for maximizing AL's expected utility, and Eq. (8b) is AM's IC constraint. Equations (8a) and (8b) constitute the risk allocation model with no consideration of IA.

Appendix I derives the solution to this constrained maximization problem. AL's optimal risk-sharing ratio is:

$$\hat{q} = \frac{m\Phi + 1}{2}, \tag{9}$$

and AM's best effort level to control risk is:

$$\hat{e} = \frac{m\Phi + 1}{2m}. \tag{10}$$

Substituting Eqs. (9) and (10) into Eq. (5) can obtain AL's max expected utility under this situation:

$$E_{\mathrm{AL}}(\hat{q}) = (1-\hat{q})(\hat{e}-\Phi) = \frac{(1-m\Phi)^2}{4m}. \tag{11}$$

Similarly, the expected utility of AM can be elicited:

$$E_{\mathrm{AM}}(\hat{e}) = \frac{1 + 6m\Phi - 3m^2\Phi^2}{8m}. \tag{12}$$

3.2 Model formulation with consideration of IA

Previous research on IA indicates an agent's expected utility decreases with the widening gulf between his/her payoff and others (Ho and Zhang, 2008; Rey-Biel, 2008; Croson and Konow, 2009; Rohde, 2010). Therefore, the authors describe an agent's fairness concerns by introducing an outcome gap to his/her utility function. As previously mentioned, Fehr and Schmidt (1999)'s IA model (FS model henceforth) is used here as the basis of the introduced model. According to the FS model, the agent's overall utility is composed of two parts. The first part is the agent's direct payoff, the other part is fairness disutility. When two subjects are involved in the game, the FS model can be modified to:

$$V_i = U_i - \delta_i \max[(U_j - U_i),\ 0] - \gamma_i \max[(U_i - U_j),\ 0], \tag{13}$$

where i is a particular subject while j is the compared subject; V_i is the overall utility of i; and U_i is direct payoff of i while U_j is direct payoff of j. Notably, the second and third terms in Eq. (13) represent two patterns of fairness disutility, namely, envy and guilt disutility (Rey-Biel, 2008). Subject i's envious preference index δ_i takes effect in calculating the overall utility when $U_j > U_i$. By contrast, the guilty preference index γ_i takes effect when $U_j < U_i$. Consequently, the expressions of $\delta_i\max[(U_j - U_i),\ 0]$ and $\gamma_i\max[(U_i - U_j),\ 0]$ measure the utility loss from disadvantageous inequity and advantageous inequity, respectively (Ho and Zhang, 2008; Rey-Biel, 2008; Katok and Pavlov, 2013).

Notably, the leader corporation usually undertakes the main construction part when delivering the infrastructure project. In other words, AL occupies a sizeable proportion in the general contract (also known as the D&C contract in Australia and D&B contract in other countries). In this situation, the AL benefits most from project success compared with other alliance partners. Thus, the main task of AL is to make sure all of the AMs' work is on budget, on schedule, and on quality, that is, AL puts more concern on risk control and management for the entire project than AMs. Therefore, the payoff from risk allocation is not on the priority list for AL to achieve. With this in mind, the authors assume that AM is IA, whereas AL has no fairness concerns when designing a risk allocation strategy. The IA-based utility function of AM can be obtained as follows:

$$V_{\mathrm{AM}} = U_{\mathrm{AM}} - \delta\max[(U_{\mathrm{AL}} - U_{\mathrm{AM}}),\ 0] - \gamma\max[(U_{\mathrm{AM}} - U_{\mathrm{AL}}),\ 0], \tag{14}$$

where δ is AM's envy index, and γ is AM's guilt index. Envious and guilty preference indexes are psychological factors, the more of their value represented, the higher agents think of distributive fairness. The original assumption of the FS model, nevertheless, allows for $\delta > 1$, but the authors assume $\delta \in [0, 1]$ to ensure that IA is not dominant but still has a substantial effect on the optimal risk allocation model, because the authors believe AM cares more about their direct payoff than about inequity in practice. As for the guilty preference index, the authors use Rey-Biel (2008)'s assumption of $\gamma \in [0, 1/2)$.

