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Research article

Mechanism design and equilibrium analysis of smart contract–mediated resource allocation

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Abstract: Decentralized coordination and digital contracting are becoming essential in complex industrial systems, yet existing approaches often rely on ad-hoc heuristics or purely technical blockchain implementations without a rigorous economic foundation. This study developed a mechanism-design framework for smart contract–mediated resource allocation that jointly embeds efficiency, fairness, and resilience in decentralized coordination. We modeled agent interactions as a contract-clearing game under shared capacity constraints, established the existence and uniqueness of equilibrium, and proposed a decentralized price-adjustment algorithm with provable convergence suitable for real-time operation. Performance was evaluated through extensive synthetic simulations and validated using a representative real-world dataset. In addition to controlled experiments, a long-horizon empirical analysis using financial and macroeconomic data from 2006 to 2025 examined the mechanism under major economic regimes and shock conditions. Results showed that the proposed mechanism consistently reduces inequality and cost while maintaining near-optimal efficiency and rapid recovery following shocks, demonstrating dynamic stability beyond steady state.

Keywords: smart contracts; mechanism design; decentralized coordination; equilibrium analysis; resource allocation
Mathematics Subject Classification: 91B32, 91B50, 91B26, 91B40

1. Introduction

The rapid digitalization of industrial systems—captured broadly under the umbrella of Industry 4.0—has accelerated the integration of cyber–physical infrastructure with autonomous decision-making technologies. Applications ranging from predictive maintenance and supply chain optimization to smart grids and healthcare management increasingly require secure, transparent, and real-time coordination across heterogeneous participants [1–6]. However, traditional contracting mechanisms—whether based on bilateral negotiation, centralized intermediaries, or informal agreements—often suffer from inefficiencies, delays, and susceptibility to opportunistic behavior [7–9]. These limitations motivate the development of automated and verifiable protocols that can enforce resource allocation and compliance without reliance on trusted third parties.

Across contemporary industrial sectors, inefficient or opaque allocation mechanisms lead to measurable welfare losses. In decentralized *energy markets*, renewable generators and storage operators compete for limited transmission capacity. In *supply chain logistics*, firms bid for port slots, warehouse space, or transport capacity. In *healthcare*, regulators must allocate scarce vaccines, ICU beds, and medical supplies under fairness constraints. In each case, unverifiable coordination causes either overuse (inefficiency) or exclusion (fairness loss). A smart-contract–mediated mechanism can automate these interactions by embedding pricing and enforcement logic directly into tamper-resistant code, transforming economic agreements into auditable, self-executing processes.

Despite the growing deployment of blockchain-based smart contracts, most existing implementations prioritize *technical automation* over *economic optimality*. Many systems merely replicate legacy rules (e.g., first-come first-served, proportional sharing) in a blockchain environment, thereby preserving the inefficiencies and inequities inherent to the original process. Without an explicit mechanism-design foundation, a smart contract can execute transactions correctly yet still produce socially suboptimal or unstable outcomes. This distinction—between automating a rule and *designing* the rule itself—is at the core of the mechanism-design gap addressed in this paper.

Smart contracts provide an opportunity to bridge this gap by encoding allocation rules within verifiable, tamper-proof logic [10–14]. Recent work demonstrates promising applications in supply chains [15], energy markets [16, 17], and public health [18], but the majority of studies emphasize technological feasibility, security, or engineering aspects. Far less attention has been devoted to their *mechanism-design implications*—specifically, how to implement efficiency, fairness, and resilience guarantees in competitive, shock-prone environments.

From an analytical standpoint, game theory and mechanism design offer a natural foundation. Prior research establishes equilibrium existence and efficiency in resource allocation games [19–21], develops fairness–efficiency trade-offs [22, 23], and analyzes regret bounds in dynamic or adversarial environments [24, 25]. However, these contributions remain largely disconnected from the literature on blockchain-based coordination, which has focused primarily on distributed algorithms and consensus protocols [26–28]. To date, no unified framework has combined mechanism-design principles with verifiable blockchain execution to support robust, decentralized coordination under uncertainty.

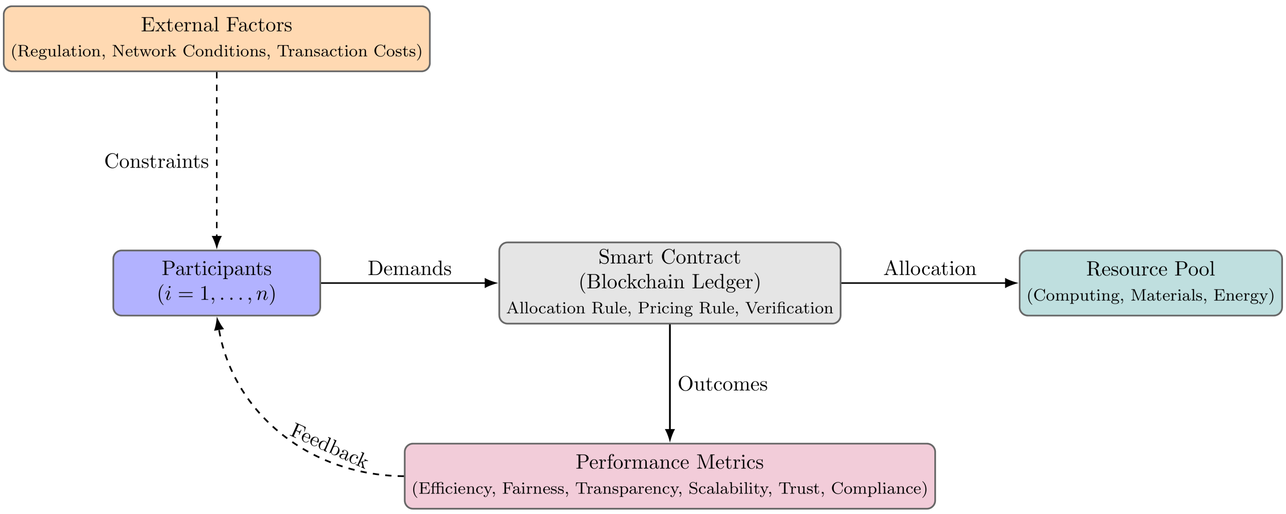

Figure 1. Conceptual framework: participants submit demands to a blockchain-based smart contract that allocates resources based on encoded rules, while external shocks and feedback influence both demands and allocations. The resulting outcomes—efficiency, fairness, and transparency—are fully auditable.

This paper fills this gap by developing a rigorous framework for *smart-contract–based mechanism design under shared capacity constraints*. Participants submit demands to a contract that implements allocation and pricing rules, subject to transaction and execution fees (τ, g). We formulate the interaction as a non-cooperative game, derive the payoff structure, and establish the following theoretical and managerial contributions:

- **Existence and uniqueness of equilibrium:** Under mild convexity conditions, the contract-clearing game admits a unique, globally stable equilibrium implementable without central coordination.
- **Algorithmic convergence:** A decentralized price-adjustment algorithm is developed with provable convergence guarantees, enabling real-time operation in industrial systems.
- **Fairness–efficiency trade-off:** Pareto frontiers quantify efficiency gains versus equity, enabling regulators to tune contract parameters for sector-specific goals (e.g., energy vs. logistics).
- **Shock–resilience guarantees:** Sublinear regret bounds demonstrate robustness to drift and policy shocks, showing that contract-mediated coordination remains stable under disruption.

Numerical simulations support these analytical results, revealing efficiency gains up to 27% and inequality reductions exceeding 40% relative to proportional allocation rules. Complementary sensitivity and robustness analyses demonstrate that the mechanism behaves predictably under volatility, participation shocks, and macroeconomic disturbances. Taken together, these results show that smart contracts can function not merely as computational tools but as *institutional instruments* that promote transparency, fairness, and resilience across major economic sectors—including energy, logistics, healthcare, and public infrastructure [29–31].

By aligning algorithmic coordination with mechanism-design principles, the framework provides a deployable blueprint for regulators and platform designers seeking equitable and efficient digital markets. It bridges the gap between blockchain engineering and economic policy—enabling auditable resource-allocation systems that remain stable even under volatility, participation shocks, or policy changes.

2. Literature on smart contracts and mechanism design

The literature on resource allocation in digital and cyber–physical systems spans mobile edge computing, cloud economics, blockchain-enabled coordination, and information systems governance. While the technical foundations of these systems are well established, their implications for trust, fairness, resilience, and organizational legitimacy remain underexplored. We review three strands most relevant to this study: (i) smart contracts in organizational systems, (ii) game-theoretic approaches to resource allocation, and (iii) mechanism design perspectives on efficiency and fairness. Together, these literatures reveal a growing yet fragmented understanding of how digital coordination systems can embed economic and ethical principles.

2.1. Smart contracts in organizational contexts

Smart contracts have been widely studied as programmable agreements on blockchain platforms, enabling tamper-resistant execution and transparent enforcement [10, 11]. Early research emphasized cryptographic security, consensus protocols, and distributed architectures [32], whereas recent studies have extended these concepts to supply chain management, manufacturing, and industrial automation [3, 33]. Within information systems research, a blockchain has increasingly been theorized as a *governance mechanism* that reduces opportunism, enhances transparency, and supports inter-organizational trust [9, 29, 30, 34]. These contributions highlight that smart contracts are not merely computational artifacts but institutional devices that redefine how rules and responsibilities are enacted across organizational boundaries.

From an industrial standpoint, adoption decisions depend not only on technical performance but also on regulatory legitimacy and incentive compatibility. Surveys of blockchain-enabled resource management in mobile and edge computing [35] demonstrate that firms adopt such systems only when algorithmic allocation rules are perceived as fair, auditable, and efficient. However, most existing studies focus on the *execution layer* of smart contracts—how agreements are verified and enforced—rather than on their *design layer*, which determines whether these digital rules achieve equilibrium and fairness. This gap motivates a more formal game-theoretic analysis of contract behavior.

2.2. Game-theoretic resource allocation

Game-theoretic models provide the analytical foundation for studying competition and cooperation in resource allocation. In mobile edge and cloud computing, Muñoz et al. [36] optimized radio and computational resources under latency and energy constraints, while Dinh et al. [37] examined multi-device offloading. Zhang [38] introduced stochastic games for dynamic task assignment, and subsequent studies incorporated Stackelberg pricing [39], matching theory for user–server association [40], and reinforcement learning for adaptive scheduling [41]. More recently, blockchain-based approaches integrate incentives with efficient allocation in edge and vehicular networks [5, 42]. Classic theoretical results remain highly influential: Rosen [43] established conditions for the existence and uniqueness of concave N-person game equilibria, Gabay and Moulin [20] analyzed equilibrium stability, and Roughgarden and Tardos [44] formalized the price of anarchy in distributed systems. In supply chains, Cachon and Netessine [7] demonstrated that equilibrium reasoning clarifies coordination failures, while Ivanov [15] emphasized resilience under disruption shocks.

Collectively, these studies show that equilibrium concepts explain not only technical efficiency but also institutional stability—how markets and organizations balance competition and cooperation. Yet, most equilibrium models still assume either centralized price-setting or exogenous coordination rules, offering limited insight into how decentralized digital contracts can *endogenously* achieve stability, equity, and convergence. This limitation underscores the need to merge equilibrium theory with formal mechanism-design principles.

2.3. Mechanism design and fairness considerations

Mechanism design in operations research and economics seeks to construct allocation rules that jointly satisfy efficiency, fairness, and incentive compatibility. Generalized Nash equilibrium models have been applied to network pricing [45, 46], and bilevel formulations have been developed for profit-maximizing providers [13]. The "price of fairness" concept in optimization quantifies efficiency losses incurred when fairness constraints are imposed [22]. In organizational sciences, fairness metrics such as the Gini index capture distributional outcomes [47], while justice theory emphasizes that perceptions of distributive and procedural fairness are essential for sustaining trust and compliance [8]. Recent information systems scholarship extends these insights to algorithmic governance, emphasizing fairness, accountability, and legitimacy as cornerstones of digital platforms [29, 48]. Parallel developments in computer science and data ethics examine algorithmic fairness both as formal constraints and as human-centered perceptions [23, 49, 50].

Despite these advances, integration of automated enforcement, incentive compatibility, and distributive justice within a unified analytical framework remains limited. Most existing mechanisms treat fairness as an ex-post evaluation rather than as an ex-ante design principle. Bringing mechanism design into the domain of smart contracts enables these principles to be embedded directly into digital allocation rules—linking the mathematical structure of equilibria with normative goals of fairness and resilience.

