

The Rules Are the Model

Path Dependence, Payout Frictions, and Selection in Synthetic Trading-Evaluation Contracts

Francisco Matilla Serrano

Independent Researcher, Varna, Bulgaria

Corresponding author: Francisco Matilla Serrano (franchimatilla@gmail.com)

ORCID: <https://orcid.org/0009-0004-9491-6374>

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Abstract

Targets and drawdowns look like the contract, but they are only its outline. A minimum-day condition, daily-loss limit, consistency test, trailing drawdown, payout buffer, or payout cap can change the outcome even when the trader, price path, nominal target, and nominal drawdown are identical. This paper measures those effects using a common-path rule engine. It extends the participant-value analysis in Matilla Serrano (2026b) and the selection analysis in Matilla Serrano (2026c). The same simulated profit-and-loss paths are applied to two benchmarks, six one-rule counterfactuals, and three synthetic contract bundles. The bundles are market-informed archetypes, not copies of named providers.

The simulation uses six latent trader types, 30,000 antithetic paths per type and stage, a 20-day horizon, and a population containing 20% positive-drift types. All contracts share a \$3,000 target and \$2,000 nominal drawdown, so their Target-to-Drawdown Ratio is 1.5. Nevertheless, outcomes differ sharply. The ideal realistic benchmark passes 28.59% of population paths and produces a first payout on 9.72% of purchased attempts. A static package with minimum days, a 50% consistency limit, and payout constraints reduces those rates to 23.45% and 6.57%. An end-of-day trailing package reduces them to 17.16% and 3.76%. A stricter intraday-trailing package reduces them to 5.04% and 0.56%. Participant expected cash flow moves from +\$143.96 in the ideal realistic benchmark to +\$4.85, -\$39.48, and -\$87.48 in the three bundles.

Rules also change who survives. Conditional on being selected, positive-drift traders constitute 32.07% of passers and 42.96% of payout events in the ideal benchmark. Those conditional shares rise to 45.75% and 74.35% in the strictest bundle. This does not mean that the strictest bundle improves outcomes for the population as a whole. Its pass and payout-event rates are far lower, and it rejects many positive-drift paths. Among one-rule counterfactuals, the \$1,000 daily-loss limit has the largest effect on pass probability and is sufficient to reverse participant expected value.

The results show why contract comparisons based only on target, drawdown, or nominal account size can fail. Rule packages are nonlinear, path-dependent systems. Their effects should be measured on common paths, both one rule at a time and as complete bundles.

Keywords: trading evaluation; trailing drawdown; daily loss limit; consistency rule; payout cap; path dependence; contract design; common random numbers

JEL Classification: C15; D81; D86; G11; G23

1. Introduction

Two trading evaluations can advertise the same nominal account size, the same profit target, and the same maximum drawdown while offering materially different contracts. One may use a fixed loss boundary. Another may move the boundary upward whenever a new intraday high is reached. One may allow a single profitable day to produce most of the target. Another may require profits to be distributed across several days. A participant may pass the evaluation yet remain unable to request the amount that made the contract look attractive in the first place.

These details are sometimes treated as footnotes. They are not. They define the stopping time, determine which paths survive, alter the amount and timing of payments, and change the types of traders observed among passers. The rules are part of the economic model.

Market Edge versus Contract Edge: Negative-Expectancy Trading under an Idealized Evaluation Contract (Matilla Serrano, 2026b) deliberately removed those rules to isolate a basic result: negative expected market P&L can coexist with positive expected participant contract cash flow when personal loss is limited to fees and successful paths retain a discrete payout. *Skill or Variance? What Trading Evaluations Actually Select* (Matilla Serrano, 2026c) made the success probabilities endogenous and showed that an evaluation is a noisy classifier. Positive drift improves success, but high variance can also carry zero- or negative-drift paths to the target.

The analysis does not replace either mechanism with “rules alone.” Outcomes arise jointly from trader type, stochastic path, monitoring convention, economic terms, and the rule state carried along the path. The common-path design isolates the incremental effect of changing the contract while leaving those other inputs fixed.

The analysis asks:

1. How much does each common rule family change passing probability, first-payout probability, and participant expected value?
2. Do trailing drawdowns differ materially according to whether they update intraday or at end of day?
3. How do payout buffers and caps change contract value even when evaluation pass probability is unchanged?
4. Do stricter packages select a larger share of positive-drift traders, and what is the cost in false negatives?
5. Can target and drawdown geometry alone rank contracts?

The empirical strategy is counterfactual simulation. The same standardized P&L shocks are replayed through every contract. The Ideal Basic benchmark preserves the \$40 fee, zero activation fee, and 100% payout share used by Matilla Serrano (2026b). The Ideal Realistic benchmark changes only the economic parameters to a \$90 fee, \$100 activation fee, and 90% share. Six marginal contracts add one rule family at a time. Three complete synthetic bundles combine rules with increasing path dependence and payout restrictions.

No bundle is presented as an existing provider. Publicly available program terms were reviewed to identify rule families and economically plausible parameter ranges, after which the values were recombined into synthetic archetypes. This design avoids a league table, an endorsement, or an allegation about a named business. It also prevents a contract from being misrepresented when public terms change. The cost is that the numerical results cannot be interpreted as an audit of the market.

The common-path comparison produces a wide outcome range despite identical target and nominal drawdown. At a 20% positive-edge population share, the Ideal Realistic benchmark passes 28.59% of paths. Contract A, a static discipline package, passes 23.45%. Contract B, which adds an end-of-day trailing drawdown and daily-loss limit, passes 17.16%. Contract C, with an intraday trailing drawdown, tighter daily-loss limit, stricter consistency condition, and lower payout cap, passes 5.04%.

The participant cash-flow ranking is more dramatic. Ideal Realistic has expected value of +\$143.96 per purchased attempt in this permissive simulation. Contract A is approximately break-even at +\$4.85. Contracts B and C are negative at -\$39.48 and -\$87.48. Because participant and provider cash flows are treated as a closed transfer before other costs or revenues, the corresponding provider margins have the opposite signs.

Stricter rules improve one measure of selection quality. Positive-drift types represent 32.07% of Ideal Realistic passers and 45.75% of Contract C passers. Among first-payout events, the shares are 42.96% and 74.35%. That result should not be described simply as “better.” Contract C also rejects most positive-drift paths and generates very few payout events. Contract design therefore trades participant access, provider financing, and selection precision against one another.