Considering the two conditions whether $U_j > U_i$ or $U_j < U_i$, this research therefore needs to rebuild risk allocation models according to different scenarios. These scenarios represent different types of IA.

Scenario I: Envious preference taking effect

When AM's utility is less than AL's utility ($U_{\mathrm{AM}} < U_{\mathrm{AL}}$), envious preference takes effect on AM's final expected utility and leads to utility loss. Substituting Eqs. (4) and (6) into Eq. (14) can obtain AM's new utility function under Scenario I:

$$V_{\mathrm{AM}}^{1} = U_{\mathrm{AM}} - \delta(U_{\mathrm{AL}} - U_{\mathrm{AM}})$$
$$= -\frac{1}{2}m(1+\delta)e^2 + (q - \delta + 2q\delta)(e+\varepsilon)$$
$$+ (1 - q + 2\delta - 2q\delta)\Phi. \tag{15}$$

Due to risk neutrality, AM's expected utility under envious preference, $E_{\mathrm{AM}}^{1}(e)$, can be described as:

$$E_{\mathrm{AM}}^{1}(e) = -\frac{1}{2}m(1+\delta)e^2 + (q - \delta + 2q\delta)e$$
$$+ (1 - q + 2\delta - 2q\delta)\Phi. \tag{16}$$

In addition, the expression of AL's expected utility under envious preference, $E_{\mathrm{AL}}^{1}(q)$, remains as Eq. (5). Ultimately, the IA-based risk allocation model under Scenario I can be expressed as follows:

$$\underset{q,e}{\mathrm{Max}}(1-q)(e-\Phi), \tag{17a}$$

$$s.t. \quad e \in \arg\max[E_{\mathrm{AM}}^{1}(e)]. \tag{17b}$$

Backward induction is still used to find the optimal risk allocation solutions, and the solving process can be found in Appendix II. AL's optimal risk-sharing ratio under Scenario I is:

$$\hat{q}_1 = \frac{1 + m\Phi + (3 + m\Phi)\delta}{2(1+2\delta)}. \tag{18}$$

Under this risk-sharing ratio, the optimal risk-management effort level for AM is:

$$\hat{e}_1 = \frac{m\Phi + 1}{2m}. \tag{19}$$

With the optimal risk-sharing ratio and risk-management effort level, AL's expected utility can be calculated as:

$$E_{\mathrm{AL}}^{1}(\hat{q}_1) = (1-\hat{q}_1)(\hat{e}_1 - \Phi) = \frac{(1+\delta)(1-m\Phi)^2}{4m(1+2\delta)}, \tag{20}$$

while AM's expected utility is seen in Eq. (21):

$$E_{\mathrm{AM}}^{1}(\hat{e}_1) = \frac{(1+\delta)(1+6m\Phi - 3m^2\Phi^2)}{8m}. \tag{21}$$

Scenario II: Guilty preference taking effect

When AM finds that the utility is more than AL's utility ($U_{\mathrm{AM}} > U_{\mathrm{AL}}$), guilty preference affects AM's final expected utility and leads to utility loss.

$$V_{\mathrm{AM}}^{2} = U_{\mathrm{AM}} - \gamma(U_{\mathrm{AM}} - U_{\mathrm{AL}})$$
$$= -\frac{1}{2}m(1-\gamma)e^2 + (q + \gamma - 2q\gamma)(e+\varepsilon)$$
$$+ (1 - q - 2\gamma + 2q\gamma)\Phi. \tag{22}$$

Equation (22) expresses the new form of AM's utility affected by guilty preference. Here, the expected utility for AM and AL can be obtained as shown in Eqs. (23) and (24):

$$E_{\mathrm{AM}}^{2}(e) = -\frac{1}{2}m(1-\gamma)e^2 + (q + \gamma - 2q\gamma)e$$
$$+ (1 - q - 2\gamma + 2q\gamma)\Phi, \tag{23}$$

$$E_{\mathrm{AL}}^{2}(q) = (1-q)(e-\Phi). \tag{24}$$

Then, the new risk allocation model under Scenario II can be rebuilt as follows:

$$\underset{q,e}{\mathrm{Max}}(1-q)(e-\Phi), \tag{25a}$$

$$s.t. \quad e \in \arg\max[E_{\mathrm{AM}}^{2}(e)]. \tag{25b}$$

Similar to the former section, AL's optimal risk-sharing ratio $\hat{q}_2$ and AM's optimal risk-management effort level $\hat{e}_2$ can be acquired. The proof can be found in Appendix III.

