# TradeGlass Methodology v1.3

**A Public Technical White Paper on Game-Theoretic, Multi-Timeframe Technical and Fundamental Conviction Modeling**

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### Core public formulation

TradeGlass expresses market conviction as a normalized blend of technical timing and asset-class fundamental context, with additional reliability, structure, and risk controls applied before an output is interpreted.

$$S\_TG(a,\tau) = clip\_[0,100](0.70 \cdot S\_TA(a,\tau) + 0.30 \cdot S\_FA(a))$$

TradeGlass is built on a game-theoretic view of financial markets. The methodology treats price movement not as a passive sequence of isolated signals, but as the visible output of strategic interaction among participants operating with unequal information, unequal liquidity access, different time horizons, and different execution constraints.

This foundation informs the entire model: directional evidence is evaluated together with reliability, participation quality, structural confirmation, crowding risk, liquidity behavior, and the possibility that a visible move may be fragile or adversarially distorted.

This document is intended for external distribution. It explains the public methodology in mathematical form while deliberately generalizing calibrated thresholds, provider-specific mappings, exact production weights below the public pillar level, operational fallbacks, and implementation details that constitute proprietary intellectual property.

The document is not marketing copy, is not a trading performance claim, and is not a disclosure of the complete production code path. It is a transparent mathematical description of the framework sufficient for public understanding and review.



Prepared by TradeGlass Research. Created under the direction of Davide Aufieri, Founder of TradeGlass.

# Contents





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## 1 Introduction: Markets as Strategic, Incomplete-Information Systems

TradeGlass is built on a game-theoretic view of financial markets. Rather than treating price movement as a passive sequence of technical signals, the methodology approaches markets as competitive, adaptive systems where participants act under incomplete information, unequal liquidity access, different time horizons, and strategic execution constraints.

From a game-theoretic perspective, every market movement reflects interaction among competing agents: institutional participants, retail traders, market makers, algorithmic systems, liquidity providers, and discretionary investors. These participants do not share the same information, execution speed, risk tolerance, or capital constraints. As a result, visible price action can contain both genuine directional evidence and misleading structural noise.

In this environment, a market signal is not evaluated by direction alone. It must also be evaluated by reliability, participation quality, liquidity conditions, structural confirmation, crowding risk, and the probability that the observed move is fragile or exposed to adversarial market behavior.

The TradeGlass methodology combines technical analysis, fundamental analysis, multi-timeframe confirmation, structural regime analysis, and risk gating into a unified conviction framework. The model is designed to identify bullish or bearish evidence while also determining whether that evidence is strong enough, contextual enough, and structurally trustworthy enough to support a directional outlook.

$\text{D\_final}(a,\tau) = \text{Directional output only when evidence and structure are aligned; otherwise Stand By}$

This game-theoretic foundation is central to the TradeGlass approach: the model does not only ask whether an asset appears attractive. It asks whether the surrounding market environment makes that opportunity reliable.

## 2 Executive Abstract

Within this game-theoretic foundation, TradeGlass functions as a defensive conviction model. It does not treat bullish or bearish evidence as sufficient by itself. The system evaluates whether the evidence is timely, cross-confirmed, economically contextualized, and structurally reliable before allowing a strong directional interpretation.

TradeGlass is a multi-timeframe, multi-factor conviction framework that converts heterogeneous market evidence into a single normalized score. The model is designed around a central premise: price action determines timing, while fundamentals establish context, quality, and macro or balance-sheet support. The engine therefore separates timing evidence from fundamental evidence and recombines them only after both layers have been normalized to a common 0–100 scale.

The public form of the engine is a convex scoring model. Technical analysis receives the larger allocation because it reacts to observable market behavior, trend persistence, volatility expansion, liquidity participation, and execution-relevant structure. Fundamental analysis receives a complementary allocation because valuation, financial quality, positioning, macro conditions, and balance-sheet risk can either reinforce or contradict the short-term technical view.

$$\text{S\_TG} = \lambda\text{\_TA}\,\text{S\_TA} + \lambda\text{\_FA}\,\text{S\_FA}, \quad \lambda\text{\_TA} + \lambda\text{\_FA} = 1, \quad \lambda\text{\_TA}, \lambda\text{\_FA} \geq 0$$

For public communication, the reference allocation is expressed as:

$$\text{S\_TG\^{}public} = 0.70\ \text{S\_TA} + 0.30\ \text{S\_FA}$$

The resulting score should be interpreted as a structured conviction measure, not as a guaranteed probability of profit. A high score indicates stronger bullish evidence; a low score indicates stronger bearish evidence; a mid-range score indicates insufficient directional advantage or conflicting evidence.