The paper contributes a rule taxonomy and a common-path measurement framework. Its specific comparison passes identical trader types and identical shocks through different state machines, first one rule at a time and then as complete packages. This attributes outcome changes to the implemented rule intervention within the synthetic design. The contribution is the controlled rule decomposition, not contract valuation or cross-provider comparison. Within the program, this paper is needed to move from the static barriers used in the first two papers to explicit event order, trailing floors, daily stops, consistency conditions, and payout frictions.

The rest of the paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 defines the rule taxonomy. Section 4 formalizes the rule engine. Section 5 describes the contracts and numerical method. Section 6 reports marginal effects. Section 7 compares complete bundles. Section 8 analyzes selection and provider economics. Section 9 discusses interpretation and design. Section 10 states limitations, and Section 11 concludes.

2. Related Literature and Positioning

2.1 Barriers, drawdown, and monitoring

A loss rule is a stopping rule. Its effect depends on the full path, not only the ending return. Magdon-Ismail et al. (2004) derive properties of maximum drawdown for Brownian motion. Kaminski and Lo (2014) show that stop-loss rules do not have a universal effect; their

usefulness depends on return dynamics. Those results caution against treating a drawdown rule as a simple reduction in maximum loss.

Monitoring frequency is especially relevant for trailing boundaries. Barrier-option research shows that continuous and discrete monitoring can produce different outcomes even when the displayed boundary is the same (Broadie, Glasserman, and Kou, 1997). An intraday trailing floor can tighten after a temporary high that disappears before the close. An end-of-day floor does not record that high. The difference is not cosmetic: the two contracts have different state variables.

2.2 Nonlinear incentives and risk shifting

Trading-evaluation rules create nonlinear rewards. Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) show that evaluation incentives can affect risk taking. Carpenter (2000), Ross (2004), Basak, Pavlova, and Shapiro (2007), and Hodder and Jackwerth (2007) demonstrate that the relation between convex compensation and chosen risk depends on the complete payoff and state.

Minimum-day and consistency rules can be read as attempts to discourage a single high-variance jump toward the target. Daily-loss limits and trailing drawdowns limit particular path shapes. Payout buffers and caps change the reward after selection. The present paper does not estimate whether these rules induce actual participants to change behavior; it first measures how the rules classify a fixed set of paths.

2.3 Selection under noise

Matilla Serrano (2026c) connects the evaluation problem to research on skill and luck. Fama and French (2010) and Barras, Scaillet, and Wermers (2010) show how realized performance can produce apparent winners even when latent ability is absent. Harvey and Liu (2022) further show how limited statistical power and undersampling can obscure true skill in return data. Rule-based selection adds another source of filtering: even before skill is estimated, the contract determines which paths remain observable. In a path-dependent evaluation, the rule set changes the selection operator. A consistency limit may reduce selection of concentrated wins. A daily-loss limit may exclude high-variance paths. Neither guarantees that surviving traders have positive expected market P&L.

Rules also create false negatives. A positive-drift trader may fail because of an early drawdown, a single bad day, an intraday high-water mark, a deadline, or a profit-distribution requirement. A contract that produces a high positive share among passers may do so by passing very few traders. Selection quality must therefore be reported together with coverage.

2.4 Direct trading-evaluation research

Lim's *The Price of a Funded Account* (2026b), Lim's cross-firm study *Phantom Generosity* (2026a), and Tomàs Fernández (2026) establish direct valuation benchmarks for trading-evaluation contracts and show that rules beyond headline target and drawdown affect value. Maile (2026) considers the industry and its policy relevance, while Ng (2026) examines a deferred-fee design. The present question is narrower: how much does each coded rule intervention change outcomes when trader types and stochastic shocks are held fixed? The

common-path design and marginal-rule decomposition provide the answer needed before the program moves to full observed products and endogenous policies.

3. Rule Taxonomy

The symbols used below describe the path and the contract state. $X_{d,k}$ is cumulative P&L on trading day d at intraday observation k , and C_d is cumulative P&L at that day's close. M denotes a running high-water mark and L a loss floor; the superscripts identify whether the quantity is intraday (ID), end of day (EOD), a floor cap (cap), or a daily loss limit (day). The target and nominal drawdown are U and D . Minimum trading days are m in the evaluation and m^P in the funded stage. The consistency fraction is c . At payout, B is the non-withdrawable buffer, C is the payout cap, and s is the participant's payout share. Each definition is restated at the rule where it first enters.

3.1 Static drawdown

A static drawdown places the loss floor at a fixed value:

$$L_t = -D.$$

If cumulative P&L $X_t \leq -D$, the stage fails. Prior profits do not tighten the boundary. Among the rules studied here, this is the closest to the idealized binary model.

3.2 End-of-day trailing drawdown

Let C_d be cumulative P&L at the end of day d . The end-of-day high-water mark is

$$M_d^{EOD} = \max(0, C_1, \dots, C_d).$$

The next day's floor is

$$L_{d+1}^{EOD} = \min(L^{cap}, M_d^{EOD} - D),$$

where $L^{cap} = 0$ in the simulations. The minimum operator means that the floor trails upward until it reaches zero and then stops. Intraday highs do not affect the floor unless they survive to the close.

3.3 Intraday trailing drawdown

Let $X_{d,k}$ be cumulative P&L at intraday monitoring point k . Define

$$M_{d,k}^{ID} = \max_{(j,l) \leq (d,k)} X_{j,l},$$

and

$$L_{d,k}^{ID} = \min(L^{cap}, M_{d,k}^{ID} - D).$$

The floor can tighten immediately after a temporary intraday gain. If the path then reverses, the contract can fail above its original starting balance. The intraday rule is therefore weakly at least as restrictive as the corresponding end-of-day rule on a sufficiently fine common path, subject to implementation order and floor caps.

3.4 Daily-loss limit

If $X_{d,0}$ is P&L at the start of day d , a daily loss limit L^{day} fails the stage when

$$X_{d,k} - X_{d,0} \leq -L^{day}$$

at any monitored intraday point. The rule resets at the start of the next day. A path may satisfy the total drawdown but fail the daily limit.

3.5 Minimum trading days

A target crossing is not sufficient before day m . Qualification requires

$$X_{d,K} \geq U \text{ and } d \geq m,$$

together with every other active rule. A path that reaches the target early must continue to carry risk until the minimum day. In this model, no special “target lock” protects early gains.

