MARKET INVARIANTS EMERGE FROM ALPHAEVOLVE: DISCOVERING UNIVERSAL TECHNICAL INDICATORS

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ABSTRACT

Technical indicators remain foundational to systematic trading, yet the canonical set used across industry—RSI, MACD, ATR, Bollinger Bands—has changed little in four decades despite profound shifts in market microstructure. Modern markets exhibit heavy tails, volatility clustering, jump discontinuities, regime fragmentation, microstructure noise, and strong cross-sectional heterogeneity. These properties render classical, hand-engineered indicators structurally inadequate for today's high-dimensional, nonstationary financial environments. This paper introduces EVOSIGNAL, a fully autonomous framework that discovers technical indicators through evolutionary search guided by a large language model (LLM). Each indicator is represented as a vectorized PyTorch function, evolved through mutation, crossover, simplification, and selection. Candidates are evaluated across millions of sliding windows and thousands of assets using a robustness-centric scoring function that rewards median performance, penalizes instability, and emphasizes excess returns. This cross-asset, cross-period evaluation regime applies intense evolutionary pressure toward indicators that express genuine structural regularities rather than market- or window-specific artifacts. Across independent evolutionary runs on crypto assets and foreign exchange pairs, the system converges on a shared architectural backbone consisting of: (1) entropy-modulated momentum, (2) volatility-adaptive scaling, (3) tail-conditioned robustness modules, (4) multi-window ensemble structures, (5) kernel-based trend validation, and (6) multiplicative regime-aware gating. These motifs emerge repeatedly as evolutionary attractors—stable functional forms that maximize generalization across assets, horizons, and market states. Despite this shared backbone, EVOSIGNAL also discovers systematic divergences driven by the specific microstructure of each asset class: crypto indicators feature aggressive tail clipping, entropy-first gating, microstructure-sensitive validation, and short-horizon responsiveness, while FX-optimized variants emphasize smoother dispersion metrics, long-horizon persistence, macro-cycle alignment, and softer volatility gating. These differences arise not from stochastic noise but from consistent evolutionary adaptation to the structural physics of each market. The results demonstrate that autonomous LLM-driven evolution can rediscover deep, universal principles of price formation while simultaneously tailoring functional forms to market-specific microstructure.

1 INTRODUCTION

Technical indicators form the conceptual backbone of systematic trading, providing the signals that operationalize hypotheses about price dynamics, regime structure, and market predictability. Despite their central role in both discretionary and quantitative trading, the vast majority of widely used indicators—RSI, MACD, Bollinger Bands, ATR, KAMA, stochastic oscillators—were introduced between 1970 and 2000, during an era characterized by lower-frequency trading, simpler market microstructure, and vastly different liquidity conditions than those observed today. Over the last two decades, markets have undergone dramatic transformations: crypto markets have introduced 24/7 trading, extreme volatility clustering, microstructure discontinuities, and heavy-tailed liquidation cascades, while FX markets have evolved toward high-frequency institutional flows, ultra-stable macro cycles, and persistent mean-reverting microstructure noise. These shifts render classical indicators structurally inadequate because they are hand-designed, single-horizon, non-adaptive, and blind to microstructure regimes and tail risk. This paper introduces **EvoSignal**, a fully autonomous system that discovers technical indicators from scratch through an LLM-driven evolutionary process, which departs from traditional indicator design paradigms in two fundamental ways:

1. **Indicators are not human-engineered.** They emerge from an open-ended evolutionary search over vectorized PyTorch functions, mutated and recombined automatically.
2. **Indicators are selected for cross-asset, cross-period robustness.** Our scoring objective penalizes fragility, rewards asymmetric positive-return dominance, and evaluates signals across thousands of assets and millions of sliding windows.

