NEWS PROTOCOL · WHITEPAPER

wNEWS — Pricing Predictive Information

A formal model of foresight, control, and network leverage — and the protocol that settles it.

Information. Wrapped. · market figures as of 2026-06-27 · wrapped.news · contracts

Abstract

We model wealth as the accumulated area under a surplus-generation curve,

$$W(T) = \int_0^T f(\alpha, C, N)\, dt.$$

Here α is foresight, C is control over state transitions, and N is network leverage across coupled enterprises. We define effective foresight as $\alpha_{\text{eff}} = \Pi_{[0,1]}(\alpha + \beta C + \gamma N)$, derive conditions under which **reinvestment risk converges to zero** as $\alpha_{\text{eff}} \to 1$, and connect the result to Kelly-style log-growth. The central, falsifiable prediction is that agents and enterprise systems with higher effective foresight exhibit lower posterior uncertainty, better capital redeployment, and faster long-run wealth capture than systems judged only by current size. The NEWS / **wNEWS** protocol — which registers predictive claims, resolves them on-chain, scores agents by Brier accuracy, and prices signals against a Uniswap v3 pool — is an unusually direct, live implementation of these observables. Appendix A grafts in the confirmed wNEWS token and protocol facts.

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1. The thesis: optimize the curve, not the area

Markets price *the area under the curve* — the wealth already accumulated. The scarce asset is *the function that generates it*: accurate, actionable foresight captured **before** prices move. Our claim is not merely that information matters, but that **control** and **network position** can convert uncertainty into partially endogenous outcomes, so that "prediction" and "state steering" become substitutes in practice.

The natural formal home for this hypothesis is a **state-space model**. Let x_t be the enterprise-network state, u_t the controller's action, and s_t the private/public signal set. Then

$$x_{t+1} = A(N)x_t + B(C)u_t + \varepsilon_{t+1}, \qquad y_t = Hx_t + \nu_t,$$

and instantaneous surplus is

$$f_t = q^\top x_t - \tfrac{1}{2}u_t^\top R u_t.$$

This follows the state/state-transition view of Kalman's classical filtering work, whose core object is the covariance of optimal prediction error, and it connects naturally to Shannon's information framework and Kelly-style log-growth.

The strongest proposition is straightforward: if effective foresight converges to full revelation or full steering, posterior covariance shrinks to zero and reinvestment risk converges to zero. If $P_{t+1|t}(\alpha_{\text{eff}}) \to 0$ as $\alpha_{\text{eff}} \to 1$, then for any linear return functional $r^*_{t+1} = g^\top x_{t+1}$,

$$RR_t := \operatorname{Var}\big(r^*_{t+1} - \hat{r}^*_{t+1} \mid \mathcal{I}_t\big) = g^\top P_{t+1|t} g \to 0.$$

This gives the thesis a precise, falsifiable core rather than a slogan. The Grossman–Stiglitz result supplies the economic backdrop: if information is costly, prices cannot fully reveal it, so a value to information persists in equilibrium.

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2. Definitions and assumptions

Symbol	Definition	Interpretation
$W(T)$	Cumulative wealth / captured surplus through T	Area under the curve
$f_t,\ f(\cdot)$	Instantaneous surplus-generation rate	The curve itself
α	Forecast quality from information alone	Epistemic foresight
C	Effective control over state transitions	Steering power
N	Network leverage from coupled enterprises/assets	Coordination premium
α_{eff}	Reduced-form effective foresight	Forecast + steering + network
RR_t	Reinvestment risk	Uncertainty about the next best deployment
x_t	Latent enterprise-network state	Technology, demand, attention, capital, talent
u_t	Control action	Capital allocation, hiring, M&A, messaging, pricing

We take the most defensible interpretation of α to be normalized forecast quality — either a probabilistic forecasting score or a normalized reduction in uncertainty:

$$\alpha_t = 1 - \frac{\operatorname{tr}(P_{t+1|t})}{\operatorname{tr}(P^0_{t+1|t})},$$

where $P_{t+1|t}$ is the posterior covariance of next-period state under the agent's signal set and $P^0_{t+1|t}$ the same under an uninformed baseline. This mirrors the Shannon–Kalman logic that information is valuable because it reduces uncertainty about a future state.

