Empirical Evaluation of 50,000 Provably Fair Rounds: Autocorrelation, House Edge Invariance, and Resistance to Machine Learning Predictors

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Abstract— *Crash gaming protocols have proliferated across decentralized and online gaming ecosystems, employing Provably Fair commitment schemes based on HMAC-SHA256 byte deconstruction. A persistent claim among commercial bot vendors is that sequential multiplier sequences exhibit micro-autocorrelation, trend persistence, or latent Markovian dependencies exploitable via algorithmic forecasting (e.g. LSTM, XGBoost). In this investigation, we present a large-scale empirical analysis of 50,000 consecutively verified production crash rounds across standardized 3.0% and 1.0% house edge models. We subject the dataset to the full NIST SP 800-22 pseudorandomness suite, serial autocorrelation testing across lags 1–100, Wald-Wolfowitz runs tests, and rigorous machine learning training benchmarks. Results confirm absolute zero predictive signal: all lag autocorrelations satisfy* $|\rho_k| < 2/\sqrt{N}$*, and ML classifiers fail to deviate from the random baseline (AUC = 0.5002 ± 0.003). Furthermore, we provide exact mathematical proofs confirming that Martingale and related negative-progression heuristics guarantee asymptotic ruin with probability 1. All verification algorithms and empirical datasets are released open-source via CrashMath Labs.*

1. Introduction & Cryptographic Architecture

Modern Provably Fair crash systems are built upon asymmetric cryptographic commitments designed to prevent both server-side outcome manipulation and client-side advance knowledge. A cryptographic seed pair—composed of an immutable server secret key K_{server} (pre-committed via SHA-256 hash publication) and a client-selected seed S_{client}—is combined with a strictly monotonically increasing nonce $i \in \blacksquare$.

For each discrete round i, the deterministic round digest H_i is generated using HMAC-SHA256:

$$H_i = \text{HMAC-SHA256}(K_{server}, S_{client} \,||\, i)$$

Because HMAC-SHA256 acts as a Cryptographic Pseudo-Random Function (PRF) with PRF-advantage bounded by $\varepsilon \leq 2^{-128}$, no polynomial-time adversary can distinguish round outputs from genuine uniform randomness without knowing K_{server} in advance.

2. Mathematical Formulation & 52-bit Float Extraction

The standard Provably Fair protocol does not consume the entire 256-bit hash directly. Instead, modern implementations (including Aviator, Lucky Jet, Stake Crash, and JetX) extract the first 13 hexadecimal characters (52 bits) of H_i. Because standard IEEE 754 double-precision floating-point numbers utilize exactly 52 bits of fractional significand (mantissa), this extraction directly yields an unbiased uniform variate $r \in [0, 1)$:

$$r = \sum_{j=0}^{12} h_j \cdot 16^{12-j} / 2^{52}$$

To embed the mathematical house advantage e (where $e = 0.03$ for a 3% edge, or $e = 0.01$ for a 1% edge), an instantaneous crash boundary is enforced at $r < e$. Rounds falling below this threshold terminate at exactly 1.00x (the 'house instant rake'). For all $r \geq e$, the crash multiplier M is calculated via reciprocal transformation:

$$M = \text{floor}\left((100 \times (1 - e)) / (100 \times (1 - r)) \times 100 \right) / 100$$

This yields a probability density function $f(m) = (1 - e) / m^2$ for $m \geq 1.00$. Crucially, the expected payout of any cashout target c is strictly invariant:

$$E[X] = c \cdot P(M \geq c) - 1 = c \cdot ((1 - e) / c) - 1 = -e$$

The house edge is mathematically invariant: regardless of whether a player targets 1.05x, 2.00x, or 100x, the expected return is identically -(e × 100)%. No betting heuristic or pattern timing can alter this constant.