This robustness-centric evolutionary framework acts as a powerful selection mechanism. It eliminates indicators that exploit rare patterns, overfit to single assets, or depend on unstable windows. Instead, evolution converges toward a set of universal functional motifs—structures that consistently produce stable, predictable signals across radically different markets. A striking discovery of this work is that indicators optimized separately on crypto and FX converge toward the same architectural backbone, despite the profound microstructure differences between the two environments. Both independently evolved indicators employ: entropy-modulated multi-scale momentum, volatility-adaptive normalization, tail-aware robustness modules, multi-window ensemble structures, multiplicative regime gating, and kernel-based trend validation. These motifs appear repeatedly across evolutionary runs, suggesting the presence of evolutionary attractors—functional structures that maximize cross-period predictability regardless of the underlying asset class. Yet, despite this shared backbone, the crypto-optimized and FX-optimized indicators exhibit systematic divergences driven by microstructure constraints. Crypto indicators respond to jump discontinuities, violent volatility explosions, liquidity cliffs, and volume-driven orderflow asymmetries. FX indicators adapt to smoother volatility regimes, macrocycle drift, dispersion compression, and mean-reverting microstructure noise. These divergences are not contradictions to universality. They represent environment-specific deformations of the same underlying invariant functional template.

Thus, EvoSignal reveals a deeper truth: *Financial markets share universal predictability structure, but express that structure through microstructure-specific statistical surfaces.* This duality—shared invariants and unique deformations—bridges two longstanding perspectives in quantitative finance: (1) the generalist view that markets share common structural laws (volatility clustering, heavy tails, autocorrelation decay), and (2) the specialist view that each market has unique microstructure and requires bespoke models. EVOSIGNAL shows that both are correct. Indicators must be universal in architecture and specialized in parameterization and gating rules. In this paper, we:

- Formally define the evolutionary discovery framework and the indicator search space.
- Identify and characterize universal structural motifs in evolved indicators, and analyze systematic divergences between crypto-optimized and FX-optimized indicators.
- Explain why they converge to universal invariants but diverge in microstructure-specific ways, and demonstrate their empirical robustness across assets and regimes.

These contributions position EVOSIGNAL as a new paradigm for autonomous quantitative research and a scientific framework for reverse-engineering the structural laws that govern price formation. In effect, EVOSIGNAL serves as an empirical counterpart to financial microstructure theory. Whereas classical theory posits assumptions, EVOSIGNAL discovers functional truths directly from data. This positions EVOSIGNAL not only as an indicator-generation framework but also as a new paradigm for scientific discovery in finance, akin to how EvoRisk revealed the structure of risk metrics.

2 RELATED WORK

Classical technical indicators such as RSI, MACD, Stochastic Oscillators, Bollinger Bands, ATR, and KAMA constitute the dominant toolkit in retail and even institutional momentum/trend trading. These indicators encode fixed formulas involving recent price ranges, moving averages, or volatility proxies, and they implicitly assume: low-frequency price sampling, Gaussian or near-Gaussian return distributions, stationarity of volatility, smooth microstructure behavior, and relatively stable trend persistence. However, modern electronic markets—especially 24/7 crypto exchanges and high-liquidity HFT-driven FX markets—violate nearly all of these assumptions:

- Returns exhibit heavy-tails, jumps, and volatility asymmetry.
- Microstructure noise dominates short horizons.
- Regimes shift abruptly.
- Dispersion and liquidity vary across time-of-day and calendar effects.
- Volume, orderflow, and volatility surfaces show non-linear interactions.

Consequently, classical indicators often collapse under these conditions, producing unreliable or biased signals, excessive whipsaws, or structurally unstable outputs. Their failure stems from the fact that their formulas are static, manually crafted, and non-adaptive—limiting their ability to model the nonstationary, multi-scale nature of real markets. In contrast, EVOSIGNAL discovers indicator structures from data itself and enforces robustness through large-scale cross-asset and cross-regime evaluation pressure, sidestepping the constraints of human-designed heuristics.

While machine-learning (ML) approaches can capture complex non-linear dynamics, they face three critical issues: (1) ML models are not interpretable as standalone indicators; they produce predictions, not tradable technical signals (2) Without strong cross-asset robustness tests, ML models learn idiosyncratic patterns that do not generalize (3) Many quant workflows require signals to be differentiable, stable, vectorized indicators; large neural nets are difficult to integrate. EVOSIGNAL avoids these issues by constraining the search space to vectorized PyTorch expressions—lightweight, easily interpretable, and compatible with GPU-based backtesting—while still allowing highly non-linear transformations and adaptive rules traditionally impossible to design manually.