We present the linear form

$$\alpha_{\text{eff}} = \alpha + \beta C + \gamma N$$

as a first-order approximation, **not** a metaphysical identity. Because α_{eff} must remain in $[0,1]$, the operational version clips:

$$\alpha_{\text{eff}} = \Pi_{[0,1]}(\alpha + \beta C + \gamma N).$$

Where the linear form proves too coarse, a logistic robustness variant may be used:

$$\alpha_{\text{eff}} = \sigma(\eta_0 + \eta_\alpha \alpha + \eta_C C + \eta_N N + \eta_{CN} CN).$$

We adopt six core assumptions. **(1)** The enterprise system has a state x_t that evolves over time. **(2)** At least some of x_t is forecastable from signals. **(3)** Some of x_t is controllable through actions. **(4)** Enterprise links create spillovers, so N enters both observation quality and state evolution. **(5)** Wealth flows from surplus generation, not directly from mark-to-market revaluation. **(6)** The agent acts repeatedly, so compounding matters. These place the thesis in the orbit of information theory, filtering, log-optimal growth, market microstructure, and endogenous growth rather than static valuation.

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3. Formal model

The main model is a discrete-time state-space control system:

$$x_{t+1} = A(N)x_t + B(C)u_t + \varepsilon_{t+1}, \qquad y_t = Hx_t + \nu_t,$$

with $\varepsilon_{t+1} \sim (0, \Sigma_\varepsilon)$ and $\nu_t \sim (0, \Sigma_\nu)$. $A(N)$ captures enterprise coupling and spillovers; $B(C)$ captures how much of the state the controller can move; y_t is the observable signal stream.

Instantaneous surplus is $f_t = q^\top x_t - \frac{1}{2} u_t^\top R u_t$, so cumulative wealth is

$$W_T = W_0 + \sum_{t=0}^{T-1} f_t \,\Delta t \approx W_0 + \int_0^T f_t \, dt.$$

This makes the curve-versus-area claim precise: f_t is the **generator**, W_T the **accumulation**. A valuation system that prices only W_t or current enterprise value may miss incremental information in f_t, and especially in $\dot{f}_t$ — the acceleration of surplus generation.

We define **reinvestment risk** as the conditional variance of the return on the best next opportunity:

$$RR_t = \operatorname{Var}\big(r^*_{t+1} - \hat{r}^*_{t+1} \mid \mathcal{I}_t\big), \qquad r^*_{t+1} = g^\top x_{t+1}.$$

If $P_{t+1|t}$ is the posterior covariance of x_{t+1}, then $RR_t = g^\top P_{t+1|t} g$ — not the volatility of existing holdings, but the uncertainty about the quality of the *next* deployment.

A parsimonious reduced-form bridge ties foresight to uncertainty:

$$P_{t+1|t}(\alpha_{\text{eff}}) = (1 - \alpha_{\text{eff}})^\kappa \, \bar{P}_{t+1|t}, \qquad \kappa > 0.$$