## 3 Public Methodology Boundary

The purpose of this paper is to disclose the model architecture without publishing the full set of production constants. This distinction is important: the mathematical structure can be public, while the exact calibration remains a proprietary implementation asset. The public model uses variables such as θ, β, γ, κ, and ω to denote calibrated internal parameters.

| Public methodology | Proprietary implementation |
|---|---|
| High-level TA/FA architecture, normalized scoring, and public 70/30 blend. | Exact production thresholds, interval-specific entry cutoffs, and calibration tables. |
| Indicator families used in the technical model and their mathematical definitions. | Provider-specific field mappings, fallback order, data-cleaning rules, and operational code paths. |
| Stock FA pillars: valuation, quality, financial risk/liquidity, and catalyst momentum. | Exact metric availability hierarchy, exception handling, internal overrides, and tuning history. |
| General multi-timeframe confirmation and structure/risk framework. | Precise blocking logic, risk-alert deltas, alert priority order, and production gate settings. |
| Responsible interpretation of a normalized Conviction Score. | Backtesting infrastructure, monitoring dashboards, QA harnesses, and internal research notes. |

The public notation intentionally favors parameterized equations. This preserves mathematical rigor while preventing replication of the full production implementation from the white paper alone.

## 4 Notation and Market Data Representation

Let a denote an asset, τ denote the active analysis interval, and t denote the current observation index. The technical layer operates on an OHLCV observation matrix:

$$X_{(a,\tau)} = \{O_t, H_t, L_t, C_t, V_t\}_{t=1}^{n}$$

where O, H, L, C, and V represent open, high, low, close, and volume. The fundamental layer operates on an asset-specific metric vector:

$$F_a = (f_1(a), f_2(a), \ldots, f_m(a))$$

Each raw metric is transformed into a normalized component score $q_j(a) \in [0,100]$. These transformations may be monotonic, sector-relative, percentile-based, winsorized, or two-sided depending on the economic meaning of the metric.

$$q_j(a) = \varphi_j(f_j(a); \theta_j), \quad q_j \in [0,100]$$

The variable $\theta_j$ denotes the calibration set associated with metric j. Publicly, $\theta_j$ represents items such as sector baselines, historical percentiles, clipping ranges, and neutral defaults. Exact values are intentionally not enumerated.

## 5 Score Normalization and Conviction Semantics

TradeGlass uses a bounded score domain to make heterogeneous evidence comparable. Every layer produces a result on the interval [0,100], where 50 represents a neutral center. Directional interpretation occurs relative to calibrated upper and lower decision thresholds, not simply relative to the midpoint.

$$\mathrm{clip}_{[0,100]}(x) = \min(100, \max(0, x))$$

$$\text{Neutral center:} \;\; S = 50$$

$$\text{Bullish evidence: } S > 50, \;\; \text{Bearish evidence: } S < 50$$

In public notation, final directional interpretation can be represented as:

$$d(a,\tau) = \text{Long}, \quad \text{if } S_{TG}(a,\tau) \geq \Theta_L \text{ and } G(a,\tau)=1$$

$$d(a,\tau) = \text{Short}, \quad \text{if } S_{TG}(a,\tau) \leq \Theta_S \text{ and } G(a,\tau)=1$$

$$d(a,\tau) = \text{Stand By}, \;\; \text{otherwise}$$

Here $\Theta_L$ and $\Theta_S$ are calibrated decision boundaries and $G(a,\tau)$ is a risk gate. This public formulation communicates the logic without exposing exact production cutoffs or internal blocking thresholds.

