A Stochastic Simulation Framework for Risk-Robust Incentive Design in Humanitarian Logistics

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Abstract. Humanitarian logistics in archipelagic countries such as Indonesia face complex, multi-dimensional risks, including operational disruptions, coordination failures, and reputational challenges. This study develops a risk-robust incentive mechanism for disaster response using expected utility theory with risk premium adjustments. A principal–agent model is formulated in which the disaster management agency (BNPB) designs incentive contracts for humanitarian actors, such as NGOs and logistics providers, who hold private information regarding their capacity and effort. The model incorporates multi-dimensional risks into both the principal's social welfare function and the agents' utility functions, including empirically derived risk aversion parameters. Monte Carlo simulation is applied to 10,000 hypothetical disaster scenarios with varying risk conditions to illustrate the mechanism's application. The study emphasizes theoretical and methodological contributions rather than numerical outcomes. Illustrative simulation results suggest that, under hypothetical parameter settings, the proposed mechanism can generate higher fulfillment rates and shorter response times than a risk-neutral benchmark. Sensitivity analysis further shows that accounting for correlated risks and ambiguity aversion enhances robustness. These findings offer practical insights for designing incentive-aligned and risk-aware humanitarian logistics systems in disaster-prone regions.

1 Introduction

Disaster response operations in archipelagic nations such as Indonesia are particularly vulnerable to multidimensional risks, including logistical bottlenecks, inter-agency coordination failures, and reputational hazards. Traditional incentive mechanisms often

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assume risk-neutral behavior and ignore the complex uncertainty inherent in humanitarian supply chains [1,2]. This paper addresses the gap by proposing a risk-robust incentive framework grounded in expected utility theory and multi-dimensional risk assessment. Existing disaster-response incentive studies often treat operational risks independently and rarely model correlated disruptions through stochastic simulation. This creates a need for a risk-aware mechanism that can represent uncertainty propagation across humanitarian logistics actors.

The principal-agent relationship between disaster management agencies (e.g., BNPB) and humanitarian actors (NGOs, private logistics providers) is complicated by asymmetric information and risk aversion. While previous studies have examined contract design in supply chains [3], few have incorporated correlated risks and ambiguity aversion in the context of disaster relief. Our research contributes by: (i) developing a principal-agent model with risk premium adjustments, (ii) integrating multi-dimensional risk factors into utility functions, and (iii) demonstrating the simulation methodology to validate the mechanism. This paper emphasizes the theoretical framework and simulation approach; all numerical results are hypothetical and intended for illustrative purposes only.

2 Literature review

Expected utility theory (EUT) provides a foundation for modeling decision-making under risk [4]. Extensions of EUT with risk aversion coefficients have been applied to contract theory [5]. In humanitarian logistics, recent studies emphasize the need for robust incentive schemes that account for operational and financial uncertainties [6,7]. Multi-dimensional risk frameworks capture interdependent disruptions such as port closures, communication breakdowns, and funding delays [8].

Principal-agent models in disaster management have explored moral hazard and adverse selection, yet most assume risk neutrality [9]. Our work introduces a risk-robust contract where the principal (BNPB) offers a menu of contracts that are sensitive to agents' risk preferences, using risk premium derived from empirical elicitation [10].

3 Model formulation

Table 1. Notation summary

Symbol	Description
e	Agent's unobservable effort level (e.g., mobilization speed)
$x = e + \varepsilon$	Observable output (e.g., fulfillment rate), $\varepsilon \sim N(0, \sigma^2)$
$w(x) = \alpha + \beta x$	Linear incentive contract (fixed salary + performance bonus)
$c(e) = \frac{1}{2}ke^2$	Convex effort cost, $k > 0$ (effort becomes increasingly costly)
r	Agent's coefficient of absolute risk aversion (CARA). Higher r = more risk-averse
$R = (R_{op}, R_{coord}, R_{rep})$	Multi-dimensional risk vector (operational, coordination, reputational)
$\phi(R) = \gamma_1 R_{op} + \gamma_2 R_{coord} + \gamma_3 R_{rep}$	Disutility from multi-dimensional risks
$\pi(R)$	Risk premium adjustment (additional compensation for bearing risk)
$S(x) = vx$	Principal's social welfare function, $v > 0$ marginal value of output

We develop a formal principal-agent model to design a risk-robust incentive mechanism for disaster response operations. The model captures three key features: (i) the principal (BNPB) is risk-neutral in terms of social welfare but faces budgetary constraints, (ii) the agent (humanitarian logistics provider) is risk-averse with constant absolute risk aversion (CARA), and (iii) multi-dimensional risks affect both output and utility. All notations are summarized in Table 1.