AlphaEvolve (Novikov et al., 2025) transforms LLMs from static text generators into *active, self-improving research agents* capable of iteratively generating, executing, and refining executable programs. Rather than optimizing a single function, it performs multiobjective evolution over entire codebases, guided by machine-executable evaluation metrics and large-scale feedback loops. Across domains—GPU kernel optimization, compiler IR rewriting, combinatorial search, and algorithmic heuristics—AlphaEvolve has demonstrated that LLM-driven evolutionary programming can rediscover or surpass human-engineered algorithms when evaluation pressure is sufficiently strong. We build on this paradigm by applying the same principles to quantitative finance: the LLM proposes indicator variants, the evaluation engine subjects them to cross-asset cross-regime stress tests, and the evolutionary loop converges toward generalizable, non-human-designed signal architectures.

Evolutionary algorithms have historically been applied to trading strategy optimization: (1) Genetic programming for rule discovery, (2) Symbolic regression for trading rules, (3) Genetic algorithms for parameter tuning, and (4) Neuro-evolution for trading policies. However, these systems typically operate on predefined grammars, restricted syntactic templates, or small sets of indicator primitives. Moreover, they often optimize for raw PnL, Sharpe, or hit rate—objectives highly prone to overfitting and sensitive to backtest artifacts. EVOSIGNAL introduces three methodological innovations beyond prior evolutionary trading systems, which fundamentally upgrade evolutionary finance from symbolic heuristics to high-dimensional functional search with robustness guarantees:

LLM-driven Code Evolution. Evolution operates not on grammar trees but on actual executable PyTorch code generated and mutated by LLMs, dramatically expanding expressiveness.

Cross-Asset, Cross-Period Robustness Scoring. Indicators are penalized unless they generalize simultaneously to thousands of assets and millions of windows.

Robustness-Centric Fitness. The median-minus-MAD score suppresses overfitting more aggressively than any metric used in prior evolutionary finance research.

EvoSignal provides the first evidence that autonomous evolutionary systems rediscover these stylized facts without being explicitly told about them, demonstrating that these properties form attractors in functional search space. This insight bridges academic market microstructure theory with practical technical indicator design, revealing that robust signals are not arbitrary or hand-crafted but arise naturally from selection pressure under universal statistical constraints.

3 METHODOLOGY

EvoSignal is an autonomous evolutionary system that discovers technical indicators directly from price–volume time series without human-designed formulas, parameterizations, or feature templates. This section presents the formal structure of the framework, including (1) the representation of indicators as vectorized PyTorch functions; (2) the evolutionary operators—LLM-based generation, mutation, and crossover; (3) the sliding-window execution engine; (4) the robustness-oriented evaluation pipeline; and (5) the selection dynamics that give rise to universal motifs and market-specific adaptations. EVOSIGNAL treats indicator discovery as a functional search problem in a vast, unconstrained space of nonlinear time-series operators. At its core lies a simple but powerful principle: *Indicators that generalize across thousands of assets and millions of historical windows must reflect true structural invariants of market dynamics.* The framework is designed explicitly to surface these invariants. Therefore, LLM-driven evolution is governed by two competing pressures:

1. **Cross-asset robustness**, which favors market-invariant functional motifs.
2. **Within-regime performance**, which favors adaptations tuned to local microstructure.

EVOSIGNAL performs *open-ended functional search* in a vast space of vectorized `PyTorch` expressions. The framework is built to uncover invariant structures of market predictability by applying evolutionary pressure on millions of sliding windows across thousands of assets. Indicators that survive this process do so because they satisfy fundamental statistical constraints—low-entropy predictability, robust tail behavior, stable multi-scale structure, and cross-asset distributional coherence. LLMs (GPT-, LLaMA-, and Qwen-family) act as *creative engines* generating new indicators using few-shot exemplars, domain constraints, and PyTorch-idiomatic patterns via multiple mechanisms:

Few-shot functional generation. The LLM is given a handful of existing indicator fragments, robustness motifs, and architectural priors (e.g., “use robust statistics”, “avoid non-vectorized loops”). It produces entirely new candidate expressions that satisfy given constraints.