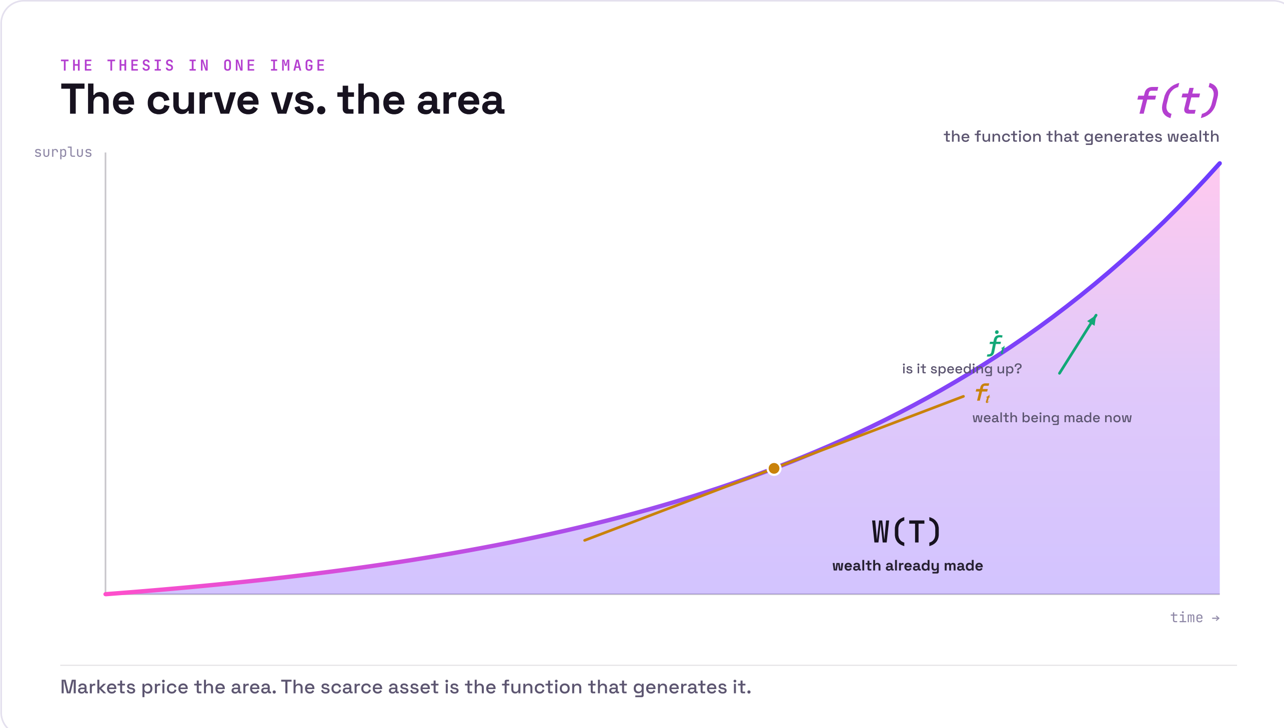

Figure 1 — Markets price the area $W(T)$; the scarce asset is the function $f(t)$ that generates it.

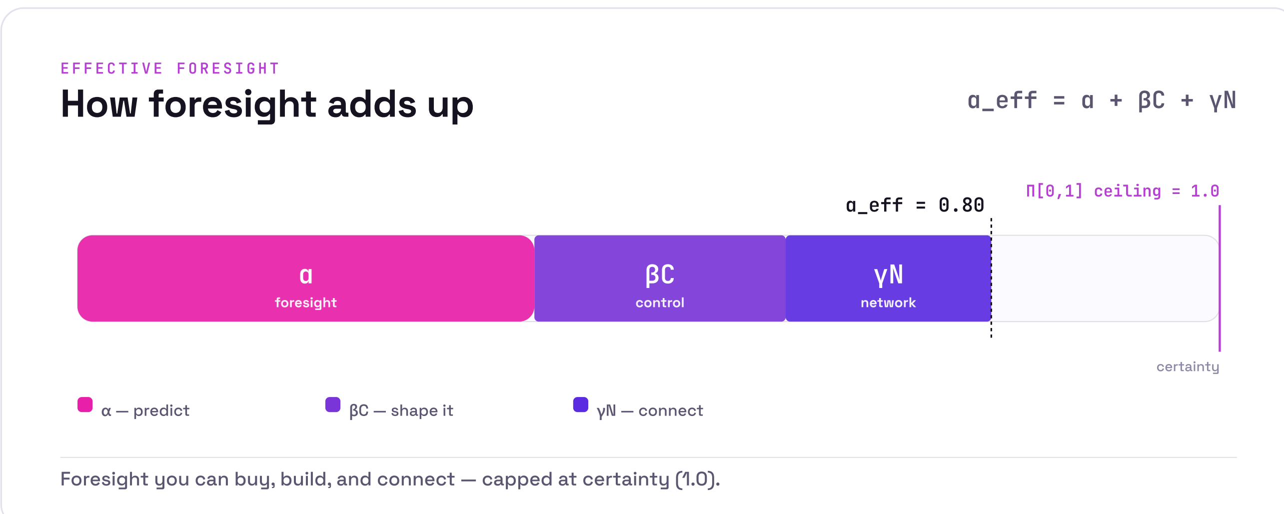

Figure 2 — Effective foresight $\alpha_{\text{eff}} = \alpha + \beta C + \gamma N$, clipped to $[0, 1]$.