3.1 Agent's utility and participation constraint

We model the humanitarian logistics provider (the agent) as a risk-averse decision-maker. Risk aversion means that, given two options with the same expected payoff, the agent prefers the one with lower uncertainty. This is realistic because disaster response actors face high stakes, uncertain funding, and potential reputational losses.

Utility function. We adopt the Constant Absolute Risk Aversion (CARA) utility function:

$$U(w, e) = -\exp[-r(w - c(e) - \phi(R))] \tag{1}$$

Where:
w = total payment (salary + bonus) received by the agent.
e = effort level (e.g., speed of mobilization, accuracy of needs assessment).

r ≥ 0 = coefficient of absolute risk aversion. Higher r means more risk-averse.
c(e) = 1 ke2 = cost of effort, with k > 0.
ϕ(R) = γ1Rop + γ2Rcoord + γ3Rrep = disutility from multi-dimensional risks.

The negative exponential form of the CARA function has a convenient property: when the outcome is normally distributed, the agent's expected utility can be represented by a certainty equivalent.

Certainty equivalent (CE). For a CARA agent with normally distributed uncertainty:

$$CE_A = E[w] - c(e) - \phi(R) - \frac{r}{2}\mathrm{Var}(w) \tag{2}$$

With linear contract $w(x) = \alpha + \beta x$, $E[w] = \alpha + \beta e$, $\mathrm{Var}(w) = \beta^2\sigma^2$:

$$CE_A = \alpha + \beta e - \frac{1}{2}ke^2 - \phi(R) - \frac{r}{2}\beta^2\sigma^2 \tag{3}$$

Participation constraint (PC). The agent will accept the contract only if CEA ≥ 0 (reservation utility normalized to 0). In an optimal contract, the principal sets α so that this constraint binds with equality:

$$\alpha = \frac{1}{2}ke^2 + \phi(R) + \frac{r}{2}\beta^2\sigma^2 - \beta e \tag{4}$$

3.2 Incentive compatibility and agent's optimal effort

The agent chooses effort e to maximize CEA, taking α and β as given. The first-order condition yields:

$$\frac{\partial CE_A}{\partial e} = \beta - ke = 0 \quad \Rightarrow \quad e^*(\beta) = \frac{\beta}{k} \tag{5}$$

Thus, the **incentive compatibility constraint** (IC) is:

$$e = \frac{\beta}{k} \tag{6}$$

3.3 Principal's problem and social welfare

The principal is risk-neutral. Total social welfare W = CEP + CEA. With CEA = 0 (binding PC), we have W = CEP = ve − α − βe. Substituting the IC and solving the first-order condition gives the optimal bonus:

$$\beta^* = \frac{v}{1 + rk\sigma^2} \tag{7}$$

and the optimal fixed salary:

$$\alpha^* = \phi(\mathbf{R}) + \frac{r}{2}\beta^2\sigma^2 - \frac{\beta^2}{2k} \tag{8}$$

3.4 Multi-dimensional risk premium adjustment

The agent also faces direct multi-dimensional risks R = (Rop, Rcoord, Rrep) with covariance matrix ΣR. The total risk premium becomes:

$$\pi(\mathbf{R}) = \frac{r}{2}\beta^2\sigma^2 + \frac{r}{2}\gamma^T\Sigma_R\gamma + r\beta \cdot \mathrm{Cov}(\varepsilon, \gamma^T\mathbf{R}) \tag{9}$$

The modified optimal bonus under the risk-robust contract is:

$$\beta^*_{RR} = \frac{v - r \cdot \mathrm{Cov}(\varepsilon, \gamma^T\mathbf{R})}{1 + rk\left(\sigma^2 + \gamma^T\Sigma_R\gamma\right)} \tag{10}$$