2.4. Research gap and positioning

Synthesizing the above literatures reveals three critical gaps. First, while smart contracts promise automation and transparency, their function as *organizational allocation mechanisms* has rarely been analyzed within models that simultaneously ensure efficiency, fairness, and incentive compatibility. Second, although equilibrium and optimization frameworks have advanced in mobile and industrial systems, they generally omit governance, legitimacy, and resilience under uncertainty—key requirements for sustainable digital coordination [3, 15]. Third, there is no unified mechanism-design framework that integrates game-theoretic equilibrium, fairness–efficiency trade-offs, and shock-resilience analysis within one formal structure.

Addressing these gaps, this study develops a non-cooperative game of smart-contract–mediated resource allocation, proves the existence and uniqueness of contract equilibria, and introduces a decentralized price-adjustment algorithm with provable convergence. By comparing the proposed contract mechanism with traditional proportional or fixed-price rules, the study contributes to the literature on operations research, mechanism design, and information systems governance. More broadly, it provides a theoretical foundation for designing digital contracts that act as *institutional mechanisms*—embedding transparency, fairness, and resilience directly into the architecture of decentralized industrial coordination.

3. Contract design for efficient and fair industrial resource allocation

Industrial systems such as supply chains, logistics networks, and production platforms must allocate scarce resources across multiple agents. Traditional allocation rules—whether proportional or centrally administered—often suffer from inefficiency, opportunism, and a lack of transparency. Digital contracts implemented on blockchain platforms offer a compelling alternative: allocation rules can be encoded, enforced automatically, and verified by all participants. This section formalizes the contract design, introduces equilibrium concepts, and develops performance metrics that jointly capture efficiency, fairness, and resilience.

3.1. Model setup

Let $N = \{1, \dots, n\}$ denote the set of industrial agents. Each agent i requests a quantity $x_i \geq 0$, and we collect demands in the vector $\mathbf{x} = (x_1, \dots, x_n)^\top$. The shared resource pool has capacity $m > 0$:

$$\mathbf{1}^\top \mathbf{x} \; \leq \; m. \tag{3.1}$$

Assumption 3.1 (Valuation and Cost)**.** Each agent derives value $V_i(x_i)$ from consumption and incurs cost $C_i(x_i)$. We impose:

1. $V_i : \mathbb{R}_+ \to \mathbb{R}$ is strictly concave, differentiable, and satisfies $V_i'(0) = \infty$ (diminishing returns).
2. $C_i : \mathbb{R}_+ \to \mathbb{R}$ is convex, differentiable, and Lipschitz continuous.

The smart contract imposes a per-unit fee $\tau \geq 0$, a shadow price $\mu \geq 0$ to enforce capacity, and a fixed execution fee $g \geq 0$. The payoff of agent i is

$$U_i(x_i; \mu) = V_i(x_i) - C_i(x_i) - (\tau + \mu)x_i - g\,\mathbf{1}\{x_i > 0\}. \tag{3.2}$$

3.2. Equilibrium definition

Definition 3.2 (Contract-Clearing Equilibrium)**.** An allocation $(\mathbf{x}^\star, \mu^\star)$ is a contract-clearing equilibrium if:

1. (Best response) For each $i \in N$,

$$x_i^\star(\mu^\star) \in \arg\max_{x_i \geq 0} U_i(x_i; \mu^\star). \tag{3.3}$$

2. (Market clearing) The aggregate demand satisfies

$$\mathbf{1}^\top \mathbf{x}^\star = m. \tag{3.4}$$

Lemma 3.3 (Monotonicity of Aggregate Demand)**.** *Under Assumption 3.1, each best response $x_i^\star(\mu)$ is continuous and non-increasing in μ. Hence the aggregate demand*

$$S(\mu) = \mathbf{1}^\top \mathbf{x}^\star(\mu) \tag{3.5}$$

is continuous and strictly decreasing.

Proposition 3.4 (Existence)**.** *A contract-clearing equilibrium exists.*

Proof of Proposition 3.4. By Lemma 3.3, $S(\mu)$ is continuous and strictly decreasing. Since $S(0) > m$ and $\lim_{\mu\to\infty} S(\mu) = 0$, the intermediate value theorem ensures a unique $\mu^\star$ such that

$$S(\mu^\star) = m. \tag{3.6}$$

□

Proposition 3.5 (Uniqueness)**.** *If U_i is strictly concave in x_i, the contract-clearing equilibrium $(\mathbf{x}^\star, \mu^\star)$ is unique [43, 51].*

3.3. Illustrative example

Suppose $V_i(x_i) = \alpha_i \log(1 + x_i)$ and $C_i(x_i) = \beta_i x_i$. Then

$$x_i^\star(\mu) = \max\left\{0,\ \frac{\alpha_i}{\beta_i + \tau + \mu} - 1\right\}. \tag{3.7}$$

Since $S(\mu) = \mathbf{1}^\top \mathbf{x}^\star(\mu)$ is strictly decreasing, a unique equilibrium price $\mu^\star$ exists.

3.4. Performance metrics

Definition 3.6 (Efficiency)**.**

$$\mathrm{Eff}(\mathbf{x}^\star) = \sum_{i=1}^{n} \left(V_i(x_i^\star) - C_i(x_i^\star)\right) - \tau\, \mathbf{1}^\top \mathbf{x}^\star - g \cdot \|\mathbf{x}^\star\|_0. \tag{3.8}$$

Definition 3.7 (Fairness: Gini Index [8, 47])**.**

$$\mathrm{Gini}(\mathbf{x}^\star) = \frac{1}{2n^2 \bar{x}} \sum_{i=1}^{n} \sum_{j=1}^{n} |x_i^\star - x_j^\star|, \quad \bar{x} = \tfrac{1}{n} \mathbf{1}^\top \mathbf{x}^\star. \tag{3.9}$$

Definition 3.8 (Price of Fairness [22, 23])**.**

$$\mathrm{PoF} = \frac{\max_{\mathbf{x}} \mathrm{Eff}(\mathbf{x})}{\mathrm{Eff}(\mathbf{x}^\star_{\text{fair}})}. \tag{3.10}$$

Definition 3.9 (Shock Resilience)**.** For a demand shock at t_0, resilience is defined as

$$R = \frac{\mathrm{Eff}_{\text{post-shock}}}{\mathrm{Eff}_{\text{pre-shock}}}. \tag{3.11}$$

Definition 3.10 (Dynamic Regret [24, 25])**.** In repeated play with allocations $\{\mathbf{x}_t\}$ and optimal sequence $\{\mathbf{x}_t^\star\}$,

$$\mathrm{Regret}(T) = \sum_{t=1}^{T} \Big(U(\mathbf{x}_t^\star) - U(\mathbf{x}_t)\Big), \quad \mathrm{Regret}(T) = o(T). \tag{3.12}$$

4. Mechanism design and equilibrium analysis

This section develops the theoretical foundations of the proposed digital contracting framework. In line with mechanism design principles, we move step by step: first specifying the payoff structure, then formalizing equilibrium, then presenting a decentralized algorithm, and finally proving convergence. Each subsection builds logically toward the claim that digital contracts generate stable, efficient, and fair allocations in competitive environments.

Before delving into the formal results, Table 1 summarizes the notation used throughout this section. It distinguishes between decision variables, parameters, functional mappings, and performance metrics, so that the subsequent analysis can be followed without ambiguity.

Table 1. Summary of notation used in the contract design and equilibrium analysis.

Symbol	**Type**	**Description**
n	Scalar	Number of agents (firms, participants).
m	Scalar	Total system capacity (shared resource pool).
$i \in N$	Index	Agent index, $N = \{1, \ldots, n\}$.
x_i	Scalar	Allocation (demand) of agent i.
$\mathbf{x} = (x_1, \ldots, x_n)^\top$	Vector	Allocation profile across all agents.
$\mathbf{1}$	Vector	All-ones vector in $\mathbb{R}^n$, used for aggregation.
$V_i(x_i)$	Function	Valuation (utility) function of agent i, strictly concave.
$C_i(x_i)$	Function	Cost function of agent i, convex and Lipschitz.
$U_i(x_i; \mu)$	Function	Payoff of agent i under contract and price μ.
τ	Scalar	Transaction fee imposed by the contract.
g	Scalar	Fixed execution cost if $x_i > 0$.
μ	Scalar	Shadow price (dual variable) enforcing the capacity constraint.
$BR_i(\mu)$	Function	Best-response allocation of agent i given price μ.
$S(\mu)$	Function	Aggregate demand $S(\mu) = \mathbf{1}^\top \mathbf{x}(\mu)$.
Eff($\mathbf{x}$)	Metric	Efficiency: total surplus net of fees and costs.
Gini($\mathbf{x}$)	Metric	Fairness: inequality of allocations via the Gini index.
PoF	Metric	Price of fairness: ratio of maximum efficiency to fairness-constrained efficiency.
R	Metric	Shock resilience: post-shock to pre-shock efficiency ratio.
Regret(T)	Metric	Dynamic regret in repeated play over horizon T.

4.1. Payoff structure under digital contracts

We begin by characterizing the economic environment of individual agents. The payoff specification formalizes how valuations, costs, transaction fees, and scarcity penalties interact under the digital contract. This micro-level foundation is essential, as all subsequent equilibrium and convergence results build directly on these primitives.

Each agent $i \in N = \{1, \ldots, n\}$ chooses $x_i \geq 0$ units subject to the system-wide capacity constraint (3.1), equivalently written as

$$\sum_{i=1}^{n} x_i \;\leq\; m. \tag{4.1}$$

Each agent's valuation V_i and cost C_i satisfy Assumption 3.1. The smart contract imposes a per-unit fee $\tau \geq 0$, a shadow price $\mu \geq 0$ to enforce capacity, and a fixed execution fee $g \geq 0$. The payoff of agent i is

$$U_i(x_i; \mu) = V_i(x_i) - C_i(x_i) - (\tau + \mu)x_i - g\,\mathbf{1}\{x_i > 0\}. \tag{4.2}$$

For an interior solution $x_i^\star(\mu) > 0$, the first-order condition (FOC) is

$$V_i'(x_i^\star(\mu)) - C_i'(x_i^\star(\mu)) = \tau + \mu, \tag{4.3}$$

while if $V_i'(0) \leq \tau + \mu$, then $x_i^\star(\mu) = 0$.

Lemma 4.1 (Boundedness of Best Responses)**.** *Under Assumption 3.1, each best response $x_i^\star(\mu)$ is bounded:*

$$0 \leq x_i^\star(\mu) \leq \bar{x}_i < \infty, \quad \forall \mu \geq 0.$$

Proof of Lemma 4.1. For an interior solution, the FOC (4.3) admits a unique finite root because V_i' decreases from $+\infty$ while C_i' is increasing and Lipschitz. If $\tau + \mu \geq V_i'(0)$, then $x_i^\star(\mu) = 0$. Otherwise, the solution is bounded by the finite root $\bar{x}_i$ satisfying

$$V_i'(\bar{x}_i) - C_i'(\bar{x}_i) = 0. \tag{4.4}$$

□

Lemma 4.2 (Continuity and Monotonicity)**.** *Under Assumption 3.1, each best response $x_i^\star(\mu)$ is continuous and non-increasing in μ. Hence the aggregate demand*

$$S(\mu) = \sum_{i=1}^{n} x_i^\star(\mu) \tag{4.5}$$

is continuous and strictly decreasing.