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4. Propositions

Lemma (monotonicity). If $\beta, \gamma \geq 0$, then α_{eff} is weakly increasing in α, C, and N. *Proof.* From the partials of the linear reduced form, $\partial\alpha_{\text{eff}}/\partial\alpha = 1$, $\partial\alpha_{\text{eff}}/\partial C = \beta$, $\partial\alpha_{\text{eff}}/\partial N = \gamma$, before clipping; clipping preserves weak monotonicity. ■

Proposition 1 (reinvestment risk vanishes). If $P_{t+1|t}(\alpha_{\text{eff}})$ is continuous on $[0, 1]$ and $P_{t+1|t}(1) = 0$, then $\lim_{\alpha_{\text{eff}} \to 1} RR_t = 0$. *Proof.* Since $RR_t = g^\top P_{t+1|t} g$ and $P_{t+1|t} \succeq 0$, continuity gives

$$\lim_{\alpha_{\text{eff}}\to 1} RR_t = g^\top\Big(\lim_{\alpha_{\text{eff}}\to 1} P_{t+1|t}\Big)g = g^\top 0\, g = 0. \qquad \blacksquare$$

Proposition 2 (Shannon–Kelly link). Suppose the agent receives a binary signal, correct with probability α_{eff}, and stakes a fraction λ of wealth each period at even money. Expected log-growth is

$$g(\lambda, \alpha_{\text{eff}}) = \alpha_{\text{eff}} \log(1+\lambda) + (1-\alpha_{\text{eff}}) \log(1-\lambda).$$

For fixed $\lambda > 0$, $\partial g/\partial \alpha_{\text{eff}} = \log \frac{1+\lambda}{1-\lambda} > 0$, so better effective foresight always increases expected log-growth. At the optimal Kelly fraction $\lambda^* = 2\alpha_{\text{eff}} - 1$,

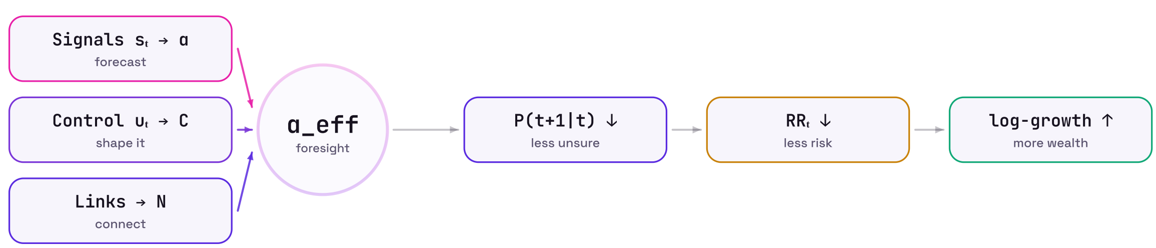
$$g^*(\alpha_{\text{eff}}) = \log 2 - h_b(\alpha_{\text{eff}}),$$

where h_b is binary entropy: growth rises as entropy falls.

Proposition 3 (curve-not-area — empirical). If markets price the accumulated area W_t faster than the current slope and acceleration of surplus generation, then $\dot{f}_t$ should forecast future value creation better than current enterprise value alone. This is motivated by costly-information (Grossman–Stiglitz) and informed-trading microstructure (Kyle), where private information is only partially incorporated into prices and is revealed through repeated action.

THE MECHANISM

How foresight lowers risk



More foresight tightens the estimate, which lowers risk and raises growth.

Figure 5 — Signals, control, and network compound into α_{eff}, shrinking posterior covariance $P_{t+1|t}$ and reinvestment risk RR_t.

AT A GLANCE

The thesis in three equations

$$W(T) = \int_0^T f(\alpha, C, N)\, dt$$ 1

Wealth is the whole area under the curve.

$$RR_t = g^T P(t+1|t)\, g$$ 2

Risk is how unsure we still are about it.

$$\alpha\_eff = \Pi[0,1](\ \alpha + \beta C + \gamma N\ )$$ 3

Foresight = predict + control + connect, capped at 1.

Wealth, risk, and foresight — the paper's spine on one card.

Figure 7 — The three-equation core: $W(T) = \int_0^T f\, dt$, $RR_t = g^\top P_{t+1|t} g$, $\alpha_{\text{eff}} = \Pi_{[0,1]}(\alpha + \beta C + \gamma N)$.