3.6 Consistency limit

Let $g_d = C_d - C_{d-1}$ be daily P&L and $g_{max} = \max_d \max(g_d, 0)$. A consistency fraction c requires

$$g_{max} \leq c X_{d,K}$$

at qualification. A 50% limit means that the best positive day cannot exceed half of cumulative profit. A trader who reaches the target with an overly concentrated day can continue trading and later qualify if total profit grows enough.

3.7 Payout minimum days, buffer, and cap

The funded stage can use its own minimum day m^P . If funded-stage equity at qualification is X^F , payout before the participant share is

$$W(X^F) = \min\{\max(X^F - B, 0), C\} \quad (1)$$

where B is a non-withdrawable buffer and C is the payout cap. The participant receives $s W(X^F)$.

These restrictions can reduce value without changing evaluation pass probability. A participant may therefore compare two contracts incorrectly if only the evaluation stage is considered.

4. Common-Path Rule Engine

4.1 Profit-and-loss inputs

The six trader types follow the specification in Matilla Serrano (2026c).

Table 1. Trader types and stochastic P&L parameters

Code	Daily drift	Daily volatility	Latent group
P-LV	\$100	\$600	Positive
P-HV	\$100	\$1,200	Positive
Z-LV	\$0	\$600	Nonpositive

Code	Daily drift	Daily volatility	Latent group
Z-HV	\$0	\$1,200	Nonpositive
N-LV	-\$75	\$600	Nonpositive
N-HV	-\$75	\$1,200	Nonpositive

Note: The six types are stylized drift-volatility scenarios inherited from Matilla Serrano (2026c), not estimates of the trader population.

At each intraday step,

$$\Delta X_{d,k} = \frac{\mu}{K} + \frac{\sigma}{\sqrt{K}} \varepsilon_{d,k}. \quad (2)$$

Here, $\varepsilon_{d,k} \sim N(0, 1)$, and $K = 10$ steps per day. Each stage lasts at most 20 trading days.

The population contains 20% positive-drift types, split equally between P-LV and P-HV. The remaining 80% is split equally among the four nonpositive types. This is a scenario, not a market estimate.

4.2 Event order

For each active path and monitoring point, the engine:

1. applies the P&L increment;
2. checks the daily-loss limit, if any;
3. updates the intraday high-water mark, if applicable;
4. checks the current drawdown floor;
5. records daily P&L at the end of the day;
6. updates an end-of-day trailing high-water mark, if applicable; and
7. checks target, minimum-day, consistency, and funded payout conditions.

The order is explicit because simultaneous or near-simultaneous events can otherwise be ambiguous. Alternative commercial implementations may use different conventions.

4.3 Cash flow

Let p_j be evaluation pass probability under contract j . Let $\acute{W}_j^F$ be the expected participant payout conditional on starting the funded stage, including zero for funded paths that never qualify. Participant expected cash flow per purchased evaluation is

$$V_j = -F_j - p_j A_j + p_j \acute{W}_j^F. \quad (3)$$

This formula accommodates a payout amount that varies with ending equity, buffers, caps, and participant share. The provider closed-transfer margin is

$$M_j = -V_j.$$

Following the cash-flow convention in Matilla Serrano (2026b, 2026c), this margin excludes operating costs and any external market revenue or loss.

4.4 Common random numbers

The same evaluation shock matrix is reused for every contract, and a second common matrix is reused for every funded-stage contract. This makes the difference between two contracts a path-by-path counterfactual. If a path passes I1 but fails M3, the change is caused by the daily-loss rule under the engine, not by a more adverse Monte Carlo sample.

Common random numbers are a standard comparison device in Monte Carlo work (Glasserman, 2003; Wright and Ramsay, 1979). Reusing the same shocks makes the contract comparison easier to interpret and may reduce the variance of estimated differences, but it is not guaranteed to do so for every response structure. It also does not remove model risk: every contract is still being applied to Gaussian synthetic P&L.

5. Contract Design and Numerical Method

5.1 Benchmarks

Every contract uses a fictitious 50K nominal label, a \$3,000 evaluation target, a \$2,000 nominal drawdown, and a \$3,000 funded target. Thus every row has $TDR = 1.5$.

Ideal Basic (I0) uses a \$40 fee, no activation fee, a 100% payout share, a static drawdown, and no additional rules.

Ideal Realistic (I1) preserves the same path rules but uses a \$90 fee, \$100 activation fee, and 90% payout share. I0 and I1 must have identical pass and payout-event probabilities. Their difference is purely economic.

5.2 One-rule counterfactuals

Each marginal specification begins with I1 and adds one rule family.

Table 2. One-rule counterfactuals relative to the Ideal Realistic benchmark

Code	Added rule
M1	5 minimum days in evaluation and funded stage
M2	50% consistency limit
M3	\$1,000 daily-loss limit
M4	End-of-day trailing drawdown capped at \$0
M5	Intraday trailing drawdown capped at \$0
M6	5 payout days, \$1,000 buffer, \$2,000 gross cap

Note: Each specification adds one rule to the Ideal Realistic benchmark while preserving the same stochastic paths and economic terms.

The marginal tests are not proposed products. They are identification devices.

5.3 Complete synthetic bundles

Table 3. Complete synthetic contract bundles

Feature	Contract A: Static Discipline	Contract B: EOD Trail	Contract C: Intraday Guardrail
Drawdown method	Static	End-of-day trailing	Intraday trailing
Daily-loss limit	None	\$1,500	\$1,000
Evaluation minimum days	5	5	7
Consistency fraction	50%	50%	30%
Payout minimum days	5	5	7
Payout buffer	\$500	\$1,000	\$1,000
Gross payout cap	\$2,000	\$2,000	\$1,500
Fee / activation / share	\$90 / \$100 / 90%	\$90 / \$100 / 90%	\$90 / \$100 / 90%

Note: Contracts A-C are synthetic bundles assembled from common rule families. They do not reproduce or rank named providers.

The bundles combine rule families found in public retail evaluation terms but do not copy any one provider's complete offer. The labels describe mechanics, not companies.

5.4 Simulation

The main run uses 30,000 antithetic paths per type and stage, a fixed seed of 20260727, ten intraday steps per day, and a 20-day horizon. Every contract is replayed over the same arrays. The code also contains deterministic hand-worked tests for:

- a basic target completion;
- enforcement of a minimum day;
- a daily-loss breach;
- different intraday and end-of-day trailing updates; and
- rejection by a consistency rule.