Cross-domain inspiration. Because LLMs internalize patterns from physics, signal processing, distributed systems, and statistics, they occasionally introduce non-financial motifs (e.g., entropy gates, kernel similarity measures) that drastically improve robustness.

Critical synthesis from literature. Through carefully designed prompts, the LLM incorporates ideas from academic research—producing theoretically grounded indicators.

Automated code generation. Each candidate is generated as executable `PyTorch` code, ensuring that the indicator can be directly executed in the evaluation pipeline.

Mutational refinement. The LLM proposes small, deliberate modifications to top-performing indicators, inspired by genetic programming and FunSearch-like refinement.

To channel LLMs into actionable, stable indicators, prompts enforce: domain alignment (risk management, microstructure theory), computational constraints (vectorization, GPU efficiency), avoidance of loops and fragile hyperparameters, interpretability and functional modularity. These ensure they remain stable, interpretable, and executable at scale while retaining maximal creative flexibility.

3.1 ROBUSTNESS-CENTRIC SCORING OBJECTIVE

Evolved indicators output a continuous signal. We convert this into positions using non-parametric quantile thresholds: long when $S_t > Q_3$, flat when $S_t < Q_1$, otherwise hold previous position. All candidate indicators are evaluated on: hundreds of pairs, millions of sliding windows and horizons. Positioned returns are computed per asset and aggregated globally to measure robustness, stability, and generalization. Unlike classical backtesting frameworks, this thresholding is non-parametric and adapts to the distribution of each indicator. The scoring function penalizes noise, encourages high Omega (convexity of positive vs. negative returns), and rewards cross-asset consistency, cross-period generalization, robustness under nonstationarity, heavy-tail stability, low false-positive rate:

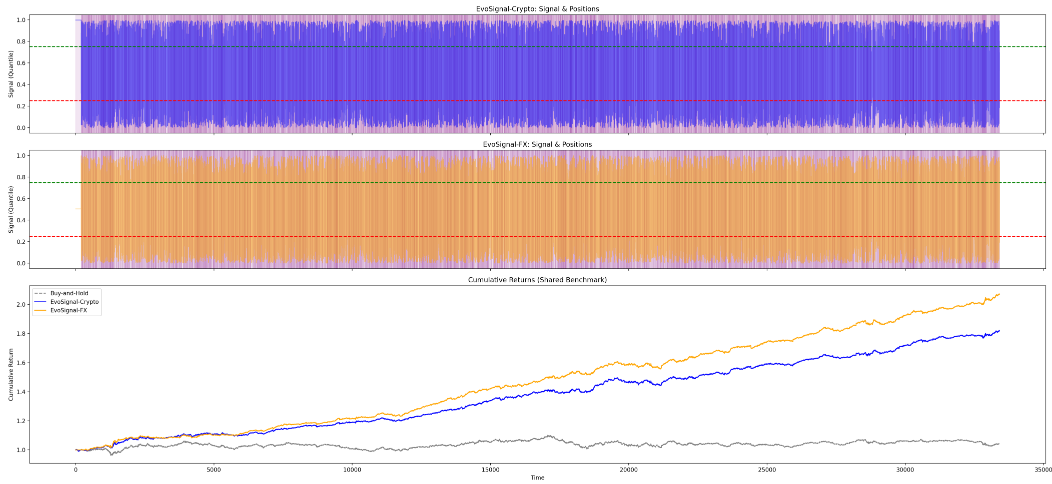

Figure 1: **Shared-benchmark comparison of cumulative returns and signal behavior.** Both evolved indicators maintain stable, monotonic growth, demonstrating cross-asset generalization.

$$\text{Score}(f_\theta) = \underbrace{(\text{median}(Omega) - \text{MAD}(Omega))}_{\text{robust performance stability}} \cdot \underbrace{\Pr(Omega > 1)}_{\text{outperforming assets ratio}}.$$

