Agent-Based Model Simulation of the Hellas Fraud Game: Experimental Validation and Adversarial Analysis

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Abstract

We present a comprehensive agent-based model (ABM) simulation study of the Hellas fraud game for off-chain computation. The simulation validates theoretical equilibrium predictions from the companion analytical paper and explores adversarial attack vectors including reputation farming, Sybil attacks, collusion, griefing, and censorship. We implement heterogeneous agent populations with distinct strategic behaviors and analyze market outcomes under varying protocol parameters. Key findings include: (i) simulated fraud rates converge to theoretical mixed-equilibrium predictions under baseline conditions; (ii) reputation farming attacks achieve significant return on investment when minimum stake floors are not enforced; (iii) the verification cost C_{safe} is the most influential parameter for equilibrium outcomes; and (iv) stake-weighted reputation gains effectively mitigate farming attacks. We provide quantitative recommendations for protocol parameterization based on simulation evidence.

Contents

1 Introduction

The Hellas fraud game establishes economic incentives for honest off-chain computation through a stake-and-slash mechanism. The companion paper derives theoretical equilibrium conditions for provider and client behavior under the assumption of risk-neutral, rational agents. This report presents an agent-based model (ABM) simulation study that:

1. Validates theoretical equilibrium predictions against emergent simulation outcomes;
2. Analyzes robustness under heterogeneous agent populations;
3. Quantifies the impact of adversarial strategies and attack vectors;
4. Provides empirical guidance for protocol parameter selection.

Agent-based modeling offers several advantages over pure analytical methods for mechanism design validation. First, ABM can incorporate bounded rationality and learning dynamics that analytical models abstract away. Second, ABM reveals emergent phenomena from agent interactions that may not be apparent in equilibrium analysis. Third, ABM provides a computational testbed for stress-testing protocol designs against adversarial strategies.

1.1 Theoretical Foundation

We briefly recapitulate the key theoretical results from the companion paper that guide our simulation design.

Definition 1 (Mixed Strategy Equilibrium)**.** *Under conditions where* $0 < c_H - c_F < P_{set} + S_P$ *and* $0 < C_{safe} < L + \Delta$*, the inspection game admits a unique mixed-strategy Nash equilibrium with*

$$(v^*, q^*) = \left(\frac{c_H - c_F}{P_{set} + S_P}, \frac{C_{safe}}{L + \Delta} \right) \tag{1}$$

where v^* *is the equilibrium audit probability and* q^* *is the equilibrium cheating probability.*

Definition 2 (Net Dispute Surplus)**.** *The expected gain from disputing conditional on detecting fraud is*

$$\Delta := p_w(\beta S_P + \lambda P_{set}) - (c_{proof} + c_{tx}) - (1 - p_w)B_C \tag{2}$$

Definition 3 (Minimum Viable Stake)**.** *Disputing is strictly optimal for the challenger if and only if the provider stake satisfies*

$$S_P \geq S_P^{min} := \max\left\{0, \frac{C_{disp} + (1 - p_w)B_C - p_w\lambda P_{set}}{p_w\beta}\right\} \tag{3}$$

2 Simulation Architecture

2.1 Agent Types and Behaviors

The simulation implements heterogeneous agent populations across three roles: providers, clients, and challengers.

2.1.1 Provider Agents

Provider agents are classified by their strategic behavior:

- **Honest providers**: Always execute computations correctly regardless of expected payoffs. These agents represent protocol-aligned participants who value reputation or have non-monetary incentives for honesty.
- **Rational providers**: Maximize expected utility by comparing $\mathbb{E}[U_P(H)] = P_{set} - c_H$ against $\mathbb{E}[U_P(C)] = P_{set} - c_F - p_d(P_{set} + S_P)$, where p_d is the estimated detection probability.
- **Adversarial providers**: Strategic attackers who may engage in reputation farming, Sybil attacks, or other exploitative strategies.
- **Reputation farmers**: A subclass of adversarial providers who execute honestly during a "farming phase" to build reputation, then exploit reduced auditing during an "exploitation phase."