All five deterministic tests have the expected result. Aggregate outputs, type-level results, failure reasons, contract definitions, and the executable workbook are provided in the Supplementary Material.

6. Marginal Rule Effects

6.1 Passing and first payout

Figure 1 compares the two benchmarks and three full bundles on identical paths.

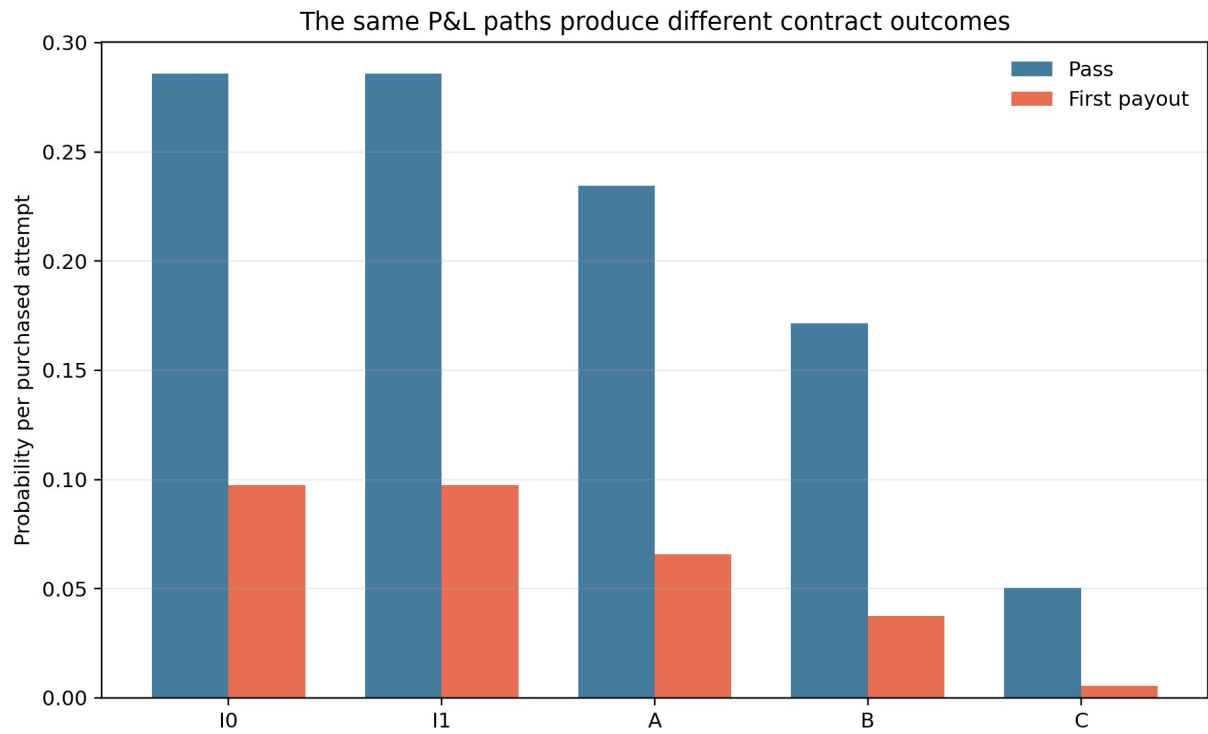


Figure 1. Common-path outcomes across benchmark and synthetic contracts. Every specification is evaluated on identical stochastic paths.

Figure 2 isolates each rule family relative to I1.

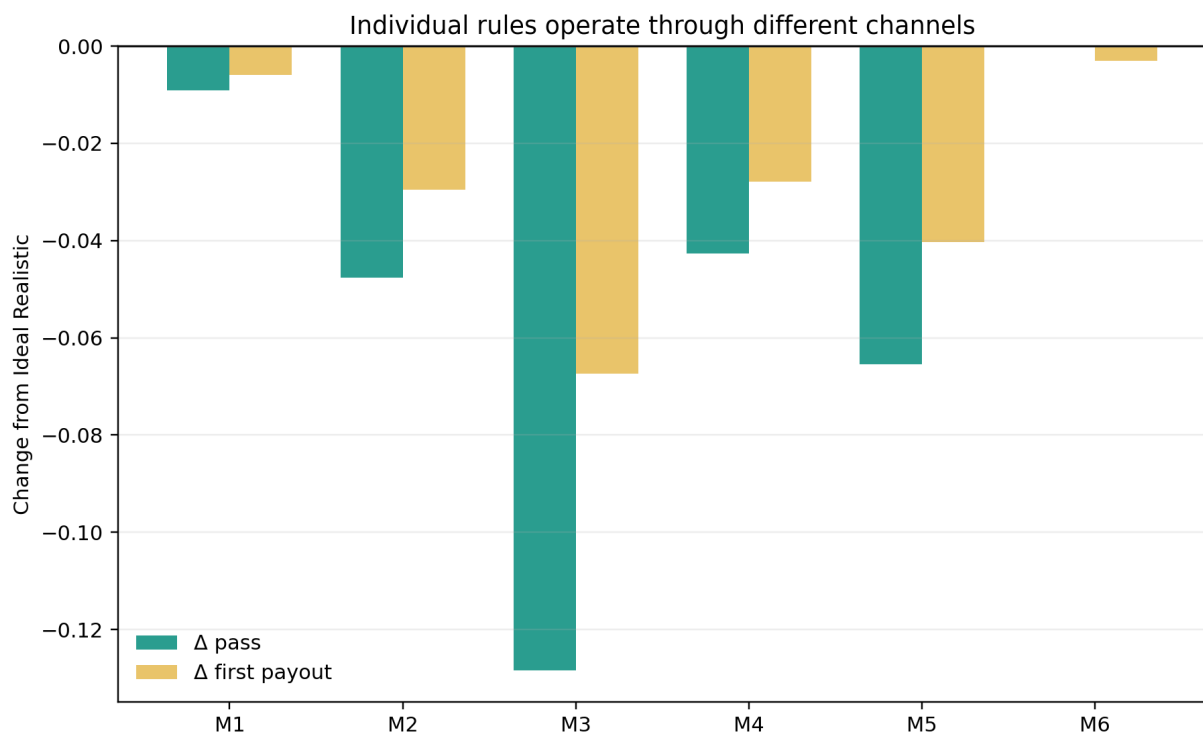


Figure 2. One-rule-at-a-time changes from the Ideal Realistic benchmark. Each bar isolates one rule family on common paths.