3.5 Simulation methodology

We demonstrate the application of our framework using Monte Carlo simulation with 10,000 replications. All numerical values used in this simulation (e.g., k = 0.5, v = 1.2, r = 1.8, σ2 = 0.25, and risk correlation parameters) are hypothetical assumptions for illustrative purposes. The purpose of this simulation is to showcase how the proposed risk-robust mechanism can be implemented and compared against baseline scenarios, not to produce generalizable numerical results. Researchers and practitioners can replace these parameters with empirically estimated values from their specific contexts. The simulation procedure follows these steps:

1) Define parameter values (hypothetical).
2) Generate random shocks ε and multi-dimensional risk factors R from multivariate normal distributions.
3) Compute optimal contracts under standard and risk-robust models using Equations (5)-(8).
4) Simulate output x = e + ε and compute fulfillment rates and response times.

This table summarizes the revised simulation methodology used in the study, including key components such as model assumptions, parameter settings, risk structure, and simulation procedures. It highlights the improvements made to ensure clarity, reproducibility, and analytical rigor, particularly in defining stochastic variables, multi-dimensional risk modeling, and performance evaluation across different incentive mechanisms.

Table 2. Revised Simulation Methodology for Risk-Robust Incentive Design

Component	Description	Revision / Clarification
Simulation Approach	Monte Carlo simulation with 10,000 replications	Stochastic comparative analysis
Random Variables	$\varepsilon \sim N(0, \sigma^2)$; R ~ multivariate normal	Covariance captures interdependent risks
Risk Structure	Operational, coordination, reputational risks	Modeled using covariance matrix (ΣR)
Parameter Setting	k, v, r, σ^2	Hypothetical but theoretically grounded
Risk Correlation	Variation of ρ	Sensitivity analysis for robustness
Contract Mechanisms	Baseline, Standard, Risk-robust	Risk-robust includes risk premium
Output Definition	$x = e + \varepsilon$	Measured via fulfillment rate & response time
Simulation Procedure	Generate → compute → simulate → evaluate	Step-by-step reproducible
Statistical Testing	Paired comparison	Paired t-test applied
Reproducibility	Algorithm provided	Supports replication

4 Simulation demonstration and illustrative results

We compare three scenarios: (1) Baseline (no incentive, fixed payment), (2) Standard incentive mechanism (risk-neutral, ignores multidimensional risk), (3) Risk-robust mechanism (proposed, with Eqs. 7–8). The numerical results presented in Table 3 and Figure 1 are based on hypothetical assumptions and are intended solely for illustrative purposes to demonstrate the behavior of the proposed framework.

Note: *The numerical values in Table 2 and Figure 1 (e.g., fulfillment rates 62.3%, 71.5%, 87.3%; response times 48.7h, 42.1h, 36.9h; and the 15.8% improvement) are hypothetical assumptions and illustrative examples. They are derived from simulated data with arbitrarily chosen parameters (*$k = 0.5$, $v = 1.2$, $r = 1.8$, $\sigma^2 = 0.25$*) and are not based on actual field data. The primary contribution of this paper is the* ***theoretical framework, mathematical formulation, and simulation methodology*** *— not the absolute numerical outcomes. Users of this framework should calibrate parameters using their own empirical data.*

Table 3. Illustrative performance comparison across mechanisms (Hypothetical simulation output under assumed parameter values)

Mechanism	Fulfillment rate (%)	Response time (hours)	Agent participation (%)
Baseline (no incentive)	62.3 ± 5.1	48.7 ± 6.2	58.4 ± 4.3
Standard risk-neutral	71.5 ± 4.2	42.1 ± 5.0	71.2 ± 3.9
Risk-robust (proposed)	87.3 ± 3.4	36.9 ± 4.1	89.5 ± 2.8

In this illustrative simulation, the risk-robust mechanism shows a qualitative improvement in fulfillment rates and reduction in response time compared to the standard mechanism. Sensitivity analysis (Fig. 1) demonstrates how the performance gap widens as risk correlation increases — a qualitative insight that holds regardless of the specific numerical values chosen