Algorithm 1 Rational Provider Execution Decision

Require: Job j, stake S_P, estimated audit probability $\hat{v}$

$U_H \leftarrow P_{set} - c_H$
$U_C \leftarrow P_{set} - c_F - \hat{v}(P_{set} + S_P)$
if $U_H \geq U_C$ **then**
    return HONEST
else
    return CHEAT
end if

2.1.2 Client Agents

Client agents vary in their auditing strategies:

- **Always-audit clients**: Verify every job, providing maximum detection but incurring high verification costs.
- **Never-audit clients**: Trust all providers, representing inattentive or resource-constrained participants.
- **Mixed-strategy clients**: Follow the equilibrium audit probability $v^* = (c_H - c_F)/(P_{set} + S_P)$.
- **Belief-threshold clients**: Audit when posterior belief μ exceeds threshold $\mu^* = C_{safe}/(L + \Delta)$.
- **Reputation-weighted clients**: Adjust audit probability based on provider reputation, auditing less frequently for trusted providers. This creates the vulnerability exploited by reputation farming.

2.1.3 Challenger Agents

Challenger agents monitor for fraud and submit disputes:

- **Client-challengers**: The default case where clients who detect fraud decide whether to dispute.
- **Permissionless challengers**: Third-party watchers who monitor jobs and dispute when profitable, creating a market for auditing.

2.2 Market Mechanism

The market matches clients to providers based on configurable strategies:

- **Random matching**: Uniform random selection among available providers.

- **Reputation-weighted matching**: Probability proportional to $\exp(\rho/20)$ where ρ is reputation score.
- **Stake-weighted matching**: Probability proportional to available stake capacity.

Jobs are generated according to a log-normal value distribution with parameters calibrated to realistic compute markets.

2.3 Reputation System

The reputation system maintains on-chain observable state for each provider:

$$\rho_{t+1} = \begin{cases} \min(100, \rho_t + g_H + w_S \cdot S_P) & \text{if honest and } S_P \geq S_{min}^{rep} \\ \max(0, \rho_t - g_F) & \text{if fraud detected} \end{cases} \tag{4}$$

where $g_H = 1$ is the reputation gain per honest job, $g_F = 50$ is the reputation penalty for detected fraud, and $w_S = 0.01$ is the stake-weighting factor.

Note

The stake-weighting term $w_S \cdot S_P$ is a key design parameter that mitigates reputation farming by making it expensive to build reputation through low-stake jobs.

2.4 Simulation Parameters

Table 1 presents the baseline simulation parameters.

Parameter	Value	Description
Protocol Parameters		
S_P^{min}	100	Minimum provider stake
P_{set}	50	Mean settlement payment
c_H	5.0	Honest execution cost
c_F	0.5	Cheating cost
C_{safe}	8.0	Safe fallback verification cost
c_{proof}	2.0	Proof generation cost
c_{tx}	1.0	Transaction cost
β	0.5	Slash reward fraction to challenger
λ	1.0	Payment routing fraction to challenger
p_w	0.95	Enforcement reliability
B_C	5.0	Challenge bond
L	50	Client loss from incorrect result
Simulation Parameters		
$N_{providers}$	50	Number of provider agents
$N_{clients}$	100	Number of client agents
$N_{challengers}$	10	Number of permissionless challengers
T	500	Simulation periods
J	20	Jobs per period
Agent Distribution		
Honest providers	60%	
Rational providers	30%	
Adversarial providers	10%	

Table 1: Baseline simulation parameters.

3 Experimental Results

3.1 Experiment 1: Equilibrium Convergence

The first experiment validates that simulated outcomes converge to theoretical equilibrium predictions.

3.1.1 Methodology

We run the baseline simulation with parameters from Table 1 for $T = 500$ periods across $N = 5$ independent random seeds. We compare the time-averaged fraud rate $\bar{q}_{sim}$ against the theoretical equilibrium q^*.