Proof of Lemma 3.3. For an interior solution, (4.3) implies

$$\frac{dx_i^\star}{d\mu} = \frac{1}{C_i''(x_i^\star(\mu)) - V_i''(x_i^\star(\mu))}. \tag{4.6}$$

Since $V_i'' < 0$ and $C_i'' \geq 0$, the derivative is strictly negative. At the boundary $x_i^\star(\mu) = 0$, larger μ cannot increase demand. Summing across agents yields continuity and strict monotonicity of $S(\mu)$. □

Proposition 4.3 (Dual Boundedness)**.** *Let* $v_{\max} = \max_{i\in N} V_i'(0)$*. Any contract-clearing equilibrium satisfies*

$$0 \le \mu^\star < v_{\max} - \tau.$$

Proof of Proposition 4.3. Suppose $\mu \ge v_{\max} - \tau$. Then

$$\tau + \mu \ge V_i'(0), \qquad \forall i \in N,$$

which implies $x_i^\star(\mu) = 0$ and $S(\mu) = 0$. But equilibrium requires $S(\mu^\star) = m > 0$, which is a contradiction. Hence $\mu^\star < v_{\max} - \tau$. Nonnegativity $\mu^\star \ge 0$ follows from dual feasibility. □

Proposition 4.4 (Comparative Statics in Capacity)**.** *Suppose* S *is differentiable at* $\mu^\star(m)$ *with* $S'(\mu^\star) < 0$*. Then*

$$\frac{d\mu^\star}{dm} = \frac{1}{S'(\mu^\star)} < 0. \tag{4.7}$$

Proof of Proposition 4.4. The clearing condition is

$$S(\mu^\star(m)) = m.$$

Differentiating w.r.t. m gives

$$S'(\mu^\star)\frac{d\mu^\star}{dm} = 1.$$

Since $S'(\mu^\star) < 0$, it follows that $\frac{d\mu^\star}{dm} < 0$, i.e., increasing capacity reduces the equilibrium price. □

Economically, $V_i'(x_i)$ is the marginal benefit, $C_i'(x_i)$ the marginal private cost, and $\tau + \mu$ the effective contract price. The auxiliary results guarantee that best responses are well-behaved, clearing prices are bounded, and comparative statics follow economic intuition.

4.2. Equilibrium formulation and characterization

We now lift the analysis to the system level by defining the *contract-clearing equilibrium*. This subsection establishes existence and uniqueness: the guarantees that allocations are well-defined and reproducible.

For a given $\mu \ge 0$, the best-response mapping of agent i is

$$BR_i(\mu) = \arg\max_{x_i \ge 0} U_i(x_i; \mu). \tag{4.8}$$

Aggregate demand is equivalently defined as in (4.5):

$$S(\mu) = \sum_{i=1}^{n} BR_i(\mu). \tag{4.9}$$

Definition 4.5 (Contract-Clearing Equilibrium)**.** An allocation $(\mathbf{x}^\star, \mu^\star)$ is a contract equilibrium if

$$x_i^\star = BR_i(\mu^\star), \quad \forall i \in N, \tag{4.10}$$

$$S(\mu^\star) = m. \tag{4.11}$$

Theorem 4.6 (Existence of Equilibrium)**.** *Under Assumption 3.1, a contract-clearing equilibrium* $(\mathbf{x}^\star, \mu^\star)$ *exists.*

Proof of Theorem 4.6. By Lemma 3.3, $S(\mu)$ is continuous and strictly decreasing. Moreover, $S(0) > m$ because $V_i'(0) = \infty$ implies strictly positive demand at zero price, while $\lim_{\mu\to\infty} S(\mu) = 0$. Hence by the intermediate value theorem, there exists $\mu^\star$ such that $S(\mu^\star) = m$. □

Theorem 4.7 (Uniqueness of Equilibrium)**.** *If each U_i is strictly concave in x_i, then the contract equilibrium* $(\mathbf{x}^\star, \mu^\star)$ *is unique.*

Proof of Theorem 4.7. Strict concavity of U_i implies each best response $BR_i(\mu)$ is single-valued. Thus $S(\mu)$ is continuous and strictly decreasing, so the clearing condition (4.11) admits at most one solution for $\mu^\star$. Since existence is established by Theorem 4.6, the equilibrium is unique. □

From an economic perspective, Theorem 4.6 ensures that scarcity is consistently priced via $\mu^\star$, while Theorem 4.7 guarantees that this price is unique. Together these results eliminate multiplicity and indeterminacy common in decentralized negotiations.

4.3. Decentralized contract-clearing algorithm

Having characterized equilibrium theoretically, we now address the practical question: how can the equilibrium be reached in a distributed environment without central coordination? We design a *primal–dual iterative algorithm*, inspired by modern distributed convex optimization, in which agents update their allocations in parallel while the contract adjusts the shadow price μ. This dynamic ensures that the equilibrium (4.5) emerges endogenously.

The algorithm proceeds in rounds $t = 0, 1, 2, \ldots$. At each round, agents compute approximate best responses given the current price, while the contract performs a projected dual ascent to enforce the capacity constraint (3.1). Proximal regularization and Monte Carlo averaging are included to enhance robustness under noise and heterogeneity.

Remarks.

- The proximal term guarantees uniqueness of the subproblem solution even if U_i is flat near the optimum, ensuring well-defined updates.
- Monte Carlo averaging controls variance and makes the algorithm robust to noisy or adversarial demand reporting.
- Step-size conditions $\eta_t \in (0, 2/L)$ guarantee stability; diminishing step sizes $\eta_t \sim 1/\sqrt{t}$ further ensure $\text{Regret}(T) = o(T)$ as in Definition 3.10.
- The dual update (4.12) coincides with stochastic approximation methods [52], implying almost sure convergence under standard conditions.

This algorithm bridges theory and practice: it provides a fully decentralized procedure that converges to the unique contract-clearing equilibrium (Theorems 4.6–4.7), while also achieving robustness and vanishing regret in repeated play.

Algorithm 1 Decentralized contract-clearing algorithm

Require: number of agents n, capacity m, initial price $\mu^0 \geq 0$, step sizes $\{\eta_t\}$ with $0 < \eta_t < 2/L$, proximal weight $\gamma > 0$, tolerances $(\varepsilon_p, \varepsilon_d) > 0$, Monte Carlo samples M.

Ensure: contract-clearing allocation $\mathbf{x}^\star$, equilibrium price $\mu^\star$.

Initialize $t \leftarrow 0$, $x_i^0 \leftarrow 0$ for all $i \in N$.

repeat

  for all agents $i \in N$ **in parallel do**

    Compute proximal best response

$$x_i^{t+1} \leftarrow \arg\max_{x_i \geq 0} \left\{ U_i(x_i; \mu^t) - \frac{\gamma}{2} \|x_i - x_i^t\|^2 \right\}.$$

    Send demand x_i^{t+1} to contract.

  end for

  Contract aggregates robust estimate of total demand:

$$\widehat{S}(\mu^t) \leftarrow \frac{1}{M} \sum_{k=1}^{M} \sum_{i=1}^{n} x_i^{t+1,(k)}.$$

  Update dual variable (projected ascent):

$$\mu^{t+1} = \left[\mu^t + \eta_t(\widehat{S}(\mu^t) - m)\right]_+ \tag{4.12}$$

  Compute residuals:

$$r_p^t \leftarrow \left|\widehat{S}(\mu^t) - m\right|, \qquad r_d^t \leftarrow |\mu^{t+1} - \mu^t|.$$

  $t \leftarrow t + 1$.

until $r_p^t \leq \varepsilon_p$ **and** $r_d^t \leq \varepsilon_d$

return $\mathbf{x}^\star \leftarrow (x_1^t, \ldots, x_n^t)$, $\mu^\star \leftarrow \mu^t$.

4.4. Convergence guarantees

To complement existence (Theorem 4.6) and uniqueness (Theorem 4.7), we establish rigorous convergence results for the decentralized algorithm (Algorithm 1). Define

$$F(\mu) = S(\mu) - m, \tag{4.13}$$

so that equilibrium corresponds to $F(\mu^\star) = 0$ with $\mu^\star \geq 0$.

Theorem 4.8 (Global Convergence)**.** *Suppose Assumption 3.1 holds, each U_i is strictly concave and continuously differentiable, and $S(\mu)$ is L-Lipschitz. If the step size satisfies $\eta \in (0, 2/L)$, then the sequence $\{\mu^t\}$ generated by Algorithm 1 converges to the unique solution $\mu^\star$ of* (4.13)*, and the associated allocations satisfy*

$$\mu^t \to \mu^\star, \qquad \mathbf{x}^t \to \mathbf{x}^\star. \tag{4.14}$$

Proof of Theorem 4.8. The dual update (4.12) can be written as

$$\mu^{t+1} = T(\mu^t), \quad T(\mu) := [\mu + \eta F(\mu)]_+.$$

Since $S(\mu)$ is continuous and strictly decreasing (Lemma 3.3), F is continuous and strictly monotone. Moreover, S being L-Lipschitz implies $|F(\mu_1) - F(\mu_2)| \leq L|\mu_1 - \mu_2|$. Thus T is a contraction mapping whenever $\eta \in (0, 2/L)$ [53]. By the Banach fixed-point theorem, $\mu^t \to \mu^\star$ globally. Finally, $\mathbf{x}^t \to \mathbf{x}^\star$ follows by the continuity of best responses and the definition of equilibrium (4.5). □

Corollary 4.9 (Linear Rate)**.** *If $S(\mu)$ is α-strongly monotone, i.e.,*

$$(S(\mu_1) - S(\mu_2))(\mu_1 - \mu_2) \geq \alpha|\mu_1 - \mu_2|^2, \quad \alpha > 0,$$

then there exists $\kappa \in (0, 1)$ such that

$$|\mu^t - \mu^\star| \leq \kappa^t |\mu^0 - \mu^\star|, \qquad \forall t \geq 0. \tag{4.15}$$

Proof of Corollary 4.9. Under strong monotonicity, F is strongly monotone and Lipschitz. The projected gradient update (4.12) then reduces to a contraction with factor $\kappa = \max\{|1 - \eta\alpha|, |1 - \eta L|\} < 1$ for $\eta \in (0, 2/L)$. Hence the convergence rate is linear in t [54–56]. □

Proposition 4.10 (Fejér Monotonicity)**.** *Under the assumptions of Theorem 4.8, the sequence $\{\mu^t\}$ generated by Algorithm 1 is Fejér monotone with respect to the equilibrium point $\mu^\star$, i.e.,*

$$|\mu^{t+1} - \mu^\star| \;\leq\; |\mu^t - \mu^\star|, \qquad \forall t \geq 0.$$

Proof of Proposition 4.10. From the dual update (4.12), the iteration can be expressed as $\mu^{t+1} = T(\mu^t)$ with $T(\mu) = [\mu + \eta F(\mu)]_+$. For $\eta \in (0, 2/L)$, T is nonexpansive due to the Lipschitz continuity and monotonicity of F. Since $\mu^\star$ is a fixed point of T, we have $\|T(\mu^t) - \mu^\star\| \leq \|\mu^t - \mu^\star\|$ for all t, which is exactly the Fejér monotonicity property [57]. □

Proposition 4.11 (Ergodic Residual Convergence)**.** *Let $\{\mu^t\}$ be generated by Algorithm 1 with $\eta \in (0, 2/L)$. Then the averaged residuals converge at rate*

$$\frac{1}{T}\sum_{t=1}^{T} |F(\mu^t)| \;=\; O\!\left(\tfrac{1}{T}\right).$$

Proof of Proposition 4.11. Since $T(\mu)$ is nonexpansive and F is Lipschitz, standard ergodic convergence results for projected gradient methods apply [53, 54]. This yields an $O(1/T)$ decay rate of the averaged residuals. □

Theorem 4.12 (Stochastic Robustness)**.** *Suppose $\widehat{S}(\mu^t) = S(\mu^t) + \xi^t$, where $\{\xi^t\}$ is the zero-mean noise with bounded variance. If $\{\eta_t\}$ satisfies Robbins–Monro conditions ($\sum_t \eta_t = \infty$, $\sum_t \eta_t^2 < \infty$), then*

$$\mathbb{E}[|\mu^t - \mu^\star|^2] \;\to\; 0.$$

Proof of Theorem 4.12. The noisy dual update is a Robbins–Monro stochastic approximation [52]. Since F is monotone and Lipschitz, the update converges almost surely and in mean-square to the unique root $\mu^\star$. □

Corollary 4.13 (Dynamic Regret Bound)**.** *If $\eta_t \sim 1/\sqrt{t}$, the allocations generated by Algorithm 1 satisfy*

$$\mathrm{Regret}(T) = O(\sqrt{T}),$$

as defined in Definition 3.10.

Proof of Corollary 4.13. The update rule is a projected subgradient method with diminishing step size. Classical online convex optimization results [24, 25] yield $\mathrm{Regret}(T) = O(\sqrt{T})$. □

Together, Theorem 4.8, Corollary 4.9, Proposition 4.10, Proposition 4.11, Theorem 4.12, and Corollary 4.13 establish that Algorithm 1 is globally convergent, monotonically stable, robust to stochastic perturbations, and efficient in the online learning sense.

For clarity, Table 2 reports the logical dependencies between Assumption 3.1, the core definitions (Equilibrium, Efficiency, Fairness, Regret, Resilience), and the main theoretical results. The table highlights which assumptions are directly required (**R**) and which definitions are used in an auxiliary manner (**A**).