Table 4. Marginal rule effects relative to I1

Contract	Pass rate	Change from I1	First-payout rate	Change from I1	Participant EV
I1 Ideal Realistic	28.59%	not applicable	9.72%	not applicable	\$143.96
M1 Minimum days	27.69%	-0.91 pp	9.13%	-0.60 pp	\$128.71
M2 Consistency	23.84%	-4.76 pp	6.77%	-2.95 pp	\$69.02
M3 Daily loss	15.75%	-12.84 pp	2.98%	-6.74 pp	-\$25.27
M4 EOD trailing	24.33%	-4.27 pp	6.93%	-2.79 pp	\$72.91
M5 Intraday trailing	22.05%	-6.54 pp	5.70%	-4.03 pp	\$41.74
M6 Payout constraints	28.59%	0.00 pp	9.43%	-0.30 pp	\$51.13

Note: Percentage-point changes are measured against I1 on identical paths. Participant expected value includes evaluation fees, activation fees, and the modeled first payout.

6.2 Minimum days

The five-day condition has the smallest marginal effect in this simulation. It reduces pass probability by 0.91 percentage points. A path that reaches the target early must remain active until day five and can give back profits or breach the drawdown before qualification.

The modest aggregate effect does not imply that minimum days are irrelevant. The effect depends on target distance, volatility, allowed position size, and horizon. A rule requiring many days relative to the expected target time would be more restrictive.

6.3 Consistency

The 50% consistency test reduces the pass rate by 4.76 percentage points and the first-payout rate by 2.95 points. It lowers participant EV by \$74.94. The rule suppresses concentrated winning paths, which are more frequent for high-variance types, but it can also reject a positive-drift strategy with lumpy payoffs.

A consistency percentage should therefore not be read as a direct probability of skill. It expresses a preference for a particular distribution of profit across days.

6.4 Daily loss

The \$1,000 daily-loss limit is the strongest marginal rule in the chosen design. It reduces pass probability from 28.59% to 15.75% and first-payout probability from 9.72% to 2.98%. Participant expected value falls by \$169.23 and changes sign.

At the population level, 72.36% of evaluation paths breach the daily-loss condition in M3. Some of those paths would later have recovered or reached the target under I1. The rule truncates them immediately.

This result is parameter-specific. A looser daily limit, lower intraday volatility, or finer risk management would produce a smaller effect. The general lesson is that a daily limit creates a second loss boundary on a different time scale.

6.5 End-of-day versus intraday trailing

The end-of-day trailing rule reduces pass probability by 4.27 percentage points. The intraday version reduces it by 6.54 points. Both begin with the same \$2,000 distance and both stop trailing at zero.

The difference comes from transient highs. Under intraday monitoring, a gain can tighten the floor before it is realized at the close. The subsequent reversal then has less room. Under end-of-day monitoring, the same temporary high leaves no trace. Contract descriptions that say only “trailing drawdown” therefore omit a material state-transition rule.

6.6 Payout constraints

M6 leaves evaluation pass probability unchanged by construction. Its first-payout event rate falls only 0.30 percentage points, yet participant EV falls from \$143.96 to \$51.13 because the buffer and cap reduce payment amounts.

This separation is important. A pass-rate calculator cannot value a contract whose economic restrictions occur after passing. The payout function belongs inside the expected-value model.

7. Complete Contract Packages

7.1 Aggregate outcomes

Table 5. Aggregate outcomes across benchmarks and complete synthetic bundles

Contract	Pass rate	First-payout rate	Expected payout per attempt	Participant EV	Provider gross margin
I0 Ideal Basic	28.59%	9.72%	\$291.72	\$251.72	-\$251.72
I1 Ideal Realistic	28.59%	9.72%	\$262.55	\$143.96	-\$143.96
A Static Discipline	23.45%	6.57%	\$118.30	\$4.85	-\$4.85
B EOD Trail	17.16%	3.76%	\$67.68	-\$39.48	\$39.48
C Intraday Guardrail	5.04%	0.56%	\$7.56	-\$87.48	\$87.48

Note: I0 and I1 have identical path rules and therefore identical event probabilities; their cash-flow difference is entirely contractual.

The comparison between I0 and I1 isolates price and payout share. The event probabilities are identical, but participant EV falls by \$107.77. Contract A combines moderate path restrictions and brings the closed-transfer model close to break-even. Contracts B and C generate positive provider gross margin before other costs and revenue.

Figure 3 displays the transfer results.