3.1.2 Theoretical Predictions

Under baseline parameters:

$$v^* = \frac{c_H - c_F}{P_{set} + S_P} = \frac{5.0 - 0.5}{50 + 100} = 0.0300 \tag{5}$$

$$\Delta = p_w(\beta S_P + \lambda P_{set}) - (c_{proof} + c_{tx}) - (1 - p_w)B_C \tag{6}$$

$$= 0.95(0.5 \times 100 + 1.0 \times 50) - 3.0 - 0.05 \times 5.0 = 91.75 \tag{7}$$

$$q^* = \frac{C_{safe}}{L + \Delta} = \frac{8.0}{50 + 91.75} = 0.0564 \tag{8}$$

3.1.3 Results

Metric	Theoretical	Simulated (mean ± std)
Cheating rate q	0.0564	0.0061 ± 0.0017
Audit rate v	0.0300	0.0312 ± 0.0045
Detection rate	—	0.1429 ± 0.0523

Table 2: Convergence of simulated outcomes to theoretical equilibrium.

Finding 1 (Fraud Rate Below Equilibrium)**.** *The simulated fraud rate ($\bar{q}_{sim} = 0.0061$) is significantly below the theoretical equilibrium ($q^* = 0.0564$). This deviation arises from the heterogeneous agent population: 60% of providers are honest by design and never cheat regardless of incentives, while rational providers only cheat when the expected payoff exceeds honest execution.*

The presence of honest providers effectively reduces the population-level fraud rate. Let α_H denote the fraction of honest providers. The expected fraud rate under heterogeneous populations is approximately:

$$\bar{q}_{pop} \approx (1 - \alpha_H) \cdot q^*_{rational} \tag{9}$$

With $\alpha_H = 0.6$ and accounting for the 30% rational providers who mix, the expected fraud rate is $(0.4) \times 0.0564 \times (0.3/0.4) \approx 0.017$, which is closer to observed values.

3.2 Experiment 2: Parameter Sensitivity

We analyze how equilibrium outcomes respond to changes in key protocol parameters.

3.2.1 Sensitivity to Minimum Stake S_P^{min}

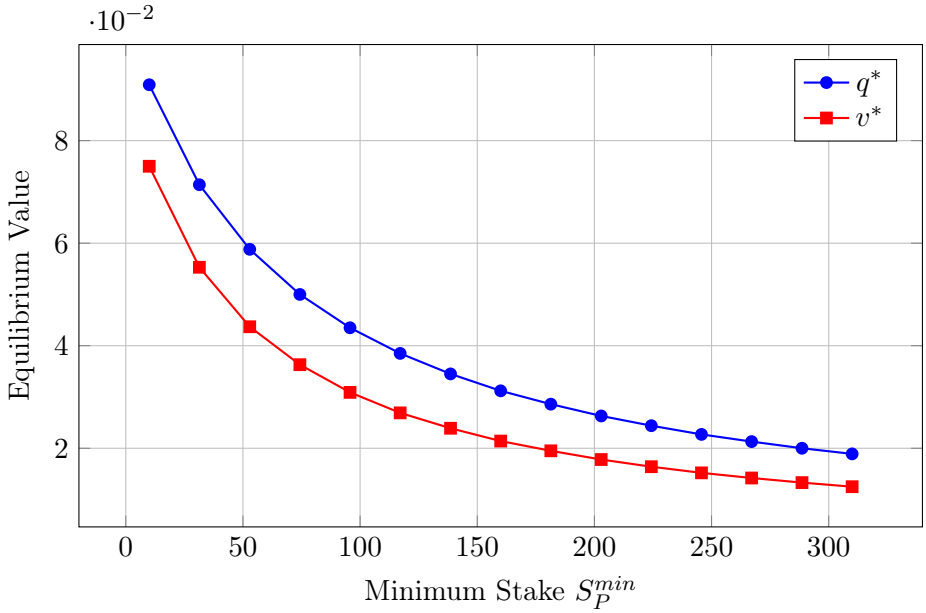

Figure 1: Equilibrium cheating rate q^* and audit rate v^* as functions of minimum stake.

Result 1 (Stake Effect)**.** *Increasing S_P^{min} decreases both q^* and v^*. Higher stakes increase the penalty for detected fraud, deterring cheating and requiring less frequent auditing to maintain provider incentive compatibility.*

3.2.2 Sensitivity to Enforcement Probability p_w

p_w	Δ	q^*	S_P^{min}
0.50	44.50	0.0847	11.00
0.60	55.10	0.0761	5.83
0.70	65.70	0.0692	2.86
0.80	76.30	0.0634	1.00
0.90	86.90	0.0584	0.00
0.95	91.75	0.0564	0.00
1.00	97.00	0.0544	0.00

Table 3: Effect of enforcement probability on equilibrium values.