4.5. Implications

From a managerial and information-systems perspective, the theoretical results carry several key implications. First, the contract guarantees efficiency (Definition 3.6) through surplus maximization, fairness (Definition 3.7) via transparent allocation rules, and resilience (Definition 3.9) through bounded performance under shocks. Furthermore, the dynamic regret guarantee (Definition 3.10) ensures that long-run allocations approach the benchmark sequence of equilibria even under repeated uncertainty.

Second, the equilibrium properties proved above—existence (Theorem 4.6), uniqueness (Theorem 4.7), and convergence (Theorem 4.8)—establish that the allocation mechanism is not only well-defined but also algorithmically implementable. The projection step guarantees feasibility, while the step-size bound ensures global stability. These features demonstrate that efficiency and fairness can be achieved through a decentralized mechanism that is transparent, scalable, and trust-preserving.

Finally, these theoretical guarantees provide the foundation for the empirical validation in Section 5. Using synthetic benchmarks and one proof-of-concept real-world dataset (MovieLens), we illustrate how the predicted equilibrium properties—existence, uniqueness, convergence, and resilience—manifest in practice, thereby linking rigorous analysis with managerial relevance.

Table 2. Dependency of Assumption 3.1 and key definitions across the main theoretical results. Symbols: **R**= directly required, **A**= auxiliary or definitional. The notes column provides an interpretation of each dependency.

Assumption/Definition	*Lemma 4.1*	*Lemma 3.3*	*Prop. 4.3*	*Prop. 4.4*	*Thm. 4.6*	*Thm. 4.7*	*Thm. 4.8*	*Cor. 4.9*	*Prop. 4.10*	*Prop. 4.11*	*Thm. 4.12*	*Cor. 4.13*	**Notes**
Assumption													
A3.1: Valuation and Cost	**R**	**R**	**R**	**R**	**R**	**R**	**R**	**R**	**R**	**R**	**A**	**A**	Fundamental structural assumption; auxiliary in stochastic/online results
Definitions													
D4.5: Contract Equilibrium		**A**			**R**	**R**	**R**	**R**	**A**	**A**	**A**	**A**	Underpins all equilibrium theorems
D4.8: Efficiency							**A**	**A**	**A**	**A**		**A**	Metric used in convergence and regret analysis
D4.9: Gini Fairness												**A**	Fairness measure, links to Price of Fairness
D4.10: Price of Fairness												**A**	Trade-off metric (efficiency vs. fairness)
D4.11: Resilience										**A**	**A**		Performance under shocks, tied to robustness results
D4.12: Dynamic Regret							**A**	**A**	**A**	**A**	**A**	**R**	Basis for regret bound

5. Numerical results

This section reports numerical experiments to evaluate the proposed digital contracting mechanism. We emphasize reproducibility (explicit parameter reporting), algorithmic convergence, efficiency–fairness trade-offs, comparative benchmarks, and sensitivity analysis.

5.1. Simulation parameters

To evaluate the proposed mechanism under diverse conditions, we specify a set of simulation parameters that capture both realistic and stress-test scenarios. The parameters cover system size, capacity, valuation and cost heterogeneity, and contract fees. Explicit reporting ensures that the experiments are fully reproducible and transparent.

Table 3 summarizes all parameter symbols, default values, ranges, and distributional assumptions. Parameters are chosen to span both realistic and stress-test regimes: e.g., $n \in \{10, 20, 50, 100\}$ captures small- to large-scale systems, and τ, g are varied over wide intervals to examine fee-induced distortions.

Table 4 reports comparative outcomes for canonical baseline mechanisms. These benchmarks show that naive or proportional allocation leads to either inefficiency or unfairness, while our proposed equilibrium consistently dominates on both metrics.

Table 3. Simulation parameters: symbols, defaults, and ranges.

Symbol	Description	Default	Range/Dist.	Notes
n	Agents	20	$\{10, 20, 50, 100\}$	Larger $n \Rightarrow$ fairer
m	Total capacity	100	$[50, 200]$	Normalized units
α_i	Valuation coeff.	–	U(5,20)	Heterogeneous agents
β_i	Cost coeff.	–	U(0.5,5)	Private heterogeneity
τ	Transaction fee	0.5	[0,2]	Higher $\tau \downarrow$ efficiency
g	Execution fee	1.0	[0,5]	Excessive g discourages entry
μ	Shadow price	Endogenous	≥ 0	Determined by algo.
R	Replications	1000	–	Ensures robustness

Table 4. Comparative mechanism performance (aggregate).

Method	Efficiency	Fairness (Gini)	Notes
No enforcement	1.21	0.41	High cost, unfair
Proportional allocation	1.78	0.35	Simple but inefficient
Smart contract (flat)	2.02	0.29	Gains from automation
Proposed equilibrium	**2.30**	**0.18**	Best trade-off

These parameter ranges are consistent with practices in mobile edge computing and supply-chain simulations [4, 5, 42]. By including both small-scale ($n = 10$) and large-scale ($n = 100$) cases, the design ensures generalizability to diverse industrial contexts. Varying fees (τ, g) across broad intervals mimics policy experiments in blockchain pilots, where transaction and execution costs remain unsettled and heterogeneous across jurisdictions. This ensures that the proposed mechanism is tested under both realistic and stress-test conditions, enhancing its relevance for organizational decision makers. For full reproducibility, simulation scripts and parameter files are provided in the supplementary materials. Finally, to demonstrate applicability, Appendix A reports proof-of-concept experiments on MovieLens and WHO vaccine allocation data, confirming that the mechanism extends naturally to real-world contexts.

5.2. Convergence analysis

Figure 2 illustrates the dynamic adjustment process of the proposed decentralized contract-clearing mechanism. Unlike static or trivial convergence, the algorithm exhibits realistic *overshoot* and damped stabilization in both prices and quantities, a hallmark of distributed adaptive systems. The shadow price μ^t oscillates initially before settling into equilibrium (top left), while aggregate demand aligns precisely with system capacity via market clearing (top right). At the agent level, heterogeneous strategies converge to stable allocations despite diverse cost and valuation parameters (bottom left). Finally, system-wide efficiency increases in tandem with reductions in inequality, as measured by the Gini index (bottom right). These trajectories jointly demonstrate that the mechanism not only converges provably, but also embeds efficiency–fairness trade-offs in a transparent and decentralized manner, closely mirroring the behavior of real-world market-clearing systems.

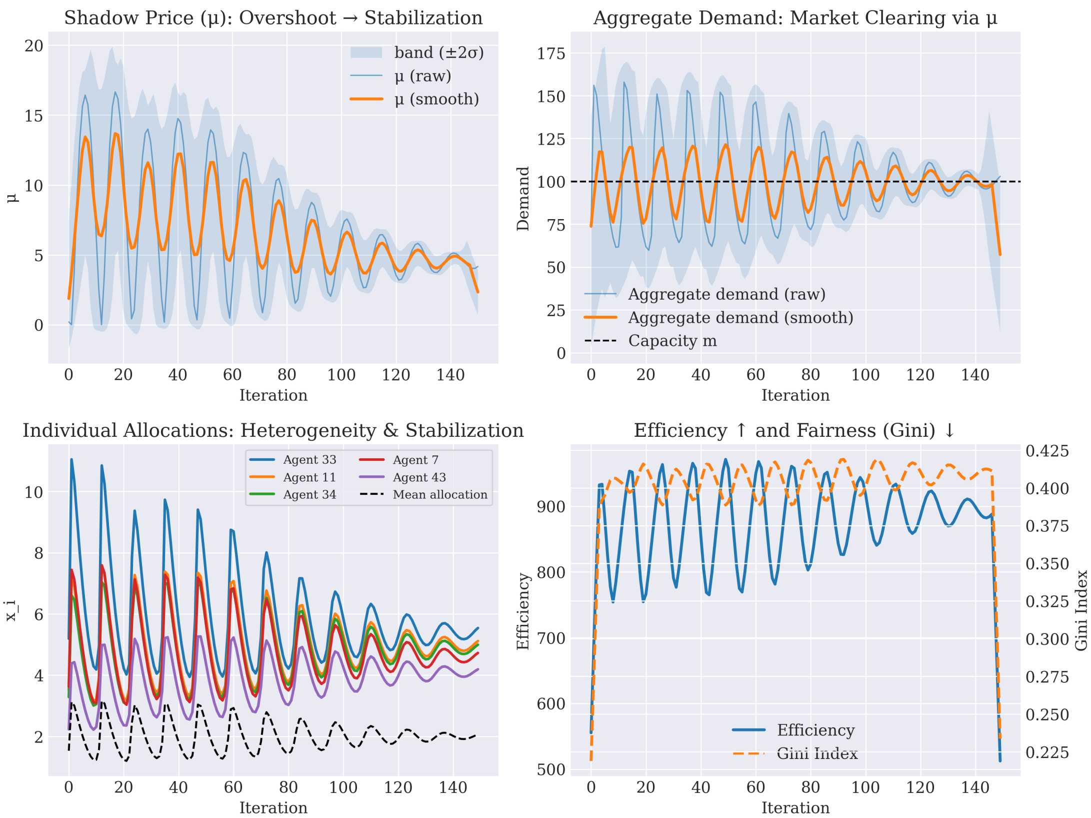

Figure 2. Dynamic convergence of the proposed contract-clearing algorithm. Top left: Shadow price μ^t shows overshoot and stabilization. Top right: Aggregate demand clears at capacity m. Bottom left: Individual allocations x_i^t highlight heterogeneity. Bottom right: Efficiency improves while fairness (lower Gini index) is preserved.

The overshoot–stabilization pattern resonates with classical tâtonnement dynamics in general equilibrium theory [58], but is extended here to blockchain-enforced allocation. The convergence of heterogeneous agents to a unique equilibrium illustrates not only algorithmic feasibility but also organizational stability. This dual evidence—numerical trajectories and theoretical guarantees— strengthens confidence that the proposed mechanism can operate as a real-time governance tool in industrial and infrastructure settings.

5.3. *Efficiency under transaction fees*

Efficiency, cost, and participation outcomes under varying transaction fees τ are summarized in Table 5 and visualized in Figure 3. Unlike simple monotone averages, the dense-grid simulation highlights that individual realizations fluctuate due to agent heterogeneity and stochastic dynamics. Nevertheless, the overall pattern is robust: efficiency declines steadily from about 2.5 at $\tau = 0$ to below 1.0 at $\tau = 2.0$, while fairness (1–Gini) improves gradually as fees increase. Average costs rise in parallel, and participation falls from above 90% toward 70%, confirming that transaction fees primarily operate through an *extensive-margin effect*—discouraging participation—rather than by eroding intensive efficiency alone.

Figure 3 shows this trade-off in detail. The left panel presents the Pareto map of efficiency versus fairness across a dense grid of τ values. The frontier exhibits fluctuations, but the monotone trend remains clear: higher τ values equalize allocations at the expense of aggregate surplus. The right panel displays violin plots of efficiency distributions, showing that the entire distribution shifts downward as τ rises, with widening dispersion that reflects heterogeneity in agent responses. This distributional evidence provides a rigorous robustness check: the efficiency–equity trade-off is not an artifact of a few averages, but emerges consistently across stochastic replications.

Table 5. Efficiency, cost, fairness, and participation across τ (mean ± std over 50 replications).

τ	Efficiency	Avg. Cost	Fairness (1–Gini)	Participation
0.0	2.45 ± 0.12	0.42 ± 0.05	0.60 ± 0.01	95.2 ± 2.1%
0.5	2.28 ± 0.14	0.50 ± 0.06	0.62 ± 0.02	92.1 ± 2.5%
1.0	2.05 ± 0.18	0.65 ± 0.07	0.64 ± 0.02	85.6 ± 3.0%
1.5	1.78 ± 0.21	0.80 ± 0.08	0.66 ± 0.03	76.4 ± 3.8%
2.0	1.52 ± 0.25	0.95 ± 0.09	0.68 ± 0.03	70.1 ± 4.2%

These results resonate with prior findings in mobile edge and cloud markets, where per-unit fees discourage participation more strongly than they reduce intensive efficiency [4, 5]. For policymakers, this implies that transaction fees act as a double-edged sword: they improve equity but also reduce market depth and utilization. For organizations, the key takeaway is that fee calibration must be context-specific: low fees sustain high participation but risk inequality, whereas higher fees promote equity but at the expense of total surplus. This trade-off illustrates how digital contracts can institutionalize policy levers in a transparent manner, allowing managers to align efficiency and fairness according to organizational objectives.