$$\hat{q}_2 = \frac{1 + m\Phi - (3 + m\Phi)\gamma}{2(1-2\gamma)}, \tag{26}$$

$$\hat{e}_2 = \frac{m\Phi + 1}{2m}. \tag{27}$$

With the optimal solution of risk allocation, AL's expected utility can be calculated as Eq. (28):

$$E_{\mathrm{AL}}^{2}(\hat{q}_2) = (1-\hat{q}_2)(\hat{e}_2 - \Phi) = \frac{(1-\gamma)(1-m\Phi)^2}{4m(1-2\gamma)}, \tag{28}$$

while AM's expected utility is seen in Eq. (29):

$$E_{\mathrm{AM}}^{2}(\hat{e}_2) = \frac{(1-\gamma)(1+6m\Phi - 3m^2\Phi^2)}{8m}. \tag{29}$$

4 Discussion

The above theoretical development shows that the optimal risk allocation for the alliance contracting is affected by an agent's IA. The effect of IA level on the optimal risk allocation ratio can be seen in Fig. 2. As AM forms a more envious preference, it prefers AL to share a higher rate of risk. Conversely, as AM forms a more guilty preference, it prefers AL to share a lower rate of risk. The proof is shown in Appendix IV and leads to the following proposition.

Proposition 1a: The optimal risk-sharing allocation to the leader corporation increases when the member's level of envious preference increases.

Proposition 1b: The optimal risk-sharing allocation to the leader corporation decreases when the member's level of guilty preference increases.

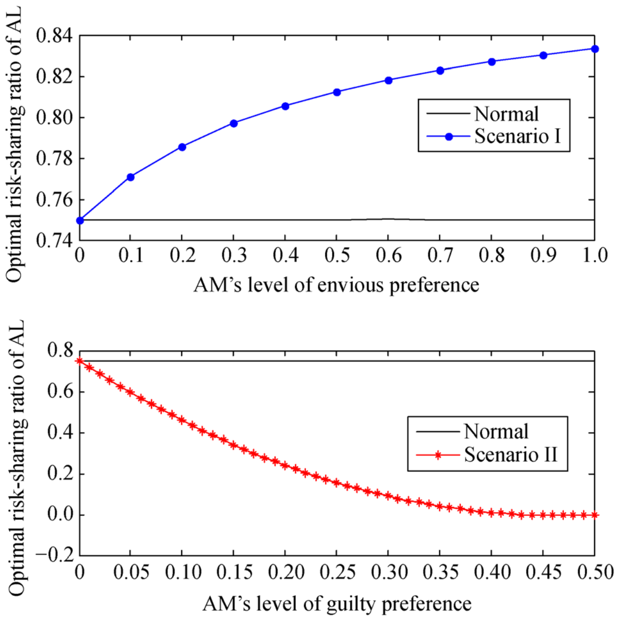

Fig. 2 Optimal risk-sharing ratio of AL vs. IA level under different scenarios (Notes: "Normal" in the picture stands for the scenario without considering IA. According to Appendix IV, the authors let $m\Phi = 0.5$ to simulate the optimal risk-sharing ratio under different scenarios).

Comparing Eqs. (19) and (27) with Eq. (10), the optimal effort level for AM to control risk remains steady in any IA situation. According to Eq. (10), the value of AM's effort level is decided by two parameters: m and Φ. Here, m measures the relationship between AM's cost and risk-management effort, in other words, m reflects the corporation's risk management capability. Φ is fixed by the average level of this specific type of risk. Thus, Φ represents the level of risk that AM needs to handle, leading to the following proposition.

Proposition 2: The AM's IA does not affect the optimal effort to control risk. By contrast, AM's effort relies on AM's risk management capability and risk level.