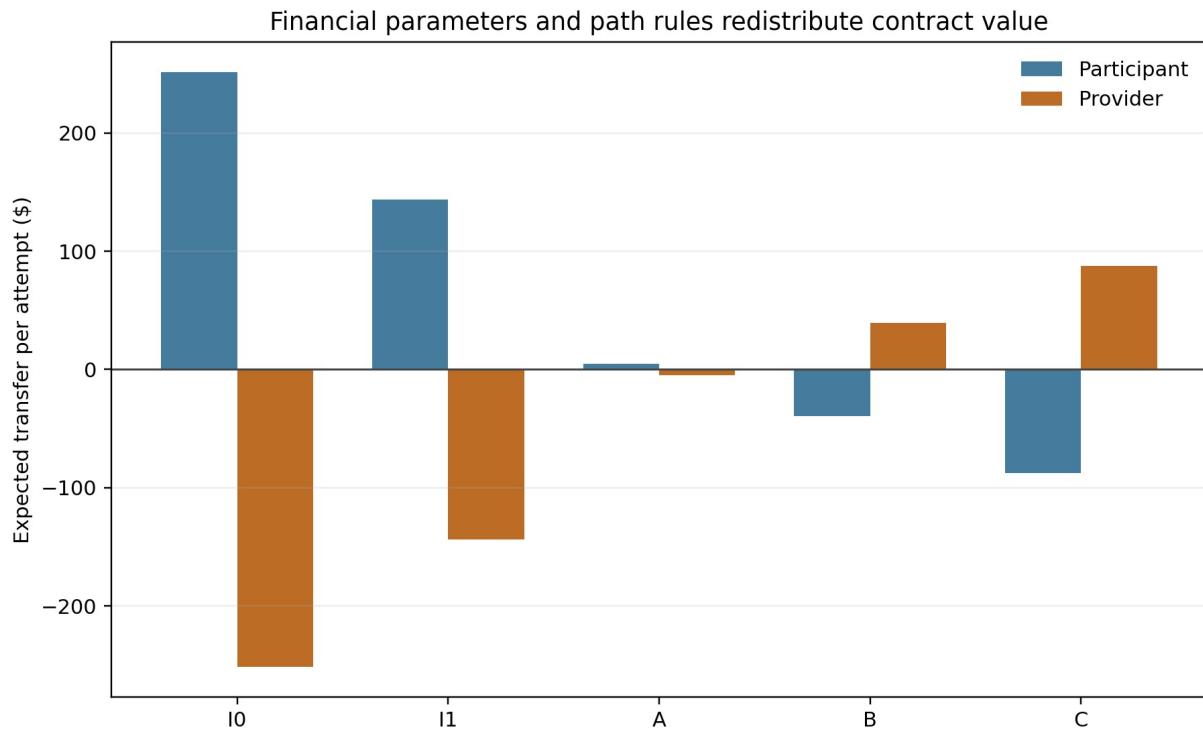


Figure 3. Participant expected value and provider gross margin. The two quantities have opposite signs in the closed-transfer benchmark.

7.2 Non-additivity

The full-bundle effects should not be obtained by adding the marginal changes. Rules interact.

A daily-loss limit can terminate a path before a trailing drawdown would bind. A consistency rule matters only for paths that survive long enough and reach the target. A minimum-day condition increases the time during which a trailing floor or daily limit can terminate an otherwise successful path. A payout buffer changes payment amounts only for funded paths that qualify under every earlier rule.

For this reason, one-rule counterfactuals explain mechanisms, while complete packages estimate the joint modeled outcome. Both are needed.

7.3 Failure channels

Figure 4 decomposes population evaluation outcomes by terminal reason.

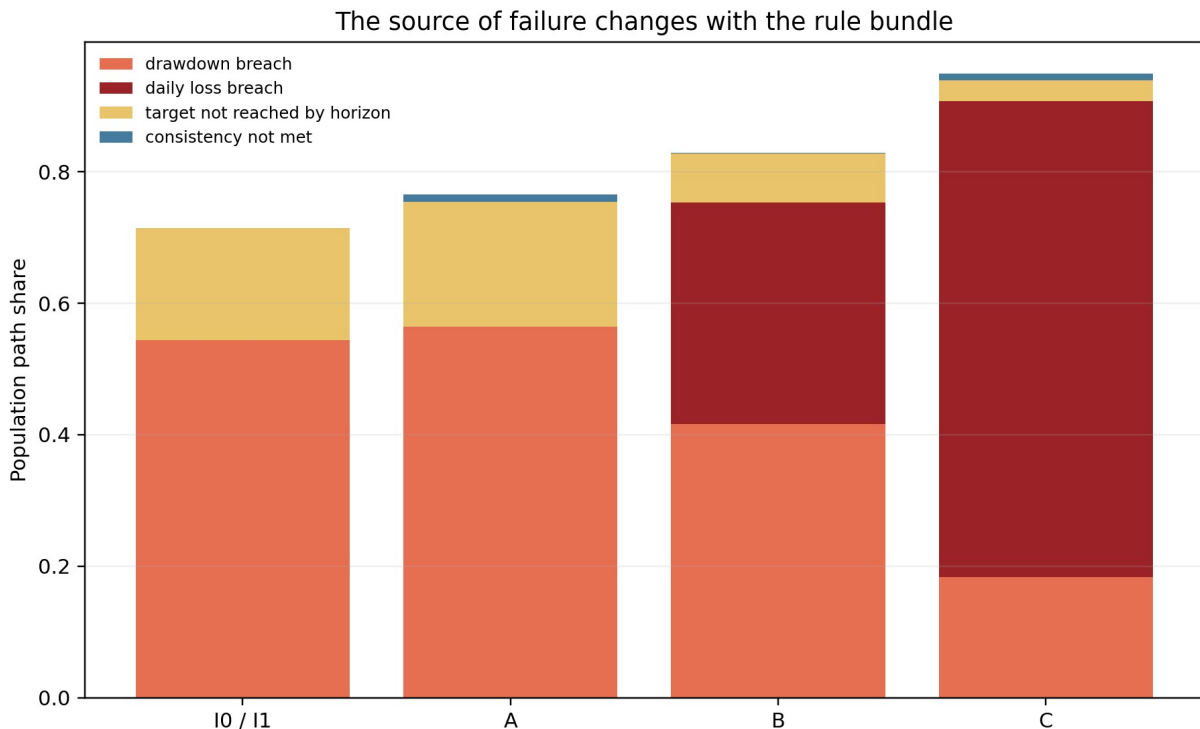


Figure 4. Failure channels across benchmark and synthetic contracts. The shared I0 / I1 label reflects their identical path rules and therefore identical failure channels.

Under I0 and I1, 54.39% of paths breach the static drawdown and 17.01% fail to reach the target by the horizon. Their failure channels coincide because their path rules are identical; only the fee, activation charge, and payout share differ. Under Contract A, the drawdown share is 56.45%, target shortfall is 19.02%, and 1.08% finish above the target without meeting consistency. Under Contract B, 33.68% breach the daily limit and 41.65% breach the trailing drawdown. Under Contract C, 72.36% breach the daily limit and 18.39% breach the trailing drawdown.

Failure labels depend on event priority. If a path could satisfy more than one condition at nearly the same time, the engine assigns the first checked terminal rule. The decomposition is therefore an implementation diagnostic, not a causal attribution in the econometric sense.

8. Selection and Provider Economics

8.1 Selection quality

Figure 5 shows the positive-edge share of selected groups.