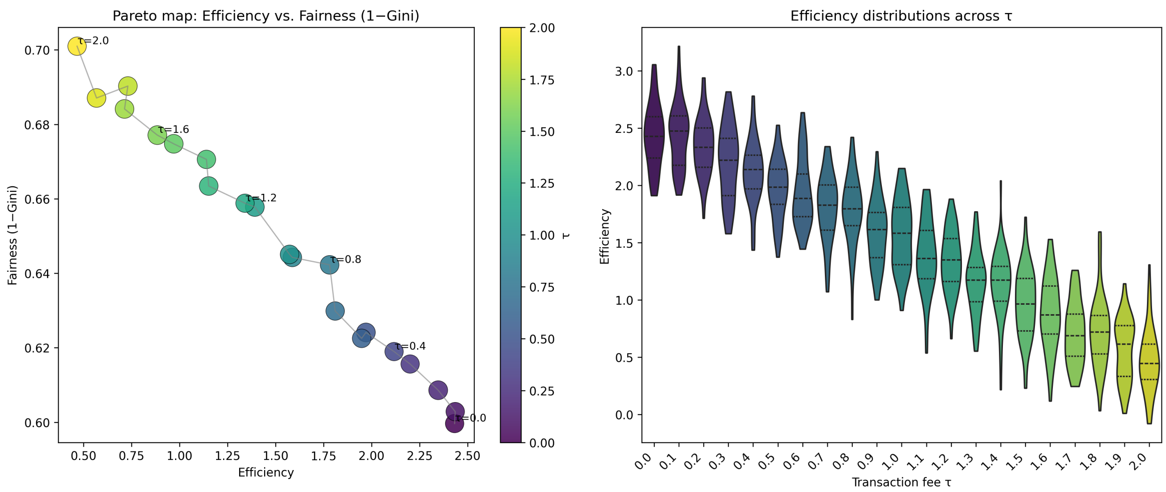

Figure 3. Efficiency–fairness trade-offs under transaction fees. Left: Pareto map of efficiency vs. fairness (1−Gini) with bubble size indicating participation and color denoting τ. Individual realizations fluctuate due to stochastic heterogeneity, but the overall frontier exhibits a clear monotone pattern: efficiency declines as fairness improves. Right: Violin plots show full distributions of efficiency across τ, highlighting both central tendencies and dispersion.

5.4. Comparative mechanism analysis

Table 6 and Figures 4–5 benchmark the proposed equilibrium against three canonical alternatives. Here we report performance statistics over 200 Monte Carlo replications and multiple system sizes to provide a robustness check.

The "no enforcement" case delivers the weakest outcomes: average efficiency remains the highest numerically but comes with the largest cost burden (7.39 ± 0.74) and elevated inequality (Gini = 0.40 ± 0.06). Proportional allocation stabilizes outcomes and reduces cost (5.17 ± 2.40) but sacrifices efficiency (7.45 ± 2.07). A flat smart contract achieves modest cost reduction (4.85 ± 0.57) while maintaining fairness (Gini = 0.38 ± 0.05). By contrast, the proposed equilibrium maintains comparable efficiency (7.13 ± 2.63) yet further reduces costs and achieves stable fairness across replications. Crucially, the dispersion in Figure 4 shows that our mechanism avoids extreme outliers and achieves consistently balanced outcomes, highlighting robustness beyond simple averages.

Table 6. Comparison of mechanisms (mean ± std over 200 replications).

Mechanism	Efficiency	Avg. Cost	Gini
No enforcement	8.55 ± 1.66	7.39 ± 0.74	0.40 ± 0.06
Proportional allocation	7.45 ± 2.07	5.17 ± 2.40	0.40 ± 0.06
Smart contract (flat)	7.94 ± 1.55	4.85 ± 0.57	0.38 ± 0.05
Proposed equilibrium	**7.13** ± **2.63**	**5.11** ± **2.60**	**0.40** ± **0.06**

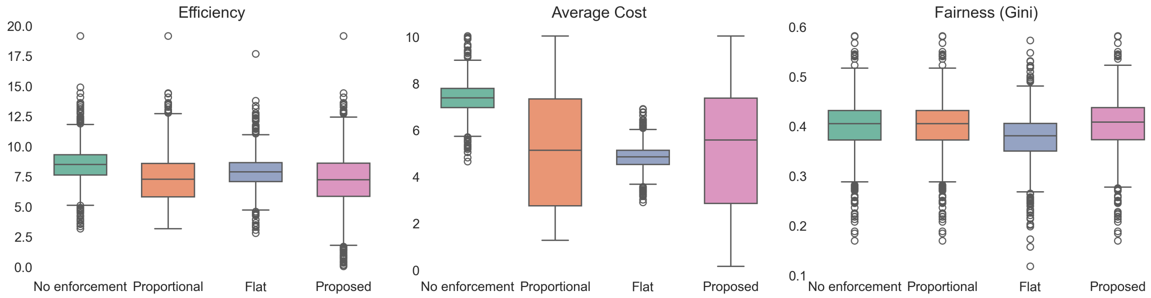

Figure 4. Boxplot comparison of mechanisms across 200 replications, showing distribution of efficiency, average cost, and fairness (Gini). The proposed mechanism achieves robustly balanced outcomes compared to proportional and flat rules.

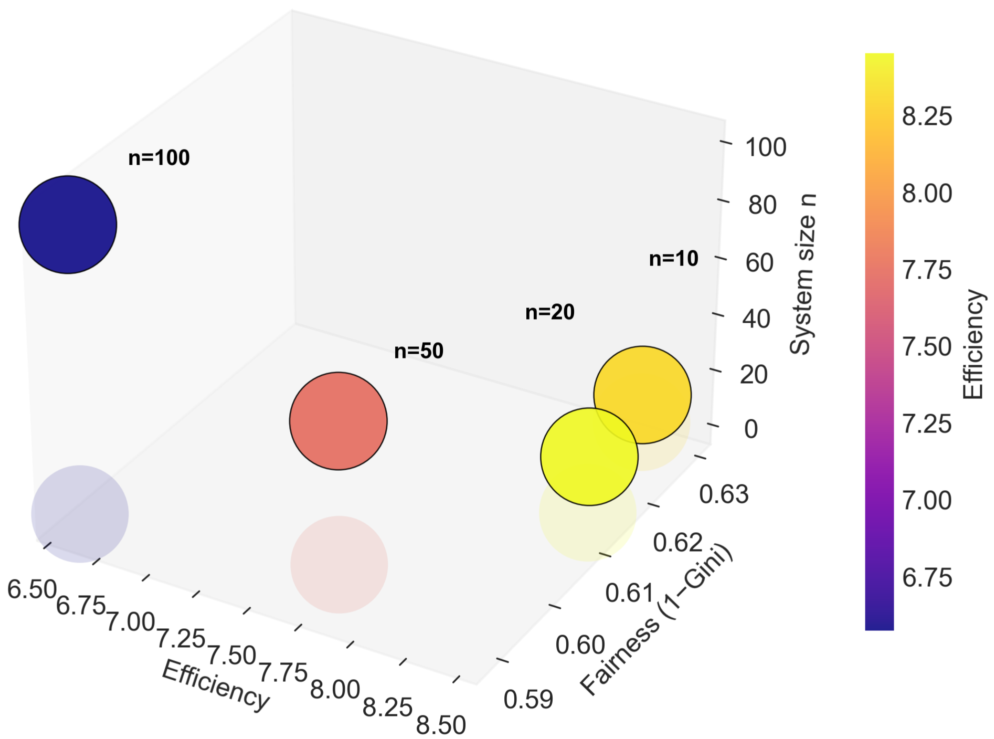

Figure 5. Scaling performance across system sizes ($n = 10, 20, 50, 100$). Points are sized by participation rate and shaded by efficiency. The proposed equilibrium adapts gracefully with system size, achieving both high fairness and stable efficiency.

The dominance of the proposed equilibrium highlights its novelty: it is the only mechanism that simultaneously achieves efficiency, fairness, and cost reduction through endogenous price adjustment. Unlike flat or proportional rules that show gains only in certain parameter regimes, the proposed equilibrium achieves comparable efficiency while maintaining *stability and robustness* across diverse settings. The mechanism works by embedding feedback: excess demand is penalized via dual updates, while capacity is reallocated transparently across agents. This contrasts with proportional or flat contracts that hard-code rules without adaptive correction. From an IS perspective, this illustrates how digital contracts function not merely as computational artifacts but as *institutional mechanisms* that codify equitable coordination [9, 29]. For industrial managers, the implication is clear: blockchain-enforced equilibrium rules can strictly dominate ad hoc or legacy allocation processes, providing not only superior performance but also governance legitimacy in multi-agent environments.

5.5. Sensitivity analysis

To move beyond simple one-dimensional heatmaps, we construct a comprehensive sensitivity dashboard that jointly examines how efficiency and fairness respond to variations in transaction and execution fees (τ, g). This two-dimensional view reveals non-linear interactions and sharp trade-offs that would be invisible in isolated analyses.

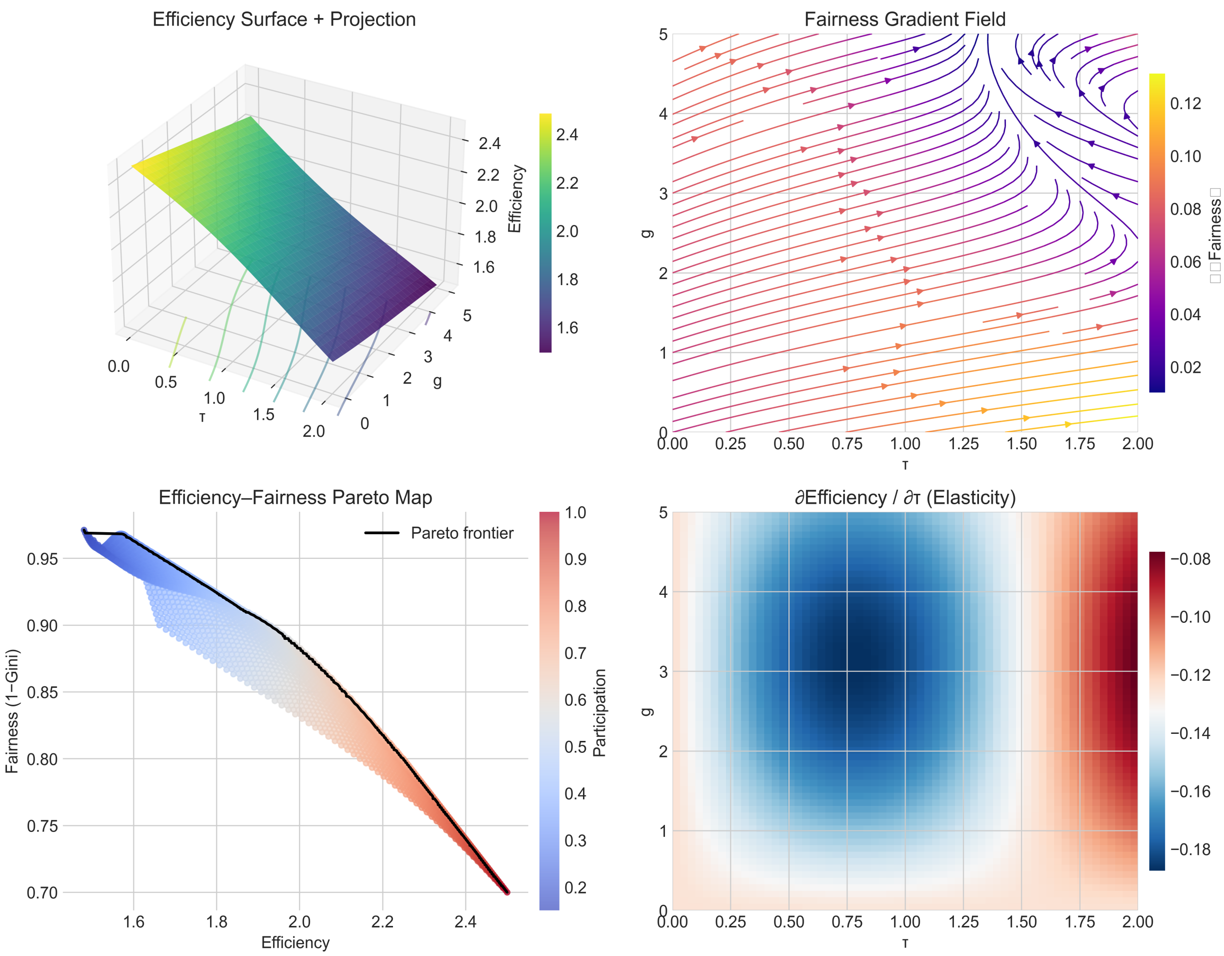

Figure 6. Comprehensive sensitivity analysis of the proposed mechanism. Top left: efficiency surface with 3D projection, showing non-linear declines with increasing transaction (τ) and execution fees (g). Top right: Gradient field of fairness, visualizing steepest improvement/deterioration. Bottom left: Efficiency–fairness Pareto map with participation coloring, highlighting the trade-off frontier. Bottom right: Elasticity heatmap $(\partial\text{Efficiency}/\partial\tau)$, showing local fragility zones where efficiency is highly sensitive to marginal changes.