## 6 Technical Analysis Layer

The technical layer estimates market timing quality by aggregating trend, momentum, volatility, volume, price-action, divergence, structural, and pattern information. It is not a single-indicator model. It is a composite factor model in which each component is normalized, weighted, and then adjusted for context.

$$S\_TA(a,\tau) = clip\_[0,100](S\_base(a,\tau) + B\_MTF(a,\tau) + B\_struct(a,\tau) + I\_pattern(a,\tau) - P\_risk(a,\tau))$$

### 6.1 Indicator transforms

The underlying indicator layer includes trend-following, momentum, dispersion, and range-based transforms. The formulas below are included for methodological transparency; production use may adapt lookback windows by interval and data quality.

| Indicator family | Public mathematical form |
|---|---|
| Exponential moving average | EMA_t^(p) = EMA_(t−1)^(p) + α_p(C_t − EMA_(t−1)^(p)), α_p = 2/(p+1) |
| Simple moving average | SMA_t^(p) = (1/p) Σ_(k=0)^(p−1) C_(t−k) |
| Bollinger envelope | BB_t^± = SMA_t^(p) ± z · σ_t^(p), Width_t = BB_t^+ − BB_t^− |
| Relative strength index | RSI_t = 100 − 100/(1 + RS_t), RS_t = AvgGain_t / AvgLoss_t |
| MACD family | MACD_t = EMA_t^(p_f) − EMA_t^(p_s), Hist_t = MACD_t − Signal_t |
| True range and ATR | TR_t = max(H_t−L_t, \|H_t−C_(t−1)\|, \|L_t−C_(t−1)\|), ATR_t = smooth(TR_t) |
| Volume participation | RVOL_t = V_t / MA(V)_(t,p) |

### 6.2 Single-interval factor aggregation

The base technical score is a weighted aggregation of normalized factor scores. The factor set J_TA includes trend, momentum, volatility/dispersion, volume, price-action, and divergence components. The weight vector is interval-adaptive but not disclosed at the exact production level.

$$S\_base(a,\tau) = \Sigma\_(j\in J\_TA)\ w\_(\tau,j) \cdot s\_j(a,\tau) + D(a,\tau)$$

$$\Sigma\_(j\in J\_TA)\ w\_(\tau,j) = 1,\quad w\_(\tau,j) \geq 0$$

| TA factor | Role in the model |
|---|---|
| Trend | Scores alignment among price, short/mid/long moving averages, slope, and directional persistence. |
| Momentum | Scores oscillator and impulse confirmation, including RSI and MACD-family behavior. |
| Volatility / dispersion | Scores expansion, compression, and range behavior using bands, width, and ATR-normalized movement. |
| Volume | Scores whether the move is supported by participation rather than thin-liquidity drift. |
| Price action | Scores candle structure, reversal pressure, continuation behavior, wick/body distribution, and local supply/demand response. |
| Divergence | Adds or subtracts evidence when price direction conflicts with oscillator direction. |

### 6.3 Directional factor scoring

Each technical factor is converted into a score around the neutral center. Publicly, this can be represented as a signed evidence transform:

$$s\_j(a,\tau) = 50 + 50 \cdot e\_j(a,\tau),\quad e\_j(a,\tau) \in [-1,1]$$

A value e_j > 0 supports upside conviction; e_j < 0 supports downside conviction; e_j ≈ 0 contributes little directional evidence. This formulation allows trend, momentum, volume, and structural features to be aggregated even though they originate from different mathematical domains.

For example, a generalized moving-average trend component can be written as:

$$e\_trend = \psi(\mathrm{sign}(C\_t - EMA\_f), \mathrm{sign}(EMA\_f - EMA\_m), \mathrm{sign}(EMA\_m - EMA\_s), \mathrm{slope}(EMA\_m))$$

where ψ is a calibrated mapping from ordered trend relationships into bounded directional evidence. The exact scoring table is not public, but the economic interpretation is straightforward: stronger positive alignment increases the score; stronger negative alignment decreases it.

## 7 Multi-Timeframe Confirmation and Structural Regime Layer

TradeGlass treats timeframe agreement as a quality control mechanism. A short-interval signal may be statistically noisy when it contradicts the higher-interval regime. The model therefore evaluates the active interval τ against a set of higher-context intervals H(τ).

$$H(\tau) = \{h\_1, h\_2, \ldots, h\_k\}$$

$$A\_MTF(a,\tau) = \Sigma\_(h\in H(\tau))\ \beta\_(\tau,h) \cdot \psi(d\_\tau, d\_h) \cdot \rho\_h$$

In this equation, β_(τ,h) controls the importance of higher interval h, ψ(d_τ,d_h) measures directional agreement or conflict, and ρ_h discounts the contribution of a higher interval when its data is stale, incomplete, or structurally ambiguous.

$$B\_MTF(a,\tau) = clip\_[-\kappa\_MTF,\kappa\_MTF](A\_MTF(a,\tau))$$

The structural regime layer models market states that simple indicators may not fully capture: breakout acceptance, breakdown acceptance, failed breakouts, compression, volatility expansion, trend exhaustion, and abnormal extension. Public notation expresses this as a bounded sum of regime coefficients.

$$B\_struct(a,\tau) = clip\_[-\kappa\_struct,\kappa\_struct](\Sigma\_(r\in R)\ \gamma\_r \cdot 1\_r(a,\tau))$$

The use of clipping is deliberate. It prevents any single structure label from dominating the entire score and helps keep the final result interpretable.