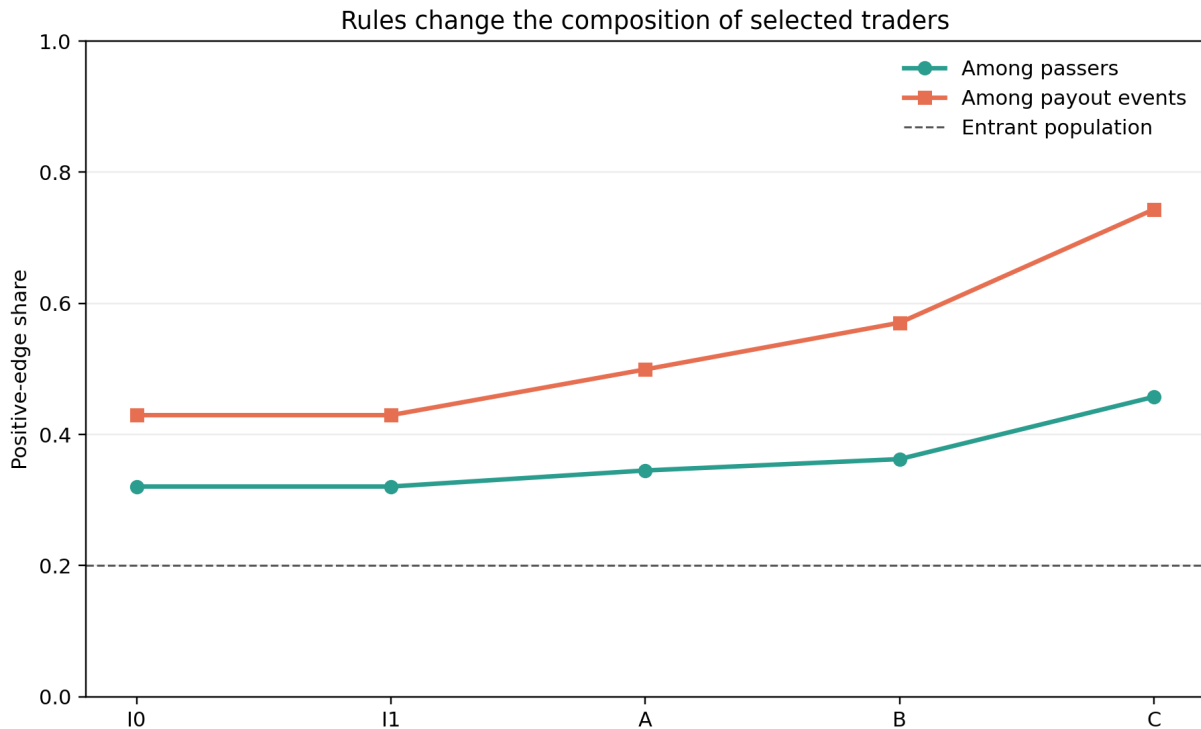


Figure 5. Positive-edge representation among passers and payout events. Shares are conditional on selection and must be read with the corresponding event rates.

I0 and I1 coincide in Figure 5 because changing fees and payout share does not change which paths pass or reach a payout event when the path rules are held fixed.

Table 6. Positive-edge representation among selected groups

Contract	Positive among passers	Positive among first payouts
I0 / I1	32.07%	42.96%
A	34.52%	49.93%
B	36.26%	57.06%
C	45.75%	74.35%

Note: Positive shares are conditional on passing or receiving a payout. Higher conditional representation does not imply higher success for the population as a whole.

Every package raises positive-edge representation relative to the benchmark, and the second stage improves it further. Contract C is the strongest classifier only on this conditional-composition measure. For the full entrant population it produces fewer passes and fewer payouts, including fewer successful outcomes for positive-drift traders. It is therefore more selective, not unambiguously better.

The classifier has low coverage. Only 5.04% of population paths pass C, and only 0.56% of purchased attempts produce a first payout. Many positive-drift paths are rejected. The higher positive share is partly a consequence of shrinking the selected set.

A complete selection report should therefore show at least:

- pass rate by latent type;
- positive share among passers;
- positive-type false-negative rate;
- first-payout event rate; and
- positive share among payout events.

Publishing only the selected-group composition would reward a contract for rejecting almost everyone.

8.2 Participant and provider sides

The rule packages move transfer value toward the provider. In the closed-transfer benchmark, Contract A is nearly balanced, while B and C produce provider margins of \$39.48 and \$87.48 per attempt. This is not net profit. Operating costs could exceed those amounts, and external-market activity could add profit or loss.

The business-model implication of Matilla Serrano (2026c) now becomes concrete. A provider need not rely only on a high fraction of negative-drift entrants. Rule design can lower pass probability, lower payout-event probability, reduce payout amount, or improve the composition of traders considered for any external copying decision. Fees, rules, populations, and market activity operate jointly.

8.3 How many non-payout attempts finance one payout?

Counts alone remain insufficient, but the contracts change them sharply. I1 produces a payout event on 9.72% of attempts, or approximately 9.28 non-payout attempts per payout. Contract A produces a payout on 6.57%, or 14.22 non-payout attempts per payout. Contract B produces one on 3.76%, or 25.60 non-payout attempts per payout. Contract C produces one on 0.56%, or approximately 177.47 non-payout attempts per payout.

Contract C also caps the gross payout at \$1,500 and retains a 10% share, so a payout event has a different dollar meaning from I1. Any cross-subsidy claim must combine event counts with activation incidence, payout amount, and costs.

9. Interpretation and Design Implications

9.1 TDR cannot rank these contracts

All eleven specifications have $TDR = 3,000 / 2,000 = 1.5$. Their pass rates range from 5.04% to 28.59%, and their participant EV ranges from $-\$87.48$ to $+\$251.72$. The ratio is identical because it records only two distances.

TDR remains a useful first description of static barrier geometry. It cannot encode:

- whether the loss boundary moves;
- when it moves;
- whether a daily limit binds first;
- how long the participant must trade;
- whether profit must be distributed across days; or
- how much profit can actually be withdrawn.

The example establishes no universal ranking of rule families. It establishes that TDR alone is insufficient.

9.2 A rule can affect probability, payment, or both

Rules fall into three economic categories.

Selection rules change whether or when a path qualifies. Drawdown, daily-loss, minimum-day, and consistency conditions belong here.

Payment rules change the amount received after qualification. Payout shares, buffers, and caps belong here.

Hybrid rules do both. A payout minimum day can keep the path exposed to failure and also delay payment.

Separating the categories helps identify the source of value changes. It also prevents a high pass probability from being mistaken for an attractive contract.

9.3 Contract comparison requires explicit state representation

A static spreadsheet that multiplies fee, pass rate, and advertised payout cannot represent an intraday trailing boundary or consistency condition unless the pass rate has already been estimated under those exact rules. A natural computational representation is a state machine that updates:

- cumulative P&L;
- day-start P&L;
- intraday or end-of-day high-water mark;
- current drawdown floor;
- number of trading days;
- best positive day;
- stage; and
- available payout.

The accompanying rule engine provides one auditable implementation. It is a reference model, not the definitive interpretation of every public contract.