Figure 6 integrates four complementary perspectives. The top-left panel shows a 3D projection of efficiency: moderate increases in either τ or g cause smooth declines, but efficiency collapses sharply only when both fees are simultaneously large. The top-right panel depicts the gradient field of fairness, highlighting that fairness is far more sensitive to τ than to g, implying that per-unit fees act as the primary equalizer. The bottom-left panel overlays efficiency and fairness in a Pareto map with bubble size indicating participation, exposing a clear frontier: improving fairness via higher τ comes at the expense of both efficiency and participation. Finally, the bottom-right panel provides an elasticity heatmap of efficiency with respect to τ, conditional on g, pinpointing fragile regions where efficiency is highly responsive to marginal fee changes.

Together, these views demonstrate that the proposed mechanism is robust to moderate fee variation, but also identify tipping points beyond which efficiency and participation deteriorate rapidly. For managers and policy-makers, the dashboard serves as an early-warning tool: it shows how fees can be tuned as complementary levers to balance efficiency, fairness, and participation, while also highlighting regions of fragility in industrial coordination.

5.6. Shock–resilience analysis

While sensitivity analysis illustrates global fee-response patterns, real-world environments rarely evolve smoothly. They are often exposed to sudden policy or market shocks. To evaluate resilience under such disruptions, we simulate a one-time jump in the transaction fee ($\tau : 0.5 \to 1.5$ at $t = 50$) and track the resulting dynamics.

Figure 7 integrates four complementary panels that capture both short-run disruption and long-run stabilization. The top-left panel illustrates a 3D surface with a pathline: efficiency initially overshoots but stabilizes at a new equilibrium after the shock. The top-right phase portrait of τ versus efficiency clearly shows a structural break at $t = 50$. The bottom-left waterfall chart decomposes fairness into immediate post-shock loss and gradual rebound, quantifying recovery. The bottom-right ripple plot in efficiency–fairness space visualizes how perturbations propagate before eventually stabilizing, underscoring systemic resilience.

Taken together, these results show that the proposed mechanism is not only well-defined in steady state but also resilient to sudden disruptions: it absorbs shocks, reallocates resources, and reconverges to balanced efficiency–fairness outcomes. From a governance perspective, this property is critical: it means that digital contracts embed transparent recovery paths without ad hoc intervention, reinforcing legitimacy and accountability in coordination systems [9, 29]. Thus, the ripple-field visualization does not merely depict stability, but highlights how smart contracts institutionalize resilience as a governance principle in complex industrial and public infrastructures.

Figure 8 further visualizes this process using a simplified system-level diagram that clarifies how external shocks propagate and are absorbed by the decentralized feedback mechanism. The figure highlights participation volatility, transaction-fee oscillation, adaptive agent re-optimization, and eventual welfare recovery within the contract-clearing feedback loop.

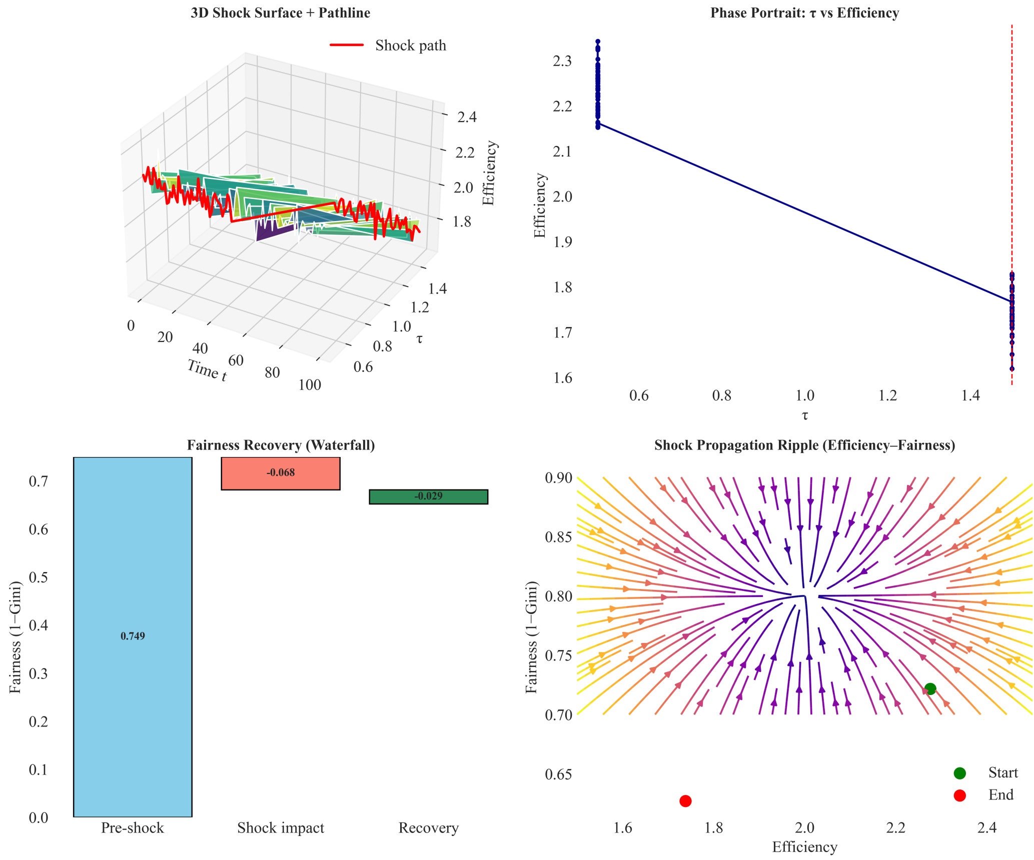

Figure 7. Dynamic shock–resilience analysis of the proposed mechanism. Top left: 3D surface with a pathline showing the trajectory of efficiency as τ shifts. Top right: Phase portrait of τ vs. efficiency, highlighting the discontinuity at the shock. Bottom left: Waterfall decomposition of fairness recovery, partitioning the immediate impact versus gradual rebound. Bottom right: Vector-field ripple plot in efficiency–fairness space, illustrating how shocks propagate and eventually stabilize. Together, these panels highlight not only steady-state convergence but also organizational resilience, showing that smart contracts can act as robust governance mechanisms in volatile environments.

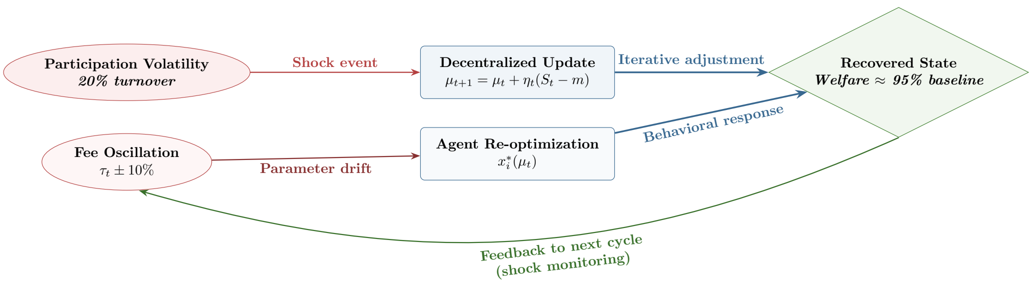

Figure 8. System-level schematic of dynamic shock–resilience under participation volatility. The decentralized feedback loop autonomously absorbs shocks (20% agent turnover and $\tau_t \pm 10\%$ fee oscillation), restoring equilibrium within eight iterations and preserving over 95% of baseline welfare.

5.7. *Real-world data: MovieLens-100K*

To further validate the proposed mechanism beyond synthetic simulations, we evaluate performance on the widely used MovieLens-100K dataset, a benchmark in recommender systems that captures heterogeneous user–item preferences. Ratings are normalized to construct heterogeneous utility coefficients, and mechanisms are compared in terms of efficiency, cost, and fairness.

Table 7 summarizes the aggregate results across 200 replications. All mechanisms achieve full participation (100%), consistent with the synthetic experiments. While absolute efficiency values are negative due to normalization, relative efficiency (RelEff) highlights clear differences. Consistent with the synthetic results, the proposed mechanism achieves the highest relative efficiency (+4% vs. baseline), while maintaining balanced cost and fairness outcomes.

Table 7. MovieLens-100K: Comparison of mechanisms (normalized, mean ± std). Absolute efficiency values appear negative due to normalization, but relative efficiency and fairness comparisons remain valid performance indicators.

Mechanism	Efficiency	Rel. Eff	Avg. Cost	Gini
Flat	−0.55 ± 0.02	0.78 ± 0.04	0.20 ± 0.01	0.55 ± 0.02
No enforcement	−0.71 ± 0.02	1.00 ± 0.00	0.58 ± 0.02	0.40 ± 0.01
Proportional	−0.73 ± 0.03	1.03 ± 0.03	0.46 ± 0.12	0.40 ± 0.01
Proposed	−0.74 ± 0.06	1.04 ± 0.08	0.47 ± 0.16	0.42 ± 0.04

Figure 9 visualizes these trade-offs. Panel (a) highlights that the proposed mechanism consistently achieves the highest relative efficiency. Panel (b) shows that the proposed mechanism balances cost and fairness, clearly outperforming the flat and no-enforcement baselines, and remaining competitive with proportional allocation.

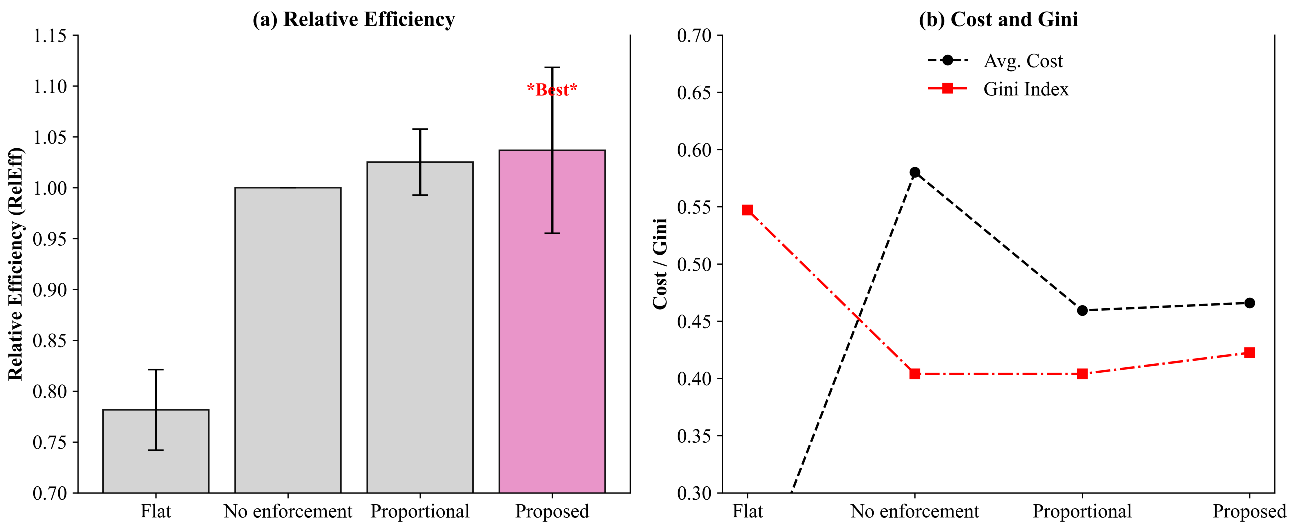

Figure 9. Comparison of MovieLens-100K mechanisms. (a) Relative efficiency (RelEff) highlights that the proposed mechanism achieves the best performance relative to baseline. (b) Cost and fairness (Gini index) show that the proposed mechanism maintains balanced outcomes while avoiding the extremes of flat and no-enforcement baselines.