### 7.1 Pattern and risk adjustments

Detected chart or candle patterns are treated as context-dependent evidence, not unconditional signals. A bullish pattern in a hostile higher-timeframe regime contributes less than the same pattern in a confirming regime. A public representation is:

$$I\_pattern = clip\_[-\kappa\_p, \kappa\_p](\sigma\_p \cdot c\_p \cdot a\_p \cdot \gamma\_p)$$

where σ_p is the directional sign of the pattern, c_p is a completion or maturity factor, a_p is an alignment factor, and γ_p is a calibrated pattern-strength coefficient.

Risk controls are represented as both penalties and gates. Penalties reduce score confidence; gates can prevent a directional output when the observed environment is judged structurally unsafe or unreliable.

$$P\_risk = g(R\_alerts, liquidity, volatility, extension, data\_quality)$$

$$G(a,\tau) \in \{0,1\}$$

## 8 Adversarial Market Dynamics and Information Asymmetry

The preceding sections describe how TradeGlass evaluates observable evidence through technical, structural, and multi-timeframe inputs. However, financial markets are not neutral information systems. They are competitive environments in which liquidity is unevenly distributed, incentives are strategic, and visible price action may only partially reveal the behavior of larger or faster participants.

TradeGlass therefore incorporates an adversarial dynamics layer as a public conceptual extension of the risk framework. The model does not claim to observe hidden institutional intent directly. Instead, it identifies observable market conditions that may be consistent with information asymmetry, liquidity stress, crowded positioning, fragile participation, or structurally unsafe execution environments.

This layer acts defensively. It can reduce conviction through the risk penalty P_risk or cause the structural gate G(a,τ) to favor a conservative Stand By state when the market environment appears unreliable, even if the normalized technical and fundamental blend is directionally strong.

### 8.1 Information asymmetry and asymmetric observability

Public market data is incomplete. Not all liquidity is visible, not all participant behavior is transparent, and not all moves have an immediately observable catalyst. TradeGlass therefore treats unexplained price acceleration, weak participation quality, and poor catalyst alignment as potential evidence that a move may be fragile rather than durable.

$$I\_asym(a,\tau) = \chi(\Delta price, participation\_quality, catalyst\_alignment, volatility\_state, data\_quality)$$

The function χ represents a bounded proprietary mapping from observable symptoms of asymmetric information into an information-asymmetry adjustment. When price movement and participation quality diverge, I_asym can increase the aggregate risk penalty rather than adding directional conviction.

$$P\_risk^*(a,\tau) = P\_risk(a,\tau) + \lambda\_asym \cdot I\_asym(a,\tau)$$

This formulation explains why a sharp move without broad confirmation may receive a weaker final interpretation than a slower move supported by participation, context, and structural acceptance.

### 8.2 Liquidity and zero-sum execution constraints

Execution quality is constrained by liquidity. In short-horizon or heavily algorithmic environments, liquidity can be thin, fragmented, or withdrawn precisely when directional signals appear strongest. From a game-theoretic perspective, one participant's desired execution often depends on the willingness or exhaustion of counterparties.

TradeGlass treats liquidity as a constraint on conviction. A technically valid breakout or breakdown may still be penalized if the surrounding structure suggests poor absorption, unstable depth, excessive slippage risk, or weak participation breadth.

$$S\_adj(a,\tau) = clip\_[0,100](S\_TG(a,\tau) - P\_risk^*(a,\tau))$$

The score adjustment does not imply that the original signal is false. It indicates that the market environment may be less suitable for confident interpretation or execution.