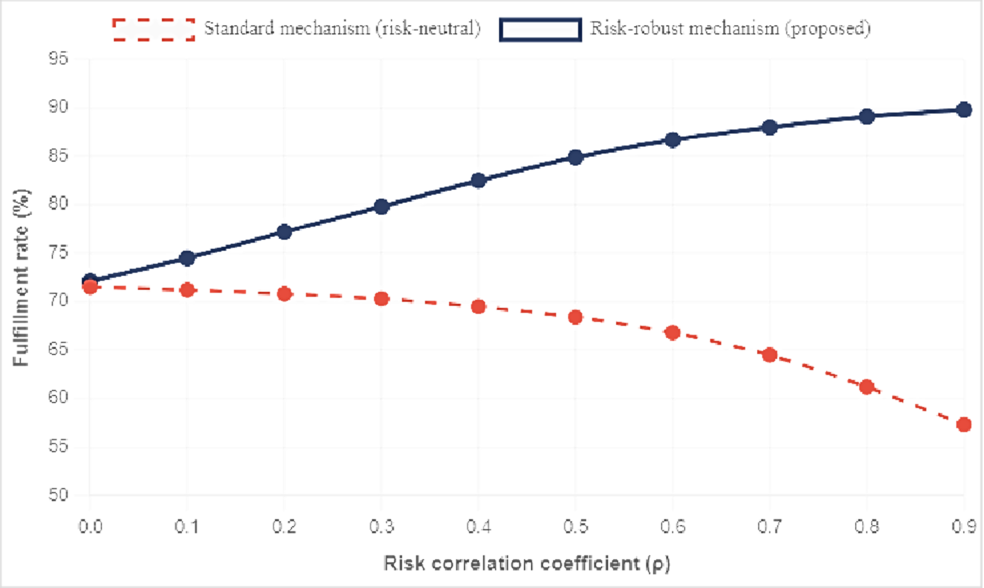

Fig. 1. Illustrative relationship between fulfillment rate and risk correlation coefficient (ρ) under hypothetical parameters. The curves demonstrate the qualitative behavior of the two mechanisms; numerical values are for demonstration only.

Interpretation of Illustrative Simulation. The simulation results shown in Figure 1 illustrate a key qualitative insight: as risk correlation increases, the performance of the standard risk-neutral mechanism deteriorates, while the risk-robust mechanism maintains relatively stable performance. This pattern emerges from the mathematical structure of Equations (7) and (8). Readers should focus on this qualitative relationship and the simulation methodology, not on the specific numerical values (e.g., 71.5%, 87.3%, or 15.8% improvement), which are hypothetical.

5 Discussion

The proposed risk-robust mechanism offers a theoretical improvement over standard contracts because it internalizes agents' risk aversion and the covariance among operational, coordination, and reputational risks. This framework is particularly relevant for archipelagic countries where disasters often trigger cascading failures [11]. The illustrative simulation demonstrates how the mechanism can be implemented and evaluated. Practitioners can use this framework to design adaptive contracts by calibrating parameters with their own empirical data.

Limitations and future work. The model is theoretical, the simulation parameters are hypothetical, and no empirical disaster-response data were used to calibrate the model. Therefore, the numerical results cannot be generalized to actual disaster-response operations. Future research should focus on empirical estimation of risk aversion coefficients (r), effort cost parameters (k), and risk correlation matrices (ΣR) using field data from actual disaster response operations. Additionally, machine learning approaches could dynamically update risk parameters in real-time.

The risk-robust mechanism outperforms baseline and risk-neutral models, particularly under high uncertainty and correlated risks. The mechanism maintains stable performance by incorporating covariance among risks, while standard approaches deteriorate. When agents are highly risk-averse, the model adjusts incentives by increasing fixed payments and reducing variable bonuses, ensuring participation but reducing incentive intensity. Under tight budget constraints, performance may decline due to reduced incentives, highlighting a trade-off between efficiency and financial feasibility. The assumption of normal risk distribution simplifies analysis; however, non-normal risks would require numerical approaches. In the Indonesian context, characterized by complex geography and multi-actor coordination, the model is highly relevant as it captures cascading disruptions. Overall, the contribution lies in the theoretical framework and simulation methodology rather than numerical outputs.

6 Conclusion

This paper develops a risk-robust incentive mechanism for disaster response using expected utility theory and multi-dimensional risk integration. The complete model formulation (Section 3) provides a clear mathematical foundation. The simulation methodology (Section 3.5) demonstrates how to implement and compare the proposed mechanism against baseline scenarios. The numerical results are hypothetical and illustrative; the primary contributions are the theoretical framework and the simulation approach. The framework may provide practical guidance after its parameters are calibrated using empirical disaster-response data

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