The main reason to explain why the AM's effort stays unchangeable is that AL's risk allocation decision is on the basis of maximizing AM's utility and therefore to stimulate AM exerting the maximum level of effort on controlling risk. In general, Propositions 1 and 2 manifest that AL can modify the risk-sharing ratio to adjust the IA situation and maintain AM at the same level of effort when IA affecting AM's risk management decision.

The analyses on expected utility in former sections indicate that IA also affects the best-expected utility of AL. Letting $\frac{(1-m\Phi)^2}{4m}$ as a constant U_c, the effect of IA level on AL's utility can be seen in Fig. 3. When AM prefers to become more envious, the maximum expected utility that AL can acquire decreases. By contrast, the guiltier that AM becomes, the higher the expected utility that AL can obtain. The proof is seen in Appendix V and leads to the following propositions.

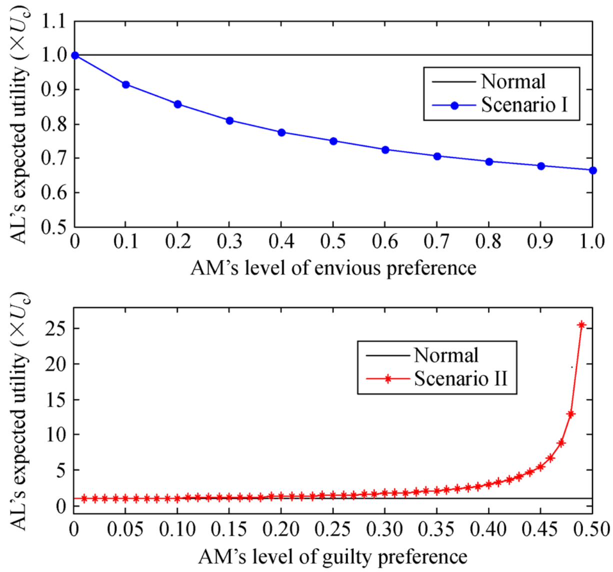

Fig. 3 AL's expected utility vs. IA level under different scenarios (Note: "Normal" in the picture stands for the scenario without considering IA).

Proposition 3a: An alliance with an envious preferred member (the IA level of envious preference above 0) leads to AL expected utility decrease.

Proposition 3b: An alliance with a guilty preferred member (the IA level of guilty preference above 0) leads to AL expected utility increase.

Comparing Eqs. (21) and (29) with Eq. (12), the expected utility of AM is obviously in a linear relation with IA level. Under Scenario I, $E^1_{\mathrm{AM}}(\hat{e}_1) = (1+\delta)E_{\mathrm{AM}}(\hat{e})$ means the function of AM's expected utility is monotonically increasing. By contrast, $E^2_{\mathrm{AM}}(\hat{e}_2) = (1-\gamma)\times E_{\mathrm{AM}}(\hat{e})$ means the function of AM's expected utility is monotonically decreasing under Scenario II. This decrease leads to the following propositions.

Proposition 4a: In the situation of envious preference taking effect, the expected utility of AM increases when AM's IA level increases.

Proposition 4b: In the situation of guilty preference taking effect, the expected utility of AM decreases when AM's IA level increases.

The propositions imply that with inequity averse agents, the utilities of AL and AM are interdependent. Thus, risk allocation needs to be more carefully designed. In particular, as the Stackelberg leader in the model, AL needs to seriously consider discovering different member's IA type and level to decide an optimal risk allocation rate leading to the maximum output of risk management.

5 Conclusions

Perceived fair allocation and sharing of risks among alliance partners is critical to the delivery performance of infrastructure projects (Love et al., 2014; Lomoro et al., 2020). Allocation of risks involves assigning various types of risks (e.g., requirement risk, technology risk, and performance risk) to the alliance partners. This paper focuses on sharing specific risks between partners (e.g., in case of cost overrun, the share of each partner on the extra costs).

Practically, whether decision-makings of optimizing project risk allocation are scientific and reasonable relies on negotiations among alliance partners. The literature on risk sharing had a high focus on the utility and ignored irrational behaviors such as social preference. FS model has been used to model an alliance partner's expected utility while considering the effect of the partner's inequity aversion. Moreover, according to the two types of social preference, this research establishes two scenarios to analyze the effect of IA on the risk allocation model. Then, the outcomes of adapted models are compared with the utility maximization model without considering IA. Using Stackelberg game theory, the optimal risk-sharing ratio is derived by identifying the value corresponding to the maximum utility of the adapted model.