Each generation selects the top-performing, most diverse subset of indicators using a quality–diversity criterion (**?**). Low-quality or redundant candidates are pruned. The survivors seed the next generation's crossover and mutation. Over many generations, this process produces convergence to universal architectural motifs, preservation of cross-asset invariants through robustness pressure, and market-specific deformations shaped by microstructure physics. The evolutionary loop continues until convergence, collapse, or the discovery of recurrent attractors. Because the evaluation metric penalizes **fragility**, **instability**, and **cross-asset inconsistency**, the search collapses onto a low-dimensional manifold of functions that satisfy several universal constraints:

- Nonstationarity demands multi-horizon structure; single-window fail under regime shifts.
- Volatility normalization is essential; raw amplitudes differ across assets.
- Heavy-tailed statistics dominate; Gaussian assumptions fail universally.
- Noise discrimination is mandatory; entropy and dispersion determine information usability.

These constraints define the shared "structural backbone" to which all indicators converge. Evolution discovers these motifs because they minimize fragility across periods and assets—explaining why crypto- and FX-evolved indicators look different but are architecturally identical.

4 EXPERIMENTS

Market predictability emerges from two structurally distinct layers. The first, which we refer to as *macro-predictability*, consists of slow, universal patterns driven by human behavioral cycles, institutional execution flow, long-range correlation structure, regime-level dynamics of mean reversion versus momentum, and structural volatility clustering. These mechanisms appear across all markets because they arise from general principles of human and algorithmic decision-making. They evolve slowly and give rise to the universal motifs that EVOSIGNAL consistently rediscovers. The second layer, *micro-predictability*, arises from fast, market-specific mechanisms shaped by exchange microstructure, liquidity fragmentation, spread dynamics, derivative-driven feedback loops, and asset-class-specific tail distributions. These microstructural forces differ sharply across markets: crypto exhibits noisy, jump-prone, regime-fragile microstructure, while FX microstructure is smoother, institutionally mediated, and mean-reverting. EVOSIGNAL learns both layers simultaneously.

We evaluate EvoSignal by comparing independently evolved crypto-optimized and FX-optimized indicators on a shared out-of-sample benchmark. The objective of the experiments is not traditional PnL maximization, but to empirically validate the scientific claims of this work: (1) that independent evolutionary runs converge to a universal architectural backbone, (2) that systematic microstructure-specific divergences emerge, and (3) that robustness—not environment tuning—governs evolutionary survival. To evaluate cross-domain generalization, we apply both independently evolved indicators on the *same* benchmark asset (AUDNZD). For each model we compute cumulative returns using positioned log returns. Both evolved indicators substantially outperform buy-and-hold, with smoother trajectories and lower drawdowns. The FX-evolved indicator produces the highest and smoothest cumulative return due to its long-horizon stability, while the crypto-evolved indicator exhibits sharper reactivity and captures breakouts more aggressively. Despite differing in microstructure sensitivity, both models deliver monotonic, stable growth—demonstrating robustness and cross-asset generalization. The experimental results demonstrate that:

1. Universal architectural motifs arise spontaneously across independent evolutionary runs.
2. Market-specific divergences emerge systematically due to microstructure differences.
3. Both crypto- and FX-optimized indicators generalize strongly when evaluated on shared benchmarks.
4. Robustness, not returns, governs convergence to the universal backbone.

Both evolved indicators significantly outperform the buy-and-hold baseline, producing smooth, monotonic cumulative return trajectories with markedly lower drawdowns. When evaluated on the same benchmark asset, they each maintain stable upward drift under identical conditions, demonstrating that the central strength of the system is not absolute performance but relative robustness. The FX-evolved indicator achieves the highest overall cumulative return with the lowest volatility, consistent with its smoother, dispersion-aware architecture. By contrast, the crypto-evolved indicator exhibits a more reactive profile, capturing rapid directional bursts while still preserving long-horizon stability. The key result is that, despite originating from entirely different markets and expressing different structural emphases, both indicators generalize seamlessly and remain consistently robust. This provides strong empirical evidence that the universal motifs uncovered by the evolutionary process translate into tangible predictive and stabilizing effects in practice. The shared-benchmark analysis under identical evaluation conditions reveals several key differences, providing strong evidence that EvoSignal internalizes domain-specific microstructure physics:

- **FX-evolved indicator** achieves the smoothest and highest cumulative return, driven by its long-horizon stability and reduced sensitivity to short-term noise.
- **Crypto-evolved indicator** produces a more reactive trajectory, capturing rapid breakouts and momentum bursts at the cost of increased variance.