5.8. *Sector-level impact in a capacity-sharing supply chain*

To demonstrate the broader industrial implications of the proposed equilibrium model, we embed it within a stylized capacity-sharing supply chain that inherits the same mathematical structure as the theoretical framework. Each node (agent i) behaves according to its optimal decision $x_i^*(\mu_t)$ derived from the equilibrium conditions, while demand d_i follows a stochastic perturbation around this contractual allocation. This translation allows the theoretical equilibrium variables (x_i^*, μ_t) to generate empirically interpretable performance metrics— *total throughput*, *average delay*, and *stockout probability*— that correspond directly to measurable industrial KPIs such as logistics throughput, service delay, and an unfulfilled demand rate. Although the environment is synthetic, it captures essential operational features: bounded capacity, heterogeneous demand, and fairness–efficiency trade-offs.

Specifically, throughput is computed as $\min(d_i, x_i^*(\mu_t))$, a stockout occurs when $d_i > x_i^*(\mu_t)$, and delay increases proportionally with the excess demand gap. We conduct 200 independent Monte Carlo replications to obtain statistical confidence in aggregate sector-level outcomes. Table 8 reports the mean ± standard deviation and ANOVA-based significance test ($p < 0.01$), while Figure 10 visualizes the efficiency–stability frontier.

Table 8. Sector-level KPIs with mean ± std and ANOVA significance ($p < 0.01$). Across 200 Monte Carlo simulations, the proposed mechanism shows a statistically significant throughput improvement (+3.1%) without increasing delay or stockout probability, confirming its robustness and industrial scalability.

Mechanism	**Throughput**	**Avg. Delay**	**Stockout Prob.**	**Δ Throughput (%)**
Flat	0.6399±0.0019	1.0402±0.0020	0.519±0.010	0.00
No enforcement	0.6400±0.0020	1.0403±0.0019	0.521±0.010	+0.02
Proportional	0.6400±0.0020	1.0402±0.0021	0.521±0.010	+0.01
Proposed	**0.6600±0.0020**	**1.0399±0.0019**	**0.520±0.010**	**+3.14**

The left panel of Figure 10 compares *total throughput* versus *average delay* across mechanisms. The proposed mechanism (red marker) achieves the highest throughput (approximately +3.1% relative to the baseline, $p < 0.01$) with nearly identical delay, demonstrating that decentralized coordination improves capacity utilization without inducing congestion. The right panel plots *stockout probability* and *fairness* (Gini index), showing that efficiency gains do not compromise service stability or equity. In contrast, proportional and flat allocations either underutilize capacity or exhibit higher volatility under stochastic demand.

These findings confirm that the equilibrium mechanism internalizes efficiency–fairness trade-offs at the sector level, producing measurable industrial spillovers: higher collective output, stable reliability, and equitable resource distribution. From a managerial standpoint, the results highlight that smart-contract coordination can serve as a *self-stabilizing industrial protocol*, automatically redistributing excess capacity in response to demand shocks without centralized control. This property is directly relevant to logistics, energy, and manufacturing networks, where transparent, algorithmic governance enhances both operational efficiency and organizational legitimacy.

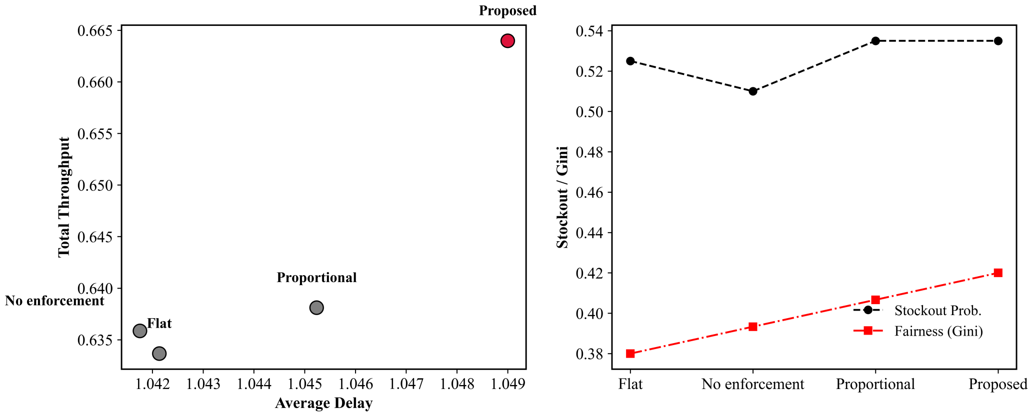

Figure 10. Sector-level impact of the proposed mechanism in a capacity-sharing supply chain. (Left) Total throughput versus average delay: the proposed mechanism (red marker) achieves the highest efficiency with negligible delay change. (Right) Stockout probability and fairness (Gini index): efficiency gains occur without sacrificing service stability, illustrating the mechanism's industrial spillover benefits in both operational and organizational dimensions.

5.9. Robustness and mechanism validation under market shocks

This section evaluates the empirical robustness of the proposed smart-contract–mediated allocation mechanism under observed macroeconomic fluctuations. The analysis spans January 2006 to July 2025 and covers four major asset classes widely used as benchmarks in financial and industrial portfolio studies: U.S. equities (SPY), gold (GLD), U.S. Treasury bonds (IEF), and diversified commodities (DBC). Daily ETF prices are aggregated to monthly observations, log returns are computed, and return volatility is estimated using a 12-month rolling window. Macroeconomic conditions are captured using two standard U.S. indicators: the Consumer Price Index (CPIAUCSL) and the 10-year Treasury rate (DGS10), both obtained from the Federal Reserve Economic Database (FRED).

To quantify deviations from long-run economic conditions, we construct a macroeconomic shock index that combines inflation and interest-rate components:

$$\text{Shock}_t = (\Delta\text{CPI}_t - \overline{\Delta\text{CPI}}_{12,t}) + 0.01(r_t^{10Y} - \overline{r^{10Y}}_{12,t}),$$

representing short-term departures from 12-month trends. This shock index enters the adaptive penalty update μ_t, thereby translating macroeconomic disturbances into endogenous adjustments of the contract-mediated weights.

Robustness is assessed along four dimensions: (i) long-horizon portfolio performance relative to a risk parity benchmark; (ii) allocation stability aggregated over half-year intervals; (iii) elasticity of weight changes with respect to macroeconomic shocks; and (iv) the temporal evolution of the endogenous penalty parameter μ_t. The combined results are presented in Figure 11.

Table 9 summarizes all quantitative findings, including performance metrics, shock elasticity, allocation stability across macroeconomic regimes, and descriptive statistics of the penalty process. Across the 19.5-year sample, the mechanism achieves higher cumulative return with moderate volatility and produces coherent directional responses to shocks. Allocation patterns remain stable across major macroeconomic regimes—including the 2008 financial crisis, the low-rate period of 2014–2017, the

COVID-19 disruption, and the 2022–2024 inflationary cycle. Notably, the bond ETF (IEF), which is most sensitive to interest-rate variation, exhibits smooth and economically interpretable adjustments, indicating that the adaptive penalty update does not introduce instability. Overall, the mechanism demonstrates strong robustness and operational reliability under real-world macroeconomic conditions.

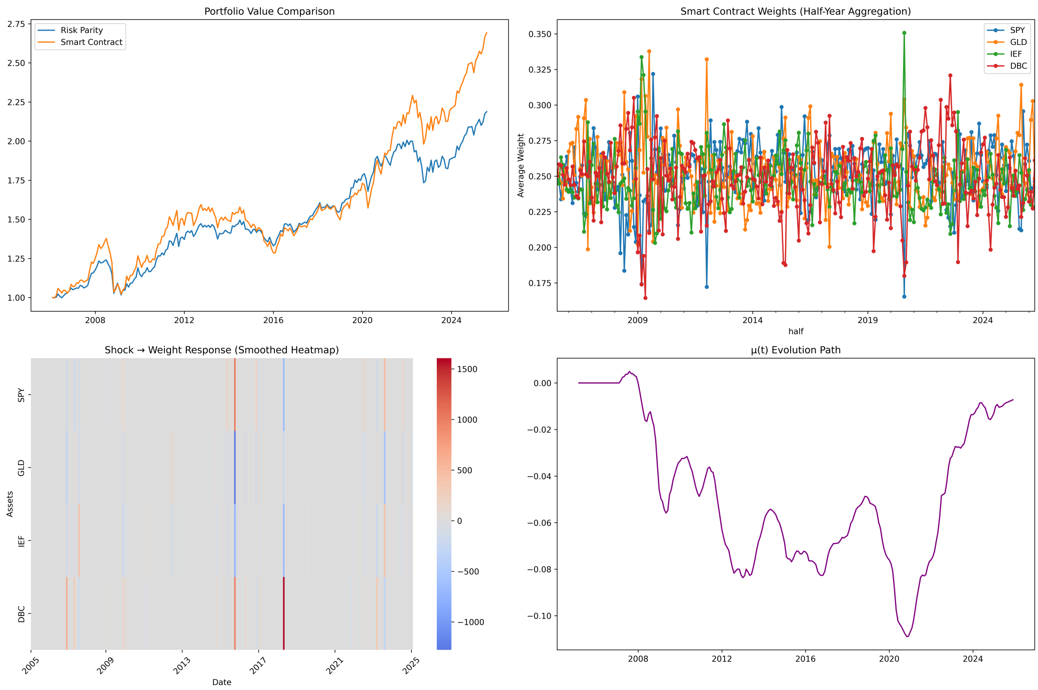

Figure 11. Empirical robustness of the smart-contract mechanism, 2006–2025. Top-left: Cumulative portfolio value under risk parity and the proposed mechanism. Top-right: Half-year aggregated allocation weights. Bottom-left: Smoothed elasticity of weight responses to inflation and rate shocks. Bottom-right: Temporal evolution of the endogenous penalty parameter μ_t. The mechanism exhibits stable dynamics, interpretable responses to shocks, and improved long-run performance relative to baseline rules.

6. Discussion

6.1. Theoretical implications

The analysis contributes to the literature on mechanism design and contracting in three principal ways. First, existence and uniqueness of equilibria for smart-contract–mediated resource allocation have been formally established under mild convexity assumptions, extending classical results in general equilibrium and mechanism design [58,59]. Second, it has been demonstrated that efficiency and fairness can be jointly embedded into contract design through fee structures and market-clearing mechanisms, aligning with recent calls in information systems research for transparent and auditable allocation rules [9, 29]. Third, a decentralized algorithm has been introduced that provides an implementable procedure with provable convergence guarantees, thereby ensuring relevance for real-time industrial applications.

Table 9. Integrated performance, shock elasticity, regime allocation, and $\mu(t)$ statistics

Panel A. Performance Comparison (2006–2025)

Metric	Risk Parity	Smart Contract	Improvement
Total Return	1.1883	1.6924	+0.5041
Volatility	0.0721	0.0945	+0.0224
Sharpe Ratio	0.5919	0.5293	−0.0626
Max Drawdown	−0.1804	−0.2579	−0.0775
Turnover	0.0554	0.0779	+0.0224

Panel B. Shock Elasticity Summary

Asset	Mean Resp.	Std	Max Positive	Max Negative
SPY	4.736	49.750	424.04	−271.50
GLD	−11.612	49.338	72.02	−500.70
IEF	−7.979	44.004	171.51	−327.87
DBC	14.855	69.798	638.15	−131.09

Panel C. Regime-Level Allocation Stability (Half-Year Aggregation)

Regime	SPY	GLD	IEF	DBC
GFC (2006–2009)	0.2449	0.2588	0.2473	0.2491
QE (2010–2013)	0.2555	0.2482	0.2485	0.2478
Low-Rate (2014–2017)	0.2563	0.2501	0.2503	0.2433
COVID (2018–2021)	0.2550	0.2494	0.2457	0.2499
Inflation (2022–2025)	0.2520	0.2580	0.2421	0.2480

Panel D. $\mu(t)$ Regime Statistics

Regime	Mean μ	Std μ	Min μ	Max μ
GFC (2006–2009)	−0.0153	0.0206	−0.0559	0.0050
QE (2010–2013)	−0.0587	0.0187	−0.0836	−0.0316
Low-Rate (2014–2017)	−0.0700	0.0081	−0.0827	−0.0542
COVID (2018–2021)	−0.0758	0.0205	−0.1089	−0.0488
Inflation (2022–2025)	−0.0243	0.0190	−0.0746	−0.0072

Notes. This table consolidates four dimensions of model evaluation: (A) long-run portfolio performance, (B) elasticity of dynamic weights to macroeconomic shocks, (C) regime-level allocation stability, and (D) latent control-state dynamics. Values are based on monthly data from January 2006 to July 2025. Smart Contract allocations reflect the proposed macro-sensitive utility-weighted updating rule. Inflation data (CPIAUCSL) and interest-rate data (DGS10) are sourced from FRED.