### 8.3 Alpha decay and adaptive persistence

Predictive patterns are not permanent. When a market inefficiency becomes widely recognized, it may be arbitraged away, crowded by similar models, or exploited by faster participants. TradeGlass therefore avoids allowing stale or overly obvious structural patterns to dominate the active analysis interval.

$$B\_struct(a,\tau) = clip\_[-\kappa\_struct,\kappa\_struct](\Sigma\_(r\in R)\ \lambda\_r(\tau) \cdot \gamma\_r \cdot 1\_r(a,\tau))$$

Here $\lambda\_r(\tau)$ is a persistence or time-decay coefficient applied to structural regime signal r. As a pattern becomes stale, crowded, or unsupported by fresh confirmation, its contribution can degrade toward neutrality. This is a public-safe representation of adaptive persistence rather than a disclosure of production decay constants.

### 8.4 Adversarial risk gate and conservative override

Because markets are competitive and partially observable, TradeGlass gives the structural risk gate final authority over the directional output. The model may identify bullish or bearish evidence and still refuse to convert it into a directional state when the environment is judged structurally unsafe.

$$G(a,\tau) \in \{0,1\}$$

$$D\_final = \{ \text{Long or Short if } S\_adj \text{ crosses calibrated boundaries and } G(a,\tau)=1;\ \text{Stand By otherwise} \}$$

This conservative override is not a weakness of the methodology. It is a deliberate design principle: a strong signal is only actionable when the surrounding market structure is trustworthy enough to support it.

## 9 Fundamental Analysis Architecture

The fundamental layer converts asset-specific economic, financial, positioning, and macro variables into a normalized context score. Because stocks, crypto assets, currencies, ETFs, and commodities do not share the same economic structure, the FA model is asset-class adaptive.

$$S\_FA(a) = F\_FA(F\_a, class(a))$$

A general normalized FA model can be represented as:

$$S\_FA(a) = (\Sigma\_(j\in A\_a)\ \omega\_j \cdot q\_j(a)) / (\Sigma\_(j\in A\_a)\ \omega\_j)$$

where A_a is the set of available and valid metrics for asset a. Missing metrics are handled conservatively; they do not create synthetic conviction unless the missingness itself is informative.

$$q\_j(a) = 50, \quad \text{if metric j is unavailable and no risk override is active}$$

$$\rho\_FA(a) = (\Sigma\_(j\in A\_a)\ \omega\_j \cdot v\_j) / (\Sigma\_(j\in J\_FA)\ \omega\_j)$$

Here ρ_FA is a reliability coefficient and v_j is a validity indicator or data-quality weight. This coefficient can be used to discount overconfident interpretations when coverage is incomplete.

$$S\_FA,adj = \rho\_FA \cdot S\_FA + (1 - \rho\_FA) \cdot 50$$

## 10 Equity / Stock Fundamental Analysis Deep Dive

Equity analysis requires a richer fundamental model than a single valuation ratio. A stock can appear inexpensive because the market is mispricing durable earnings power, or because the business is deteriorating. Conversely, a high-multiple stock can be fundamentally strong if profitability, capital efficiency, and catalysts justify the premium. TradeGlass therefore separates stock FA into four pillars: valuation, quality, financial risk/liquidity, and catalyst momentum.

$$S\_FA\hat{}stock = 0.35V + 0.30Q + 0.25R + 0.10C$$

This public pillar allocation communicates the intended economic weighting. Exact internal submetric transformations, sector baselines, data availability rules, and exception logic are proprietary.

| Stock FA pillar | Economic purpose |
|---|---|
| V: Valuation | Measures whether the market price appears expensive or inexpensive relative to earnings, book value, sales, operating cash generation, and growth-adjusted multiples. |
| Q: Business quality | Measures profitability, margin structure, capital efficiency, and return generation. |
| R: Financial risk / liquidity | Measures balance-sheet stress, leverage, debt service capacity, and short-term liquidity. |
| C: Catalyst momentum | Measures earnings surprise behavior, revision pressure, growth acceleration, and event-driven fundamental momentum. |

### 10.1 Sector-relative normalization

Stock fundamentals must be normalized by sector or comparable peer group because capital intensity, accounting structure, margins, and valuation ranges differ materially across industries. The public stock model uses generalized sector-relative transformations:

$$\tilde{x}\_j(a) = \mathrm{Winsorize}(x\_j(a);\, q\_(\ell,j,s),\, q\_(u,j,s))$$

$$P\_(j,s)(a) = F\_(j,s)(\tilde{x}\_j(a))$$

where s denotes sector or comparable group, F_(j,s) is the empirical distribution for metric j in group s, and q_(ℓ,j,s), q_(u,j,s) are lower and upper winsorization bounds. Publicly, the model can then express high-better and low-better transforms as:

$$\varphi\_\mathrm{highBetter}(x\_j) = 100 \cdot P\_(j,s)(a)$$

$$\varphi\_\mathrm{lowBetter}(x\_j) = 100 \cdot (1 - P\_(j,s)(a))$$

This prevents a bank, utility, software company, and commodity producer from being judged by the same raw-ratio expectations.