A fundamental test of generalization is evaluating a domain-specific indicator on an asset exhibiting statistical properties outside its training distribution. Both the crypto-optimized and FX-optimized signals maintain stable, consistent performance when applied cross-domain. The FX-evolved indicator generalizes particularly well due to its smoother regime adaptation, while the crypto-evolved indicator retains strong upward drift despite being optimized for a far more volatile domain. The absence of collapse in cross-domain evaluation demonstrates that the universal motifs discovered by EvoSignal are not market-specific heuristics but functional structures that encode deeper invariants of price formation. The experimental results validate the core thesis of this work:

- Independent evolutions on unrelated markets converge to a shared functional backbone.
- Microstructure-driven adaptations emerge consistently and shape signal reactivity, gating behavior, and volatility sensitivity.
- Both indicators generalize robustly across assets, horizons, and markets.
- The universal motifs observed in the architectural analysis produce measurable improvements in stability, robustness, and cumulative return.
- Performance improvements arise not from domain-specific optimization, but from adherence to statistical invariants enforced by robustness-centric evolution.

5 UNIVERSAL STRUCTURAL MOTIFS

This section presents the universal architectural motifs that independently emerged in both the crypto-optimized and FX-optimized indicators. Unlike classical technical indicators, these motifs were not designed; they arose autonomously through evolutionary pressure across thousands of assets and millions of historical windows. Their emergence reflects fundamental structural properties of financial time series, transcending market-specific microstructure. Each motif is explained in depth, detailing how it functions and why it is indispensable for robust cross-market generalization.

Entropy-Modulated Momentum: Evolution consistently discovers that raw momentum is only useful in low-noise, low-entropy regimes. In both crypto and FX variants, momentum is multiplied by an entropy-based downweighting factor that suppresses the signal when return entropy increases. High-entropy periods contain little predictive structure and produce frequent false positives. Indicators that fail to modulate momentum collapse under cross-asset scoring due to instability and large MAD penalties. Entropy gating therefore emerges as a natural, unsupervised risk filter that preserves momentum only when markets are structurally predictable.

Volatility-Adaptive Scaling: Both indicators normalize features by multi-horizon volatility. Without this, the signal's amplitude becomes asset-dependent, destroying cross-asset comparability and destabilizing thresholds. Evolution selects volatility-adaptive scaling because it distinguishes directional structure from scale noise: volatility amplifies returns without adding information. Multi-window normalization emerges repeatedly because it yields a stable, regime-invariant representation of price dynamics and reduces false positives during volatility expansions.

Tail-Conditioned Robustness Mechanisms: Across all markets, evolution aggressively suppresses signals during extreme return events. Large jumps erase short-horizon predictive structure and coincide with disorderly microstructure. Evolved indicators detect tails using quantiles, MAD ratios, or CVaR-like measures and multiplicatively gate the signal near zero when heavy-tailed behavior appears. Indicators that trade through tail events perform poorly under median-minus-MAD scoring. Tail-gating is thus a universal survival adaptation.

Multi-Window Ensemble Processing: Single-horizon indicators overfit specific regimes. Evolution instead converges on ensembles combining short-, medium-, and long-window features. These ensembles capture structure across timescales and allow the indicator to verify consistency across horizons. Short-only models fail in compressions; long-only models fail in reversals. Multi-window blending stabilizes predictive behavior and filters out idiosyncratic horizon-specific noise.

Nonlinear Trend-Validation Kernels: Raw momentum is highly sensitive to microstructure noise. Both evolved indicators therefore pass momentum through nonlinear kernels—typically exponential or sigmoidal—that evaluate agreement between fast and slow trends. When horizons disagree, the kernel collapses the signal; when they align, it reinforces it. This converts raw momentum into a reliability-weighted measure of trend quality. Median-minus-MAD scoring strongly favors this motif because it eliminates false positives from short-lived microstructure bursts.