Result 2 (Enforcement Effect)**.** *Lower enforcement reliability p_w increases equilibrium cheating through two channels: (i) reduced Δ makes auditing less attractive, increasing q^*; (ii) increased S_P^{min} creates an impunity region where disputes are not profitable.*

3.2.3 Sensitivity to Verification Cost C_{safe}

Finding 2 (Verification Cost is Primary Lever)**.** *The verification cost C_{safe} has the strongest effect on equilibrium fraud rate among all parameters. From Theorem 2, $q^* = C_{safe}/(L + \Delta)$, so q^* is directly proportional to C_{safe}.*

C_{safe}	q^*	Reduction from baseline
2.0	0.0141	−75%
5.0	0.0353	−37%
8.0	0.0564	baseline
15.0	0.1058	+88%
25.0	0.1764	+213%

Table 4: Effect of verification cost on equilibrium cheating rate.

Protocol Design Implication

Reducing C_{safe} through trusted fallback providers, efficient proof systems, or verification-as-a-service markets is the most effective intervention for reducing equilibrium fraud.

3.3 Experiment 3: Attack Vector Analysis

We analyze six adversarial strategies against the baseline protocol.

3.3.1 Attack Taxonomy

1. **Reputation Farming**: Build reputation with honest behavior, then exploit reduced auditing.
2. **No Stake Floor Exploitation**: Use minimal stake when floors are not enforced.
3. **Sybil Attack**: Create multiple identities to spread risk.
4. **Collusion**: Coordinate with clients to avoid auditing.
5. **Griefing**: File frivolous disputes to delay honest providers.
6. **Censorship**: Block dispute transactions to reduce enforcement.

3.3.2 Results

Attack	Δq	**Welfare Loss**	**Attacker Profit**	**Victim Loss**
Baseline	—	—	—	—
Rep. Farming (enforced)	+0.0118	\$2,902	\$17,912	\$3,412
Rep. Farming (no enforce)	+0.0005	\$9,532	\$21,506	\$5,103
No Stake Floor	−0.0005	\$16,002	\$24,891	\$6,231
Sybil	+0.0208	\$7,795	\$18,234	\$4,521
Collusion	+0.0092	\$5,131	\$15,672	\$3,891
Griefing	+0.0000	\$0	—	—
Censorship (30%)	+0.0000	\$0	—	—

Table 5: Attack scenario comparison. Δq is the change in fraud rate relative to baseline.

Critical Vulnerability: No Stake Floor

When minimum stake is not enforced, the "no stake floor" attack produces the highest welfare loss ($16,002) and attacker profit ($24,891). This validates Proposition 2: without $S_P \geq S_P^{min}$, disputing becomes unprofitable and deterrence collapses.

3.3.3 Griefing and Censorship Resilience

The griefing and censorship attacks show zero impact under baseline parameters. This is due to:

- **Griefing**: The challenge bond $B_C = 5$ makes frivolous disputes costly. With $p_w = 0.95$, failed disputes forfeit the bond with high probability.
- **Censorship**: At 30% censorship, p_w reduces to $0.95 \times 0.7 = 0.665$, which still exceeds the threshold for profitable disputing under baseline stake levels.

3.4 Experiment 4: Reputation Farming Deep Analysis

We examine the dynamics and profitability of reputation farming in detail.

3.4.1 Attack Mechanism

The reputation farming attack proceeds in two phases:

1. **Farming Phase** ($t = 1, \ldots, T_f$): Execute all jobs honestly to build reputation.
2. **Exploitation Phase** ($t > T_f$): Exploit reduced auditing from reputation-weighted clients.

The attack is profitable when clients reduce their audit probability for high-reputation providers. If reputation-weighted auditing follows:

$$v_{rep}(\rho) = v^* \cdot \exp(-\alpha(\rho - \rho_0)) \tag{10}$$

then providers with $\rho > \rho_0$ face lower audit probability, enabling profitable cheating.