9.4 “Realistic” is not a single contract

Matilla Serrano (2026b) moved from an Ideal Basic to an Ideal Realistic case by changing fees, activation cost, and payout share while leaving the mechanics permissive. That step was useful because it isolated economic parameters. The present results show why it was not the endpoint. Once path rules are introduced, there is no single realistic contract. Each combination defines a different probability and cash-flow system.

10. Limitations and Further Work

First, the contracts are synthetic. They are informed by public rule families, but they do not reproduce a named provider or estimate the frequency of each term in the market. Public terms can change rapidly, and complete historical rule archives are difficult to reconstruct.

Second, the model uses Gaussian arithmetic P&L with constant drift and volatility. Intraday trailing and daily-loss rules are especially sensitive to tails, serial dependence, and volatility clustering. Realistic strategy paths or bootstrap samples could change the ranking.

Third, the intraday grid has ten observations per day. A finer grid creates more opportunities to record temporary highs and losses. Intraday-rule results are therefore conditional on monitoring resolution.

Fourth, every trader keeps the same process under every contract. Real participants adapt position size and behavior to the rules. A consistency limit may induce smoother risk, while an approaching deadline may induce risk seeking. The fixed-path design identifies mechanical effects but not behavioral equilibrium effects.

Fifth, the evaluation and funded stages use the same mechanical rules except for stage-specific minimum days and payout calculations. Commercial programs may change loss floors, sizes, payout eligibility, scaling, or other terms between stages.

Sixth, the rule engine adopts one event order and one interpretation for each condition. Terms that sound similar can differ in the treatment of unrealized P&L, commissions, open positions, trading-session boundaries, threshold touches, or end-of-day calculations.

Seventh, the 20% positive-edge population is hypothetical. Selection results depend on the prior type mixture. Further work should estimate or bound the mixture using complete attempt histories.

Eighth, the provider margin is a closed transfer before costs and external market activity. It is not an estimate of provider net profit.

Natural extensions would compare traders’ risk choices across the same contract packages, add re-entry and later-payout states, examine payment-review frictions, and test non-Gaussian and regime-switching P&L. With suitable data, an empirical implementation could replay anonymized account paths through versioned rule packages and compare evaluation selection with subsequent out-of-sample performance. These extensions are not part of the present results.

11. Conclusion

The target and drawdown are not the contract. They are two inputs to a path-dependent state machine.

Using identical stochastic paths, this paper finds that common rule families materially change pass probability, first-payout probability, participant expected value, provider transfer margin, and the composition of selected traders. A \$1,000 daily-loss rule has the largest marginal effect in the chosen design. Intraday trailing is more restrictive than end-of-day trailing because it records temporary highs. Payout restrictions can reduce expected value substantially even when evaluation pass probability does not change.

Complete packages magnify those differences. At a 20% positive-edge population share, pass rates range from 28.59% in the ideal benchmark to 5.04% in the strictest synthetic bundle despite identical target, nominal drawdown, and TDR. Participant expected value moves from +\$143.96 in the Ideal Realistic benchmark to −\$87.48 in the strictest bundle.

Stricter rules also increase positive-edge representation among passers and payout recipients. That improvement is not free: the selected group becomes smaller and false negatives increase. Contract design therefore determines both financing and selection.

The practical implication is simple. Comparing evaluations requires the full rule package, a path model, and a payout function. Anything less can miss the mechanism that determines the result.

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Appendix A. Rule State Definitions

For each path, the engine stores:

Table A1. Rule-engine state variables

State	Definition
$X_{d,k}$	Cumulative P&L
$X_{d,0}$	P&L at day start
$M_{d,k}^{ID}$	Intraday high-water mark
M_d^{EOD}	End-of-day high-water mark
$L_{d,k}$	Current loss floor

State	Definition
g_{max}	Best positive daily P&L
d	Trading-day count
Stage	Evaluation or funded
$W(X^F)$	Available payout before participant share

Note: These variables are the minimum state required by the declared event order; alternative commercial implementations may maintain additional state.

The engine does not track positions, instruments, commissions, unrealized versus realized P&L, or exchange-session conventions. All inputs arrive as account-level P&L increments.

Appendix B. Deterministic Hand Tests

Table B1. Deterministic rule-engine tests

Test	Expected behavior	Validation status
Static target	A path reaching \$3,300 passes on day 3	Passed
Minimum days	The same path waits until day 5	Passed
Daily loss	A \$1,100 same-day loss breaches a \$1,000 limit	Passed
Trailing update	Intraday high tightens immediately; EOD waits	Passed
Consistency	A \$2,500 best day exceeds 50% of \$3,000 total	Passed

Note: Each deterministic path tests one declared rule behavior. Passing these tests validates implementation against the stated semantics, not against a named provider.

The tests verify code behavior against the declared semantics. They do not validate the semantics against any named commercial implementation.

Appendix C. Pathwise Counterfactual Logic

Let $R_j(\omega)$ be the outcome of applying contract j to standardized path ω . The marginal pass effect of rule j relative to I1 is

$$\Delta p_j = \frac{1}{N} \sum_{n=1}^N \left[1\{R_j(\omega_n) = \text{pass}\} - 1\{R_{I1}(\omega_n) = \text{pass}\} \right].$$

Because the same ω_n appears in both terms, the estimator focuses on paths whose classification changes. Independent simulations would estimate the same expectation in principle but with more comparison noise.

For packages, Δp is a joint effect. It should not be decomposed additively unless interaction terms are modeled.

Appendix D. Anonymized Market-Rule Review

The contract taxonomy was informed by a dated review of public terms from multiple retail trading-evaluation programs. The review recorded whether each source used a static, end-of-day trailing, or intraday trailing loss method; whether a daily-loss limit applied; whether minimum trading days or consistency conditions existed; and whether payouts were subject to days, buffers, caps, or shares.

The public programs are not named in this manuscript or reproduced as rows in the model. Parameter values were recombined rather than copied as complete packages. This choice prevents identification but limits external replicability of the market-calibration step. The mathematical and simulation results remain fully reproducible for the synthetic contracts supplied.

Declarations

Funding. No external funding was received for this research.

Conflicts of interest. No financial or commercial ties exist with any trading-evaluation provider. The contracts analyzed here are synthetic and do not represent named providers.

Supplementary materials. The rule-engine code, contract parameters, simulated aggregate outputs, workbook, and figure-generation materials are available on Zenodo: <https://doi.org/10.5281/zenodo.22770436>.

Use of synthetic data. No customer-level or provider-confidential data are used. Contracts, trader types, and P&L paths are synthetic.