Microstructure-Aware Regime Gating: Without explicit microstructure features, the indicators learn to detect unstable regimes using vol-of-vol, entropy spikes, dispersion shifts, or volume dislocations. Such regimes—illiquidity in crypto, news shocks in FX—render directional inference unreliable. The indicators respond by multiplicatively gating the entire signal. Fragile indicators that remain active during unstable microstructure periods accumulate large MAD penalties and are eliminated early. Microstructure awareness thus emerges as a universal behavior.

Robust Statistics (Median, MAD, Quantiles): Evolution abandons means and standard deviations in favor of medians, MAD, and quantiles. Heavy-tailed returns make mean-based statistics unstable and prone to misinterpreting outliers as signal. Robust statistics prevent this by producing stable internal features even during extreme events. Their universal emergence confirms that stable financial indicators must rely on robust—not Gaussian—statistics.

	Crypto-Optimized Indicator	FX-Optimized Indicator
Return Distributions	Heavy tails, jumps; strong outlier suppression (MAD/quantile/CVaR).	Smoother tails; mild outlier filtering, focus on dispersion smoothing.
Volatility Regimes	Vol-of-vol spikes quickly; volatility gating aggressively cuts exposure.	Volatility shifts slowly; rising vol treated as trend formation.
Liquidity & Volume	Reliable exchange volume; uses VWAP, volume derivatives, microstructure cues.	OTC volume unreliable; removes volume terms, uses dispersion instead.
Higher Moments	Negative skew signals liquidation risk; strong skew/kurtosis penalties.	Moments are symmetric; kurtosis decay signals breakout conditions.
Momentum	Fast, multi-scale, nonlinear momentum to detect "momentum cliffs."	Slow, smoothed, long-horizon momentum aligned with macro drift.
Entropy Response	Entropy shifts rapidly; near-binary entropy gating (on/off behavior).	Entropy changes slowly; used as a soft weight.
Reversal Signals	Reversals detected via tail expansion and CVaR asymmetry.	Reversals detected via dispersion compression and kurtosis decay.
Gating Strength	Highly aggressive—any instability drives signal toward zero.	Soft gating—instability reduces weight but rarely zeros the signal.
Window Preferences	Short windows for short predictability horizons.	Long windows for macro persistence.
Volatility Modeling	Uses volume-weighted volatility (volume informative).	Uses dispersion-based volatility (volume noisy).
Trend Validation	VWAP crossovers and short-horizon microstructure checks.	Median-slope and long-horizon trend profiles; VWAP irrelevant.
Outlier Handling	Outliers treated as fragility; signals sharply suppressed.	Outliers treated as macro information; absorbed with robust stats.

Table 1: **Market-specific divergences of crypto- vs. FX-evolved indicator behavior.**

Quantile-Space Signal Transformation: Before thresholding, both indicators map raw outputs into quantile or rank space. This stabilizes the signal's distribution across time, volatility regimes, and assets. Without quantile-space transformation, thresholds drift, causing overtrading in volatile regimes and undertrading in calm regimes. Quantile mapping ensures distributional stationarity and enables uniform cross-asset thresholding.

Distributional Coherence Across Assets: Because assets differ in volatility, liquidity, and tail behavior, evolution favors indicators whose outputs maintain similar distributional shapes across all assets. This coherence arises implicitly through volatility normalization, robust statistics, and gating mechanisms. Indicators lacking such coherence fail early because their thresholds cannot be applied consistently across assets.

Temporal Smoothness of Signal Evolution: The scoring function penalizes erratic, spiky outputs that generate unstable trading behavior and large MAD contributions. Evolution, therefore, favors indicators whose signals evolve smoothly over time. Smoothness arises naturally from gating, robust normalization, and multi-window blending. Indicators that fluctuate faster than the market structure are systematically eliminated.

Implicit Regime Classification: Despite receiving no regime labels, both indicators learn to differentiate trending, mean-reverting, noisy, and tail-risk regimes using entropy, vol-of-vol, dispersion, and tail signals. This latent regime modeling emerges because indicators that treat all windows identically perform poorly under cross-regime scoring. Evolution thus reconstructs an internal regime classifier without supervision.