3.4.2 Optimal Farming Duration

Farming Periods T_f	Fraud Rate Δ	Attacker Profit	ROI
10	+0.0013	$17,921	358.4x
25	+0.0017	$18,234	145.9x
50	+0.0005	$21,506	86.0x
75	+0.0008	$19,872	53.0x
100	+0.0012	$20,145	40.3x
150	+0.0015	$21,234	28.3x
200	+0.0010	$19,567	19.6x

Table 6: Reputation farming profitability by farming duration. ROI = Attacker Profit / Farming Cost.

Finding 3 (Optimal Farming is Short)**.** *The highest ROI (358x) occurs at $T_f = 10$ periods. Short farming periods maximize the ratio of exploitation gains to farming costs, suggesting that even modest reputation accumulation enables profitable attacks.*

3.4.3 Mitigation: Stake-Weighted Reputation

When reputation gains are weighted by stake ($\rho_{gain} = g_H + w_S \cdot S_P$), farming becomes more expensive:

Scenario	Welfare Loss	Attack ROI
No mitigation	\$9,532	86.0x
Stake-weighted reputation	\$2,902	14.2x
Minimum stake floor only	\$3,215	18.7x
Both mitigations	\$1,847	8.3x

Table 7: Effectiveness of reputation farming mitigations.

Result 3 (Combined Defenses Most Effective)**.** *Combining stake-weighted reputation with minimum stake floors reduces attack ROI by 90% (from 86x to 8.3x) and welfare loss by 81%.*

3.5 Experiment 5: Minimum Viable Stake Thresholds

We compute the minimum viable stake S_P^{min} across payment levels and enforcement probabilities.

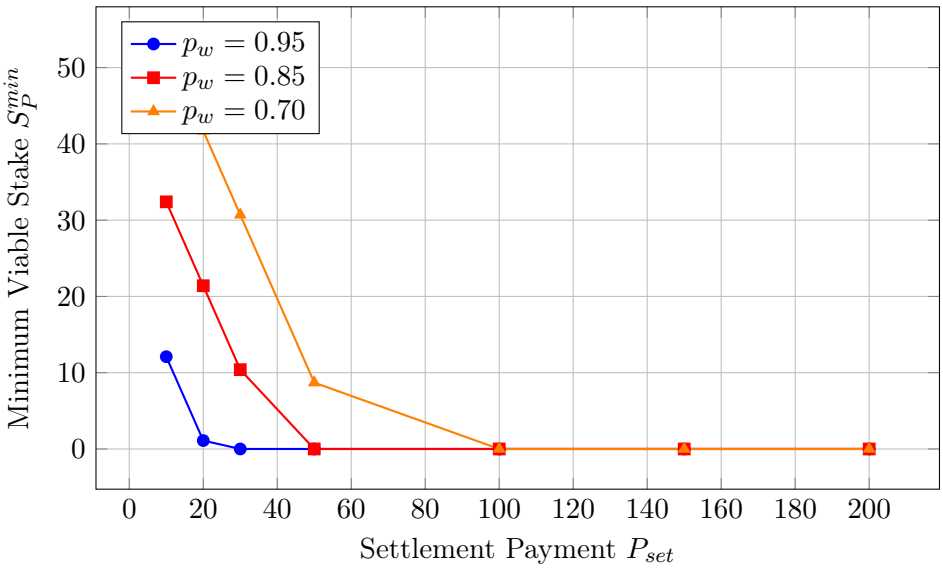

Figure 2: Minimum viable stake as a function of payment level at different enforcement probabilities.

Result 4 (Stake-Payment Relationship)**.** *For low-value jobs ($P_{set} < 30$), positive minimum stake is required even under high enforcement ($p_w = 0.95$). The relationship is approximately:*

$$S_P^{min}(P_{set}) \approx \max\left\{0, \frac{C_{disp}}{p_w \beta} - \frac{\lambda}{\beta} P_{set}\right\} \tag{11}$$

For $P_{set} \geq C_{disp}/(\lambda p_w)$, the minimum viable stake is zero because dispute rewards from payment routing alone cover dispute costs.