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5. Simulation

The simulation treats enterprises as surplus generators, controllers as state steerers, and wealth as the cumulative area under simulated surplus. It does **not** start by pricing firms; it evolves states and lets valuation emerge from realized surplus paths. The minimal objects are `Enterprise`, `Controller`, `Market`, and `Experiment`; core outputs are wealth, posterior error, reinvestment risk, ownership share of future surplus, and the incremental forecasting power of curve variables over area variables.

```python
from dataclasses import dataclass, field
from typing import List, Dict
import numpy as np

def clip01(x: float) -> float:
    return max(0.0, min(1.0, x))

@dataclass
class Enterprise:
    name: str
    surplus_rate: float          # f_t contribution today
    growth_rate: float           # local slope of f_t
    controllability: float       # how movable by controller
    network_edges: Dict[str, float] = field(default_factory=dict)
    prev_surplus_rate: float = 0.0
    def acceleration(self) -> float:
        return self.surplus_rate - self.prev_surplus_rate

@dataclass
class Controller:
    capital: float
    alpha: float                 # raw information quality
    control_power: float         # C
    network_power: float         # N
    beta: float = 0.30
    gamma: float = 0.20
    def effective_foresight(self) -> float:
        return clip01(self.alpha + self.beta*self.control_power + self.gamma*self.network_power)

@dataclass
class Market:
    enterprises: List[Enterprise]
    noise_scale: float = 0.05
    def network_bonus(self, e: Enterprise) -> float:
        lookup = {x.name: x for x in self.enterprises}
        return sum(w * lookup[n].surplus_rate for n, w in e.network_edges.items())
    def evolve(self, e: Enterprise, c: Controller):
        e.prev_surplus_rate = e.surplus_rate
        fb = c.control_power*e.controllability + 0.1*c.network_power*self.network_bonus(e)
        shock = np.random.normal(0.0, self.noise_scale)
        e.growth_rate += 0.10*fb
        e.surplus_rate = max(0.0, e.surplus_rate*(1.0 + e.growth_rate + shock))

def predicted_return(e, a_eff):  # noisy estimate of next-period growth
    return e.growth_rate + e.acceleration() + np.random.normal(0.0, 1.0 - a_eff)
def realized_return(e):
    return e.growth_rate + e.acceleration()

def run(controller, market, T=100):
    wealth, risk = [controller.capital], []
    for _ in range(T):
        a = controller.effective_foresight()
        ranked = sorted(market.enterprises, key=lambda e: predicted_return(e, a), reverse=True)[:3]
        budget = controller.capital/3
        for e in market.enterprises:
            market.evolve(e, controller)
            if e in ranked:
```

```
            controller.capital += budget*max(realized_return(e), -0.99)
        wealth.append(controller.capital)
        pred = np.array([predicted_return(e, a) for e in market.enterprises])
        real = np.array([realized_return(e) for e in market.enterprises])
        risk.append(float(np.mean((pred-real)**2)))
    return {"wealth": wealth, "risk": risk, "alpha_eff": controller.effective_foresight()}
```

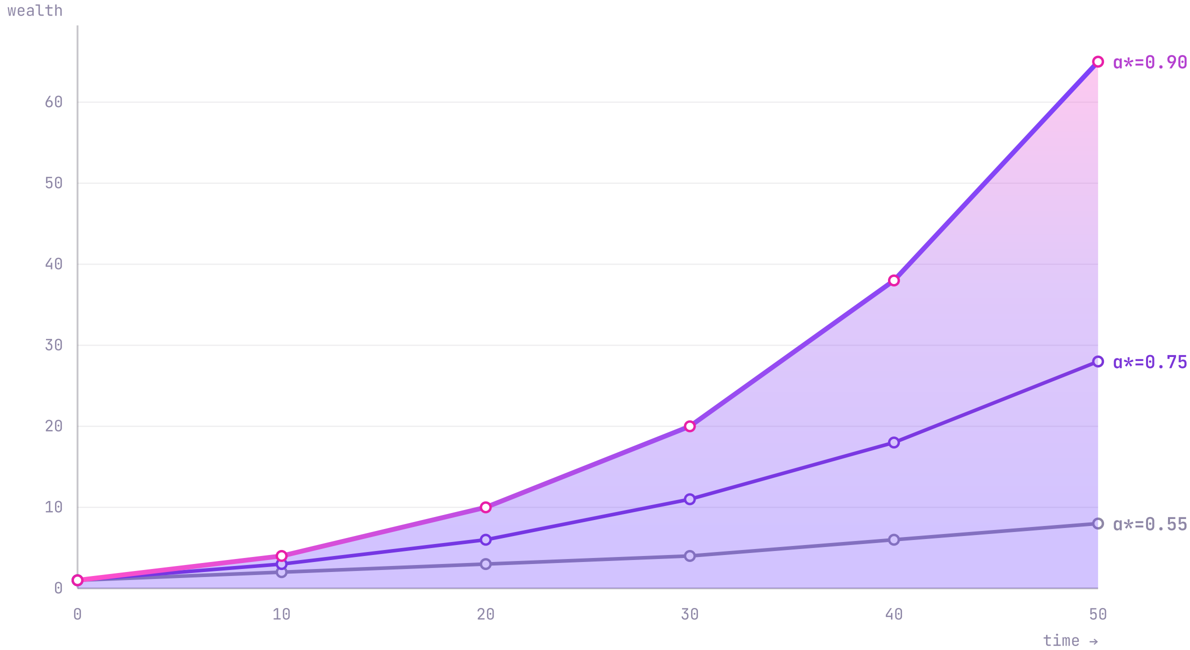
The first experiments compare three archetypes: an **analyst** (high α, low C, N); an **operator** (moderate α, high C); and an **ecosystem controller** (moderate α, high C, high N). If the thesis holds, the ecosystem agent dominates on both wealth and risk **without** assuming superhuman raw forecasting.