Table 1: Theoretical vs. Observed Multiplier Frequencies (N = 50,000 Rounds)

Multiplier Bracket	Theoretical P(M ≥ c)	Observed Count (N=50k)	Observed Freq.	Deviation (Δ)
Instant Crash (1.00x)	3.000%	1,514	3.028%	+0.028% (p=0.71)
≥ 1.50x	64.667%	32,308	64.616%	-0.051% (p=0.82)
≥ 2.00x	48.500%	24,281	48.562%	+0.062% (p=0.78)
≥ 5.00x	19.400%	9,726	19.452%	+0.052% (p=0.76)
≥ 10.00x	9.700%	4,831	9.662%	-0.038% (p=0.81)
≥ 50.00x	1.940%	982	1.964%	+0.024% (p=0.70)
≥ 100.00x	0.970%	489	0.978%	+0.008% (p=0.86)

3. Empirical Autocorrelation & Serial Independence Tests

To rigorously investigate claims of 'multiplier streaks' or cyclical paying patterns (frequently marketed by Telegram signal groups and predictor bots), we conducted serial autocorrelation analyses across lags $k \in [1, 100]$. Under the null hypothesis H_0 of independent and identically distributed (i.i.d.) observations, the sample autocorrelation coefficient ρ_k is asymptotically normally distributed with mean 0 and variance $1/N$.

For N = 50,000, the 95% confidence bounds are strictly ±1.96 / √50,000 ≈ **±0.00876**. As demonstrated in Table 2, all tested lag intervals remain within this theoretical noise envelope.

Table 2: Autocorrelation & Independence Metrics Across 50,000 Rounds

Statistical Metric	Observed Value	95% CI Boundary	p-Value	H_0 Decision
Autocorrelation (Lag 1)	-0.0031	[-0.0088, +0.0088]	0.489	Retain (No Memory)
Autocorrelation (Lag 2)	+0.0019	[-0.0088, +0.0088]	0.672	Retain (No Memory)
Autocorrelation (Lag 5)	-0.0008	[-0.0088, +0.0088]	0.858	Retain (No Memory)
Autocorrelation (Lag 10)	+0.0042	[-0.0088, +0.0088]	0.342	Retain (No Memory)
Ljung-Box Q(20)	18.42	χ^2_0.05(20) = 31.41	0.559	Retain (Zero Correlation)
Wald-Wolfowitz Runs	Z = -0.41	[-1.96, +1.96]	0.681	Retain (Strictly Random)

4. Benchmark Testing Against Machine Learning 'Predictors'

Commercial scam applications regularly claim to utilize artificial intelligence or deep learning to predict the next crash point. To empirically test whether high-capacity non-linear models can detect subtle multi-round hash relationships, we configured three state-of-the-art architectures: (1) an LSTM recurrent network with 128 hidden units, (2) an XGBoost gradient-boosted tree model, and (3) a 4-layer Multilayer Perceptron (MLP). Each model was trained on historical sliding windows $W \in [5, 50]$ to predict the binary target $M \geq 2.00$x.

Model Architecture	Input Features	Test Accuracy	ROC-AUC	Empirical Edge
Theoretical Zero-Info	None	48.50%	0.5000	0.00% (Baseline)
LSTM (128 units, 3 layers)	Window = 20 rounds	48.51%	0.5004	+0.01% (Within Noise)

XGBoost (500 trees)	Lags 1-50 + rolling stats	48.48%	0.4998	-0.02% (Within Noise)
Deep MLP (4 layers)	Window = 10 rounds	48.52%	0.5002	+0.02% (Within Noise)

As expected from cryptographic theory, all machine learning architectures achieved an ROC-AUC indistinguishable from 0.5000. Because HMAC-SHA256 is non-invertible without the pre-image, software programs claiming to 'predict' multipliers are either marketing deceptions or client-side RNG animations designed to defraud users.

5. Conclusion & Open-Source Cryptographic Tooling

Our empirical evaluation of 50,000 real rounds establishes conclusive findings: (1) Provably Fair crash games adhere with exactitude to the Pareto reciprocal multiplier distribution; (2) consecutive rounds exhibit zero serial correlation ($|\rho| < 0.0088$); (3) predictive software tools violate fundamental cryptographic hardness assumptions and fail all empirical tests; and (4) negative expected value is invariant across all strategy formulations. Players and researchers are strongly advised to audit rounds independently using client-side Web Crypto implementations.

In support of public verification and reproducible research, CrashMath Labs has released **@crashmath/provably-fair**, an open-source, zero-dependency W3C Web Crypto verification library. The complete source code, test suites, and documentation are publicly accessible under the MIT License at:

https://github.com/crashmath-labs/provably-fair

Interactive browser audits and historical Monte Carlo simulators are available at **https://crashmath.org**.

References

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