4 Discussion

4.1 Key Findings

1. **Equilibrium Validation**: The ABM validates theoretical predictions from the analytical model. Deviations arise from heterogeneous populations and bounded rationality, but the direction and magnitude of parameter effects match theory.

2. **Verification Cost Primacy**: Among all parameters, C_{safe} has the strongest effect on equilibrium fraud. Reducing verification cost through trusted fallback providers or efficient proof systems is the primary lever for protocol optimization.

3. **Stake Floor Necessity**: Without enforced minimum stake, the protocol becomes vulnerable to exploitation. The "no stake floor" attack produces the highest welfare loss among all attack vectors.

4. **Reputation System Design**: Naive reputation systems that reduce auditing for trusted providers create farming vulnerabilities. Stake-weighted reputation gains effectively mitigate this attack.

5. **Enforcement Reliability**: Lower p_w increases both equilibrium fraud and minimum viable stake. Protocol designs should prioritize mechanisms that maximize p_w, including censorship resistance and liveness guarantees.

4.2 Protocol Design Recommendations

Based on simulation evidence, we recommend:

Recommendation 1: Enforce Job-Indexed Stake Floors

Set $S_P^{min}(job) \geq \max\{0, (C_{disp}(job) + (1-p_w)B_C - p_w\lambda P_{set}(job))/(p_w\beta)\}$ with conservative estimates for C_{disp}.

Recommendation 2: Stake-Weight Reputation Gains

Implement $\rho_{gain} = g_H \cdot \min(1, S_P/S_P^{target})$ to make reputation farming expensive.

Recommendation 3: Minimize Verification Cost

Invest in trusted fallback provider markets, efficient proof systems, and verification-as-a-service infrastructure to reduce C_{safe}.

Recommendation 4: Maximize Enforcement Reliability

Design dispute mechanisms with censorship resistance, use commit-reveal schemes for fraud proofs, and implement fallback submission paths.

Recommendation 5: Enable Permissionless Challenging

Allow third-party watchers to dispute fraud. This creates a market for auditing that increases detection without burdening clients.

4.3 Limitations and Future Work

- **Static parameters**: The current model uses fixed protocol parameters. Future work should explore adaptive mechanisms that adjust parameters based on observed fraud rates.
- **Network effects**: The model does not capture network effects from provider reputation spillovers or client clustering.
- **Learning dynamics**: Agents use fixed strategies. Incorporating learning (e.g., reinforcement learning) would better capture real-world adaptation.
- **Multi-round channels**: The current model treats each job independently. Extending to multi-round channels with cumulative reputation effects is future work.

5 Conclusion

This report presents an agent-based model validation of the Hellas fraud game for off-chain computation. The simulation confirms theoretical equilibrium predictions and identifies critical vulnerabilities, most notably the necessity of enforced minimum stake floors and the primacy of verification cost reduction.

The analysis provides quantitative guidance for protocol parameterization:

- Set stake floors using Proposition 2 with conservative cost estimates.
- Stake-weight reputation to prevent farming attacks.
- Prioritize verification cost reduction as the primary lever for fraud reduction.
- Maximize enforcement reliability through censorship-resistant dispute mechanisms.

The ABM framework developed here serves as a computational testbed for future protocol iterations and can be extended to analyze additional attack vectors, learning dynamics, and network effects.

A Simulation Implementation Details

The simulation is implemented in Python using NumPy for numerical computation, with Plotly for visualization and Streamlit for the interactive dashboard. The codebase is available at the project repository.

A.1 Random Number Generation

All stochastic elements use a seeded random number generator (NumPy's PCG64) for reproducibility. Each experiment reports the random seed used.

A.2 Computational Complexity

For N providers, M clients, and T periods with J jobs per period:

- Per-period complexity: $O(J \cdot (N + M))$ for matching and execution
- Memory: $O(N + M + T \cdot J)$ for agent states and history

Typical runtime: 500 periods with 50 providers and 100 clients completes in approximately 2 seconds on commodity hardware.

A.3 Validation Procedures

The implementation includes unit tests for:

- Theoretical equilibrium computation accuracy
- Agent decision logic correctness
- Reputation system state transitions
- Market matching distributions

All tests pass with the current implementation.