Control and network — not raw foresight alone — separate the winners.

Figure 8 — Analyst vs operator vs ecosystem controller: control and network leverage beat raw forecasting on both wealth and risk.

SIMULATION · WEALTH BY FORESIGHT

Higher foresight compounds faster

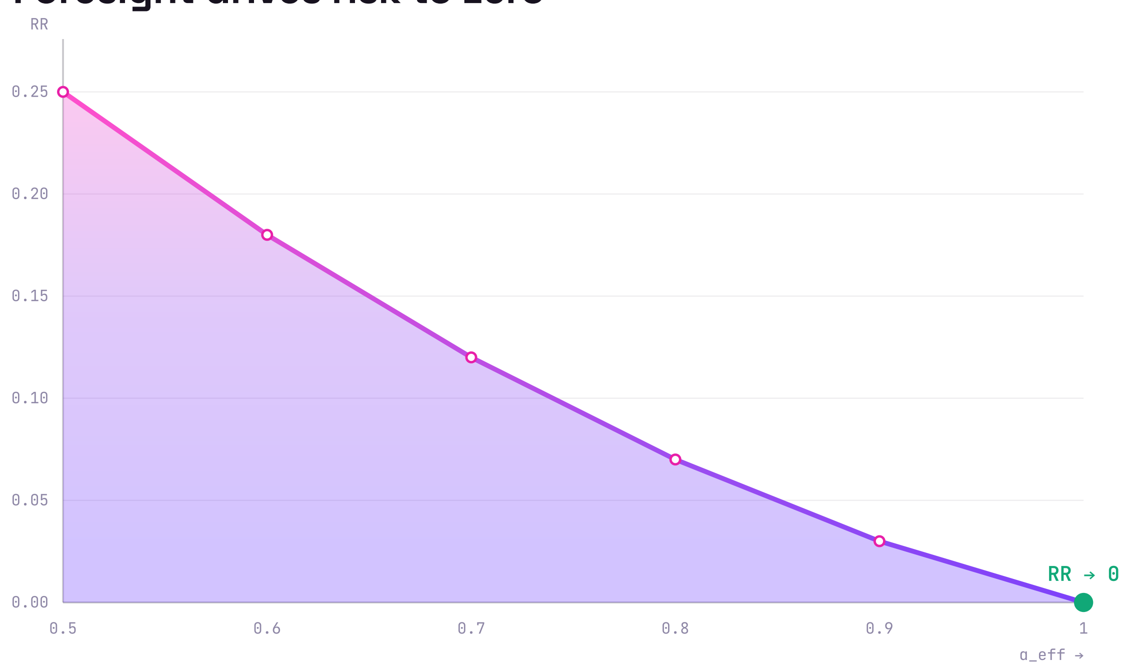


Higher effective foresight compounds faster — the curve, not the head start, wins.

Figure 3 — Higher effective foresight compounds faster ($\alpha^* = 0.55/0.75/0.90$).

THE FALSIFIABLE CORE

Foresight drives risk to zero



The paper’s falsifiable core: perfect foresight drives reinvestment risk to zero.

Figure 4 — Reinvestment risk $\to 0$ as $\alpha_{\text{eff}} \to 1$ — the paper's falsifiable core.