The simulation results showed that the agent's IA was a vital factor in alliance risk–benefit negotiations. However, the results depend on different scenarios. Specifically, the AM's expected utility increases with the IA level when envious preference takes effect. Simultaneously, the AL's utility decreases with AM's IA level. Under this circumstance, the AL needs to use a high risk-sharing ratio to facilitate the member's working effort. For practitioners, this finding inclines that ALs can find a balance between the working requirements and AM's envious preference. ALs should increase their focus on members who perform high levels of requirements and adapt different incentives to keep these members' envious preference at low levels. By contrast, the AM's expected utility decreases with the IA level when guilty preference takes effect. In this condition, the AL can allocate more risk-sharing ratio to AM. At practice, the two types of social preferences can be converted to each other to a certain extent. Thus, AL cannot increase AM's risk-sharing ratio continuously and needs to validate the statement of AM's social preference. Generally, the optimal risk-sharing ratio is highly related to alliance partner's IA and its preference category. The findings suggest that ALs should focus on the IA levels of AMs, and adjusting risk-sharing ratio accordingly will result in optimal efforts of alliance partners in dealing with the risks. The findings of this research will be of interest to academics and practitioners involved in designing alliance negotiations.

Some limitations of this paper lead to several directions for future research. First, this study is conducted in the setting of a bi-vitiate relationship between ALs and AMs. As a result, the findings of this study ignore the effects of other alliance partners. However, in practice, alliance partners are likely to compare their shares of risk and utilities with other partners to form perceptions of fairness of the risk-sharing arrangements. Due to ignoring the existence of other project partners, the approach taken by this study can be further improved. Second, this study assumed that AL and AM were risk-neutral. This assumption helps in focusing on the effect of IA of the alliance partners. Future studies could consider modeling risk aversion for alliance partners. Such an undertaking will require substantial effort in reformulating the utility functions. Finally, the findings need to be validated in alliance projects empirically.

Overall, the authors of this paper hoped to spark a new line of research to explore the optimal risk arrangements on the basis of cognizing agent's behavior, which can eventually lead to interdisciplinary studies of traditional project management theory and modern behavior science in an institutional level.

Appendix

I Derivation of the optimal risk-allocation ratio with no consideration of IA

Differentiating Eq. (7) with respect to e yields:

$$\frac{\partial E_{\mathrm{AM}}(e)}{\partial e} = q - me = 0. \tag{A1}$$

Simplifying Eq. (A1), the IC constraint can be replaced by:

$$e = \frac{q}{m}. \tag{A2}$$

Substitute Eq. (A2) into Eq. (5):

$$E_{\mathrm{AL}}(q) = -\frac{q^2}{m} + \left(\Phi + \frac{1}{m}\right)q - \Phi. \tag{A3}$$

Differentiating Eq. (A3) with respect to q yields:

$$\frac{\partial E_{\mathrm{AL}}(q)}{\partial q} = -\frac{2q}{m} + \left(\Phi + \frac{1}{m}\right) = 0. \tag{A4}$$

Simplifying Eq. (A4) can obtain the optimal risk-allocation ratio as seen in Eq. (9). In this case, AM's effort level can be obtained by substituting Eq. (9) into Eq. (A2).

II Derivation of the optimal risk-allocation ratio under Scenario I

Differentiating Eq. (16) with respect to e yields:

$$\frac{\partial E^1_{\mathrm{AM}}(e)}{\partial e} = -m(1+\delta)e + q - \delta + 2q\delta = 0. \tag{A5}$$

Simplifying Eq. (A5), the new IC constraint under Scenario I can be obtained:

$$e_1 = \frac{q-\delta+2q\delta}{m(1+\delta)}. \tag{A6}$$

Substitute Eq. (A6) into $E^1_{\mathrm{AL}}(q)$:

$$E^1_{\mathrm{AL}}(q) = \frac{(1-q)(q-\delta+2q\delta)}{m(1+\delta)} - (1-q)\Phi, \tag{A7}$$

then differentiate Eq. (A7) with respect to q:

$$\frac{\partial E^1_{\mathrm{AL}}(q)}{\partial q} = -\frac{2(1+2\delta)}{m(1+\delta)}q + \frac{3\delta+1}{m(1+\delta)} + \Phi. \tag{A8}$$

Yielding Eq. (A8) to 0, the optimal risk-allocation ratio can be obtained as seen in Eq. (18). Substituting Eq. (18) to Eq. (A6) can acquire AM's best effort level under Scenario I.