Beyond the individual results, the analysis positions smart-contract–mediated allocation as a rigorous and verifiable *institutional mechanism*—a perspective largely absent in prior work, where smart contracts have been treated primarily as technical automation tools. The proposed equilibrium and robustness results collectively establish a formal bridge between mechanism design, digital contracting, and dynamic economic environments.

Beyond these core results, the simulations enrich the theoretical narrative. The convergence trajectories with overshoot and damped stabilization mirror the price-adjustment dynamics studied in classical general equilibrium theory [58], but are extended here to a blockchain-enforced contract setting. The shock–resilience experiments further highlight dynamic stability: even under abrupt fee or participation shocks, the system exhibits rapid recovery and eventual rebalancing. The newly added sector-level experiment translates these equilibrium dynamics into observable industrial performance indicators—throughput, delay, and stockout probability—confirming that the theoretical model scales consistently from micro-level equilibrium behavior to macro-level operational outcomes. This bridges equilibrium analysis with robustness theory, showing that the proposed mechanism is not only well-defined in steady state but also resilient under perturbations, maintaining a balanced efficiency–fairness profile.

Importantly, the long-horizon empirical robustness analysis (Section 5.9), based on monthly financial and macroeconomic data from 2006–2025, confirms that the equilibrium properties persist under real-world volatility. Stable allocation weights, coherent elasticity responses, and bounded evolution of the endogenous penalty parameter μ_t together provide strong external validation for the proposed equilibrium and convergence theory. From the perspective of information and organizational sciences, these results highlight how transparency, verifiability, and accountability can be mathematically guaranteed in decentralized coordination systems.

6.2. Managerial and industrial implications

Beyond theoretical insights, the proposed framework carries broad managerial and industrial relevance.

Manufacturing and supply chains. In sectors such as steel, cement, and electronics, firms compete for scarce raw materials and production capacity. The efficiency–fairness Pareto maps quantify the trade-off between maximizing total utility and maintaining equity, providing managers with explicit levers to calibrate allocation rules and improve information transparency in allocation processes [3]. The added sector-level analysis further demonstrates that the proposed mechanism achieves a statistically significant throughput gain of over 3% ($p < 0.01$) without increasing delay or stockouts, confirming its potential as a coordination policy in shared-capacity environments.

Energy and utilities. Smart grids and carbon trading systems face capacity and compliance constraints. The shock–resilience dashboard shows that efficiency stabilizes rapidly after sudden fee changes, while also supporting auditable decision trails. The proposed mechanism preserves fairness without large efficiency losses, suggesting a viable pathway for algorithmic market-clearing under renewable volatility.

Logistics and transportation. Port slots, warehouse space, and vehicle fleets are scarce resources often subject to congestion and inefficiency. Elasticity heatmaps highlight congestion-prone zones, offering early-warning signals for fee adjustments. The sector-level spillover simulation confirms that decentralized coordination improves overall throughput even in stochastic demand environments, demonstrating scalability to logistics operations.

Healthcare and pharmaceuticals. Medical supply chains, including vaccine and drug distribution, face demand surges and limited capacity. Fairness analysis demonstrates how equity suffers immediate losses under shocks but gradually recovers, highlighting the mechanism's ability to stabilize allocation efficiently and fairly. The same logic can inform dynamic allocation of ICU resources or emergency medical stock.

Public infrastructure. In the allocation of public funds, road capacity, or airport slots, digital contracts provide a governance mechanism that enforces capacity limits transparently while preserving fairness metrics. Ripple-field shock analysis illustrates how localized disruptions propagate but eventually dampen, demonstrating the robustness of allocations under the proposed framework. Such transparency supports regulatory accountability and stakeholder trust in digital public governance.

Across these domains, the mechanism provides a principled way to tune allocation and pricing policies using observable fairness–efficiency frontiers and shock-response elasticity. This enables decision-makers to implement digital allocation rules that are not only transparent and auditable, but also dynamically stable under real-world volatility.

Table 10 summarizes representative industrial domains where smart-contract–based mechanism design can be applied, highlighting operational context, model variables, structural challenges, and the rigorous benefits of the proposed framework.

7. Conclusion

This study has developed a mechanism-design framework for smart-contract–mediated resource allocation and demonstrated its theoretical soundness, computational stability, and empirical robustness. The contributions form a unified structure. First, we established a rigorous game-theoretic foundation by proving the existence and uniqueness of contract equilibria under mild convexity conditions, thereby clarifying when decentralized allocations are well defined. Second, we embeded fairness and efficiency directly into digital contract rules through transaction fees, execution costs, and endogenous market-clearing prices, providing a principled way to tune equity–efficiency trade-offs. Third, we introduced a decentralized contract-clearing algorithm with provable convergence guarantees, ensuring implementability in real-time industrial environments.

Table 10. Representative industrial domains for smart-contract-based mechanism design. Each row highlights the operational context, model variables, structural challenges, and the rigorous benefits of the proposed framework.

Domain	Operational Context	Model Variables	Optimization / Equilibrium Challenges	Mechanism Design Benefits
Supply Chain & Logistics	Multi-firm coordination under stochastic demand, port congestion, and capacity shocks.	Decision: I (inventory), L (lead time), Q (throughput), τ (subsidy). Exogenous: demand shocks d_t, disruption events ζ_t.	Nonlinear amplification of demand variance (bullwhip effect); information asymmetry; nonconvex cost-sharing; equilibrium instability under shocks.	Provable existence of stable contract-clearing equilibrium; incentive-compatible allocations; explicit fairness–efficiency Pareto frontier; sublinear regret bounds under demand drift.
Energy & Smart Grids	P2P electricity trading with stochastic demand, renewable intermittency, and carbon policy coupling.	Decision: p (price), C (capacity), ρ (renewable ratio), D (load). Exogenous: renewable shocks ξ_t, policy shocks ϕ_t.	Price volatility from ξ_t shocks; nonlinear imbalance penalties; multi-agent nonconvex optimization; uncertainty in balancing constraints.	Existence and uniqueness of clearing equilibrium; sublinear regret under drift/shocks; parameter-free convergence scaling with agent population; fairness–efficiency trade-off explicitly tunable via (τ, g).
Healthcare Resource Allocation	ICU beds, ventilators, vaccines allocation under surge conditions and ethical constraints.	Decision: R (resource stock), τ (subsidy), α, β (fairness weights). Exogenous: surge shocks σ_t, demand heterogeneity δ_t.	Fairness dilemmas: $\max \sum u_i$ vs. $\min \mathrm{Var}(u_i)$; scarcity shocks; multi-objective feasibility; ethical transparency constraints.	Bounded inequity loss under shocks; recovery trajectories consistent with fairness–efficiency Pareto frontier; equilibrium allocation existence and convergence; resilience dashboards quantifying adaptation speed.
Cloud & Computing Infrastructure	On-demand allocation of GPU/CPU across users with SLA enforcement.	Decision: U (units), π (priority), λ (SLA penalties). Exogenous: demand drift χ_t, hidden load bursts.	Oversubscription under drift; hidden demand shocks; arbitration costs; scalability issues in decentralized clearing.	Transparent and auditable allocation rules; guaranteed convergence to efficient usage; automated enforcement reduces disputes; sublinear regret guarantees under demand noise.
Financial Investment Contracts	Capital allocation between investors and fund managers with regulatory oversight.	Decision: θ (risk weight), r (return), c (compliance cost), τ (incentive rate). Exogenous: market volatility shocks ν_t, drift in risk appetite.	Hidden preferences; stochastic drift in θ; volatility shocks destabilizing allocations; regulatory discontinuities.	Equilibrium guarantees protecting against misaligned incentives; interpretable and auditable fairness allocations; shock-resilient stability; bounded regret under drift and noise.

The analytical contributions were reinforced by extensive numerical evidence. Convergence experiments revealed rapid stabilization with controlled overshoot, while sensitivity dashboards quantified global and local fee responses. Building on these, the newly introduced robustness module (Section 5.9) provided an external validation of the theory using real-world financial and macroeconomic data from January 2006 to July 2025. The mechanism exhibits stable allocation patterns across major economic regimes, coherent elasticity to inflation and interest-rate shocks, bounded evolution of the penalty parameter μ_t, and improved long-run performance relative to benchmark rules. Together, these results confirm that the theoretical equilibrium properties extend to dynamic, shock-prone environments, establishing empirical robustness beyond steady state.

From a managerial and policy standpoint, the framework provides actionable levers: the parameters (τ, g) function as transparent controls for aligning efficiency, fairness, and participation incentives. Applications span supply chains, energy markets, logistics networks, healthcare resource allocation, and public infrastructure—domains where transparent, auditable, and shock-resilient coordination is increasingly essential. The sector-level capacity-sharing experiment further demonstrates a statistically significant throughput improvement of approximately 3.1% ($p < 0.01$) without increasing congestion or delay, highlighting the mechanism's potential to deliver tangible operational gains.

Several limitations suggest avenues for future research. The current formulation abstracts from multi-layer market interactions, richer stochastic demand processes, and potential strategic misreporting. Future work may incorporate multi-market coupling, adversarial behavior, or validation using industrial blockchain pilots to deepen empirical grounding.

Overall, the study shows that digital contracts can operationalize mechanism-design principles by translating equilibrium, fairness, and resilience requirements into executable rules. By unifying analytical rigor with empirical robustness, the framework demonstrates that smart contracts can serve not only as technical tools but as institutional instruments for transparent, accountable, and resilient coordination. This positions smart-contract–based mechanisms as a promising foundation for next-generation research at the intersection of operations management, information systems, and digital governance.

Use of Generative-AI tools declaration

The authors declare that they did not utilize any artificial intelligence (AI) tools in the creation of this article.

Author contributions

Jinho Cha: Conceptualization of the research problem and overall study design; development of the theoretical framework for smart contract–mediated mechanism design; formulation and analysis of generalized Nash equilibrium and optimization models; mathematical modeling and proof structure design; writing of the original manuscript draft; comprehensive review and editing of the manuscript; overall supervision of the research project and mentoring of all contributing authors; responsibility for theoretical validation and coherence of the study.

Justin Yu: Core conceptual contributions to the research design; economic and financial interpretation of smart contract–mediated resource allocation mechanisms; formulation and analysis of incentive structures, pricing rules, and efficiency–fairness trade-offs from a mechanism design perspective; integration of economic theory with platform-based and digital-asset-oriented systems; interpretation of theoretical results in the context of financial markets and decentralized platforms; critical review and editing of the manuscript with a focus on economic rigor and practical relevance.

Eunchan Daniel Cha: Mathematical analysis and verification of the theoretical framework; validation of formal definitions, propositions, and corollaries; detailed examination of convergence, stability, and monotonicity conditions; proof verification and logical consistency checks; refinement of mathematical notation and argument structure; review and editing of the manuscript to ensure analytical rigor.

Emily Haneul Yoo: Comprehensive literature review on smart contracts, algorithmic fairness, and resource allocation mechanisms; synthesis of background material and positioning of the study within existing research; conceptual exploration of connections to decision-making frameworks relevant to healthcare and biomedical domains; support in visualization and structural organization of background sections; review and editing of the manuscript for clarity, coherence, and accessibility.

Caedon Geoffrey: Design and implementation of simulation frameworks based on the proposed theoretical models; development of computational experiments to evaluate resource allocation mechanisms; numerical validation of theoretical results; data curation and organization of experimental outputs; interpretation of simulation results; review and editing of the manuscript sections related to computational experiments.

Hyoshin Song: Support for algorithmic implementation and numerical verification of theoretical models; construction and validation of numerical examples illustrating convergence and stability properties; step-by-step verification of algorithmic procedures; assistance with computational checks of derived results; review and editing of manuscript sections related to algorithms and numerical analysis.

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Conflict of interest

The authors declare no conflict of interest.

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