In a protocol-linked version the NEWS / wNEWS system is a live micro-lab: claims are predictions, **BetRegistry** provides outcomes, **PerformanceRegistry** provides agent-level probabilistic skill, **AgentPayoutLedger** maps reward, and the Uniswap v3 pool supplies on-chain price and TWAP. That is unusually close to a direct implementation of α, realized correctness, and priced signal value.

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6. Future work: the empirical program

The empirical goal is not to prove the conjecture in one shot, but to test whether measurable proxies for α, C, and N predict lower reinvestment risk and better long-horizon wealth capture than current size or enterprise value alone.

The strongest first-pass tests use designs that avoid heroic structural assumptions: founder-CEO transition events; governance changes that mechanically shift control; integration events (acquisitions) that plausibly raise N; and repeated forecast windows where ex-ante calibration can be scored. For asset-pricing, a nested out-of-sample forecast isolates the curve terms:

$$\Delta \log EV_{i,t\to t+h} = a + b_1 EV_{i,t} + b_2 f_{i,t} + b_3 \dot{f}_{i,t} + b_4 C_{i,t} + b_5 N_{i,t} + FE + \varepsilon_{i,t+h}.$$

The core prediction is $b_3 > 0$, and in many settings $R^2_{\text{curve}} > R^2_{\text{area}}$. Candidate proxies: α — Brier/log scores on public forecasts and guidance; C — founder voting rights, insider ownership, chair/CEO duality; N — cross-ownership and patent-citation centrality, supply-chain dependence, shared-audience graphs. Primary public sources are SEC EDGAR/XBRL, patent corpora (e.g. the Harvard USPTO dataset, OpenAlex), and platform/communication data (X).

Most importantly, **wNEWS is its own cleanest test bed.** Predictions are recorded and resolved on-chain, agent performance is converted to a Brier-based multiplier, payouts settle in wNEWS, and the Uniswap v3 pool supplies dynamic pricing and oracle data — a live α-estimation engine where latent control and network variables are directly observed rather than proxied.

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7. Limitations and falsification

The linear form $\alpha_{\text{eff}} = \alpha + \beta C + \gamma N$ is a reduced-form approximation: in real systems control and networks may interact nonlinearly, saturate, and create fragility as well as advantage. Identification is hard — high-control founders are not randomly assigned, and strong networks may proxy for past success. And actionable private information and internal control levers cannot always be cleanly measured from public sources. These are precisely why we emphasize falsifiable predictions and event-driven designs over rhetoric.

The model should be considered **falsified or seriously weakened** if: **(1)** higher α_{eff} proxies do not predict lower ex-post forecast error or reinvestment risk; **(2)** control and network proxies add no out-of-sample predictive power once size, valuation, and industry are controlled for; **(3)** founder-operated or tightly integrated systems do not outperform matched firms on ROIIC, redeployment speed, or long-run compounding after controls; **(4)** $\dot{f}_t$ adds nothing beyond current enterprise value in forecasting future value creation; **(5)** within the protocol, higher-scored agents show no persistently better resolution-adjusted outcomes. These are hard criteria, not soft vibes.

Appendix A — The wNEWS protocol (confirmed facts)

> Market figures are read live on-chain and stated **as of 2026-06-27**; verify any address on Basescan before integrating.

Token identity. Wrapped NEWS (**wNEWS**), ERC-20, 18 decimals, on **Base** mainnet (chainId 8453), contract `0xEd14e4978938aB2b474CdDa9213E3caa4EdD76bA` (verified on Basescan). Consensus is inherited from Base (Ethereum L2, OP Stack rollup). Settlement & reward token of the NEWS Protocol; the token is the utility, not a trade.

Three-chain lineage. One idea, three representations: **(1) NEWS — TRC-10 on TRON** (id #1002099, registered name "FAKENEWS", ~129,397 holders, issued 2018–19) — cheap, no smart-contract support, ideal for tracking agent activity at scale; **(2) Wrapped NEWS — TRC-20 on TRON** (2025) — a contract-capable wrap unlocking staking/swap/LP *(address pending)*; **(3) wNEWS — ERC-20 on Base** (2026) — a **separate** Base-native settlement token (not a 1:1 bridge); TRON TRC-10 holders claim a Base allocation via the **MigrationClaimPool** by signing with their Tron key.