III Derivation of the optimal risk-allocation ratio under Scenario II

Differentiating Eq. (23) with respect to e yields:

$$\frac{\partial E^2_{\mathrm{AM}}(e)}{\partial e} = -m(1-\gamma)e + q + \gamma - 2q\gamma = 0. \tag{A9}$$

Simplifying Eq. (A9), the new IC constraint under Scenario II can be obtained:

$$e_2 = \frac{q+\gamma-2q\gamma}{m(1-\gamma)}. \tag{A10}$$

Substitute Eq. (A10) into Eq. (24):

$$E^2_{\mathrm{AL}}(q) = \frac{(1-q)(q+\gamma-2q\gamma)}{m(1-\gamma)} - (1-q)\Phi, \tag{A11}$$

then differentiate Eq. (A11) with respect to q:

$$\frac{\partial E^2_{\mathrm{AL}}(q)}{\partial q} = -\frac{2(1-2\gamma)}{m(1-\gamma)}q + \frac{1-3\gamma}{m(1-\gamma)} + \Phi. \tag{A12}$$

Yielding Eq. (A12) to 0, the optimal risk-allocation ratio can be obtained as seen in Eq. (26). Substituting Eq. (26) to Eq. (A10) can acquire AM's best effort level under Scenario II.

IV Proof for Propositions 1a and 1b

Differentiating Eq. (18) with respect to δ:

$$\frac{\partial \hat{q}_1}{\partial \delta} = \frac{(1-m\Phi)}{2(1+2\delta)^2}. \tag{A13}$$

The optimal risk-sharing ratio for AL when no social preference exists is $\hat{q} = \frac{m\Phi+1}{2}$ and $\hat{q} \in [0, 1]$, then $m\Phi \leqslant 1$ can be deduced. Consequently, $\frac{\partial \hat{q}_1}{\partial \delta} \geqslant 0$ can be obtained, suggesting that the function of optimal risk-sharing ratio under Scenario I is monotonically increasing with respect to the level of envious preference δ. This result supports Proposition 1a. Similarly, $\frac{\partial \hat{q}_2}{\partial \gamma} = \frac{m\Phi-1}{2(1-2\gamma)^2} \leqslant 0$ can be found, and it implies the function of optimal risk-allocation ratio under Scenario II is monotonically decreasing with respect to γ, then Proposition 1b can be obtained.

V Proof for Propositions 3a and 3b

Differentiating Eq. (20) with respect to δ:

$$\frac{\partial E^1_{\mathrm{AL}}(\hat{q}_1)}{\partial \delta} = \frac{(1-m\Phi)^2}{4m}\frac{\delta-1}{(1+\delta)^2}. \tag{A14}$$

Given that $(1-m\Phi)^2 > 0$, $4m > 0$, $(1+\delta)^2 > 0$ and $\delta \in [0, 1]$, $E^1_{\mathrm{AL}}(\hat{q}_1)$ can be found to be an increasing function of δ. Moreover, $\delta = 0$ means that no IA is present, and Eq. (11) equals Eq. (20). Thus, when AM has a level of envious preference ($\delta > 0$), the maximum utility AL can obtain in this situation is consistently less than in the situation in which no IA exists, supporting Proposition 3a. Similarly, differentiating Eq. (28) with respect to γ can find $E^2_{\mathrm{AL}}(\hat{q}_2)$ as a decreasing function. Therefore, when AM has a level of guilty preference ($\gamma > 0$), the maximum utility AL can obtain in this situation is always more than in the situation where no IA exists. This finding supports Proposition 3b.

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