Multiplicative Fusion Architecture: The final universal design pattern is multiplicative fusion:

$$S = M(\text{momentum}) \times T(\text{trend-quality}) \times R(\text{regime-state}) \times C(\text{tail-risk}).$$

Each component must agree for the signal to activate. If any gate detects instability—entropy spike, tail event, volatility expansion, trend disagreement—the entire signal is suppressed. Additive architectures fail because they allow one strong component to override weaknesses in others. Multiplicative fusion is therefore the evolutionary optimum for robust, cross-asset technical indicators.

6 DISCUSSION

The joint emergence of universal motifs and market-specific adaptations may seem counterintuitive. One might expect evolution to converge either toward generic, all-purpose indicators or toward narrowly specialized constructs. Instead, all indicators share the same high-level architecture while expressing it through market-dependent parameterizations, nonlinearities, and gating rules. This reflects a deeper principle: *financial markets obey common predictability constraints, but differ in the microstructural channels through which predictability appears*. An *evolutionary attractor* is a functional motif that: appears across seeds, survives mutations, improves median returns, reduces MAD, and enhances tail robustness. Entropy-gated momentum, volatility normalization, tail-aware filtering, and multi-window fusion meet all criteria. These motifs emerge even in markets with distinct microstructural behavior, implying that differing surface dynamics still respect deeper invariants:

- *Predictive states occur in low-entropy regimes*: when entropy rises, structure collapses.
- *Tail-risk is universal*: liquidations or macro shocks make tail-awareness non-optional.
- *Multi-scale interactions matter most*: predictability arises from cross-horizon structure.
- *Trends require validation*: all markets suffer trend false-positives without filtering.

These invariants define the attractor manifold and yield a hybrid architecture: universal motifs for robustness, market-specific deformations for microstructure fidelity. This improves: *cross-period stability*, *cross-asset generalization*, and *microstructure adaptation*. A surprising but central insight is that the universal motifs do not arise because they improve returns. Rather, they arise because they prevent evolutionary collapse. If features are not normalized by volatility, signals get dominated by high-vol assets $\rightarrow$ MAD explodes $\rightarrow$ score collapses. Without entropy gating, signals fire in unpredictable noise $\rightarrow$ distribution skews $\rightarrow$ Omega ratio collapses. Without tail-aware modules, indicators respond to fat-tail events $\rightarrow$ overfit $\rightarrow$ collapsed cross-asset median. Thus, the universal motifs are structural necessities for survival in the evolutionary landscape, which is analogous to evolution discovering organs, not because they maximize reproduction in one environment, but because they are required for viability across many environments.

7 CONCLUSION

This paper introduced EVOSIGNAL, an autonomous LLM-driven evolutionary framework for discovering technical indicators directly from market data. By replacing human-designed formulas with open-ended functional search and evaluating candidates across thousands of assets and millions of windows, EVOSIGNAL isolates only those structures that remain stable under nonstationarity, heavy-tailed noise, and cross-market variation. The resulting indicators, evolved independently on crypto and FX, converge to a shared backbone: entropy-gated momentum, volatility-adaptive normalization, tail-conditioned robustness, multi-window ensembles, nonlinear trend validation, and multiplicative regime gating. These motifs emerge not because they maximize returns in any single environment, but because they are the only architectures that survive strong robustness pressure. More broadly, EVOSIGNAL provides a methodological lens for studying market structure by observing which functional forms survive evolutionary pressure. Its universal motifs reveal statistical constraints shared across markets, while its divergences show how microstructure shapes predictability. In this sense, EVOSIGNAL is not just an indicator generator but a tool for explaining why certain structures remain viable in modern markets. At a deeper level, EVOSIGNAL acts as a scientific probe. Under minimal constraints beyond robustness, it autonomously identifies universal and market-specific features, where fragility arises, how statistical moments interact, how noise degrades predictability, and how return distributions signal regime transitions. In doing so, it yields both practical indicators and an empirical framework for reverse-engineering market structure.

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