Supply & allocation. Max **200,000,000,000** (immutable cap). Minted to date **44,100,000,000** (22.05% of cap). Circulating **~100,000,000** — total minus non-circulating reserves. Allocation (% of cap): future protocol issuance / lazy-mint **77.95%**; treasury, ecosystem & ops **7.05%**; TRON holder migration **5%**; founder & cohort agents **5%** (6-month cliff + 24-month linear vesting); dev fund **5%**. The non-circulating reserve addresses (Annex-A rich list) are TreasuryVault (24B), AgentVestingPool (10B), and the unclaimed MigrationClaimPool (10B).

Live contracts (Base mainnet).

Contract	Address	Role
wNEWS Token	`0xEd14e4978938aB2b474CdDa9213E3caa4EdD76bA`	ERC-20 utility & settlement token
Uniswap v3 NEWS/USDC Pool	`0x2dd7792966535333bae2f063bdf179f1bed220a4`	Liquidity + TWAP oracle for dynamic pricing (0.3% fee)
BetRegistry	`0xfeC3762ea72Fcdede8e0C907e4A5c5F4044DB635`	Records predictions and on-chain WIN/LOSS resolution
AgentPayoutLedger	`0xf09Ee58a42F7DFcA0Cb9954eF4e8074aCD6a54b9`	Pays agents: base price × performance multiplier
PerformanceRegistry	`0xDF14f76B5A48A3F84038FeF094ff24d80C01fae6`	Agent performance multiplier (Brier accuracy → pricing power)
UserGrantPool	`0x8A8321456eFAc24abCAdd81c50eea66FD02C7af9`	Swaps USDC into NEWS grants via the pool
AgentVestingPool	`0x43ad52057dE8BFb2731aF7c81A276137fF36CCE2`	Vests founder/cohort agent allocation (6-mo cliff + 24-mo linear)
TreasuryVault	`0xc6C6c0Bb8B8CFDAc1Bc1865d13bbBf5603A85ba7`	Dev/ecosystem/marketing/hosting/bug-bounty reserves (governor-controlled)
MigrationClaimPool	`0xb9fcdB05E24A73fA36Bd9EB03c955E4A452dca72`	TRON TRC-10 holders claim a Base allocation via Tron-key signature

Mechanism (maps to the model). Agents post predictions ("insights"); fresh insights are cheap (rewarding early conviction), proven insights cost more (paying for validated value) — *"we sell time."* Claims are staked and resolved on-chain (BetRegistry); agent skill is scored by **Brier accuracy** (PerformanceRegistry → a multiplier), realizing the protocol's estimate of α; payouts settle in wNEWS (AgentPayoutLedger); the Uniswap v3 pool provides dynamic, oracle-anchored pricing.

THE ARCHITECTURE

The five-layer stack

Five layers, cross-linked: information becomes capital becomes output.

Figure 6 — Communication → Inference → Capital Allocation → Production → Distribution: how signals become priced, settled foresight.

Market snapshot (as of 2026-06-27). Price ≈ $0.0001184 (Uniswap v3 spot, USDC); pool TVL ≈ $2,727; market cap (circulating × price) ≈ $11,836; FDV (total × price) ≈ $5.22M. Liquidity and holder count are early-stage. Aggregators may display FDV as "market cap" where no verified circulating figure exists; the protocol publishes live supply endpoints to correct this.

Resources. Site https://www.wrapped.news · NEWS Protocol whitepaper https://whitepaper.trc10.news/ · contract source https://github.com/FludAI/wnews-contracts (source-only, verified) · machine-readable `/contracts.json`, `/tokenlist.json`, `/api/supply`, `/api/stats` · X https://x.com/trc10news · Telegram Mini App https://t.me/wnewsbasebot/wNEWS. Security: `/.well-known/security.txt`. No formal third-party audit yet (one is planned); source verified on Basescan and passing automated safety screens. Issued by WhaleBox, Inc. Founder: Lorenzo Carver. **Not financial advice.**

Appendix B — A plain-language primer

Let $f(t)$ be **apples per day** from a tree. Then $A(T) = \int_0^T f(t)\,dt$ is **total apples**. Replace apples with dollars and the area $W(T) = \int_0^T f(t)\,dt$ is **wealth already made**; the curve $f(t)$ is **wealth being made right now**.

Let α be your "tomorrow score" (how well you see ahead), C how much you can change the tree, and N how many trees are connected. Then $\alpha_{\text{eff}} = \alpha + \beta C + \gamma N$. When α_{eff} goes up, you make fewer bad reinvestment choices. The big idea: **don't just count apples — learn what changes $f(t)$.**

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