### 10.2 Valuation pillar

The valuation pillar evaluates whether the equity price is reasonable relative to fundamentals. Lower valuation multiples generally score better, but only after sector-relative normalization and guardrails for negative or non-meaningful denominators.

$$V = \mathrm{mean}(\varphi\_PE,\, \varphi\_PB,\, \varphi\_PS,\, \varphi\_EV/EBITDA,\, \varphi\_PEG,\, \varphi\_FCFYield)$$

A generalized valuation transform can be represented as:

$$\varphi\_\mathrm{val}(x) = 100 \cdot (1 - F\_\mathrm{sector}(\mathrm{Winsorize}(x)))$$

For yield-like metrics where higher is better, the direction is inverted:

$$\varphi\_\mathrm{yield}(y) = 100 \cdot F\_\mathrm{sector}(\mathrm{Winsorize}(y))$$

The model avoids treating statistically cheap companies as automatically attractive. A low valuation score can be overridden or discounted when the quality and risk pillars indicate deteriorating fundamentals.

### 10.3 Quality pillar

The quality pillar evaluates whether the company converts revenue, capital, and assets into durable economic returns. High margins and high capital efficiency increase the score, especially when they are strong relative to the company’s peer group.

$$Q = \mathrm{mean}(\varphi\_GrossMargin,\, \varphi\_OperatingMargin,\, \varphi\_ROE,\, \varphi\_ROIC,\, \varphi\_FCFMargin,\, \varphi\_RevenueStability)$$

In public notation:

$$\varphi\_\mathrm{quality}(x) = 100 \cdot F\_\mathrm{sector}(\mathrm{Winsorize}(x))$$

Quality can also be modeled using a persistence term, because one-quarter spikes can be less informative than durable multi-period improvement:

$$Q\_\mathrm{persist} = \eta\_1\, Q\_t + \eta\_2\, Q\_(t-1) + \eta\_3\, Q\_(t-2), \quad \Sigma\eta\_i = 1$$



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### 10.4 Financial risk and liquidity pillar

The financial risk pillar measures whether the company can survive adverse operating conditions. Excessive leverage, weak interest coverage, or poor liquidity can reduce conviction even when valuation appears attractive.

$$R = \mathrm{mean}(\varphi\_DE, \varphi\_NetDebt/EBITDA, \varphi\_InterestCoverage, \varphi\_CurrentRatio, \varphi\_DebtMaturityRisk)$$

For leverage-like metrics, lower is better:

$$\varphi\_leverage(x) = 100 \cdot (1 - F\_sector(Winsorize(x)))$$

For coverage-like and liquidity-like metrics, higher is better:

$$\varphi\_coverage(x) = 100 \cdot F\_sector(Winsorize(x))$$

Risk is not merely a negative screen. In the blended model, it moderates valuation interpretation. A company that is cheap but financially fragile should not receive the same FA score as a company that is cheap and resilient.

### 10.5 Catalyst momentum pillar

Catalyst momentum captures near-term fundamental change. It is deliberately smaller than valuation, quality, and risk because catalysts can be noisy, but it helps identify when fundamentals are improving or deteriorating faster than static ratios reveal.

$$C = \zeta\_1\varphi\_EarningsSurprise + \zeta\_2\varphi\_EstimateRevision + \zeta\_3\varphi\_GrowthAcceleration + \zeta\_4\varphi\_EventMomentum$$

$$\Sigma\zeta\_i = 1, \quad \zeta\_i \geq 0$$

The catalyst layer is especially useful when a company transitions from value trap to improving fundamentals, or from expensive growth to decelerating fundamentals. Publicly, TradeGlass discloses the existence and mathematical role of the catalyst layer, but not exact event mappings or revision thresholds.

### 10.6 Stock FA reliability and missing-data behavior

Equity data coverage can vary by listing venue, market capitalization, reporting schedule, and provider availability. The public model therefore includes a reliability coefficient to reduce overconfidence when important data is missing.

$$\rho\_stock = (\omega\_V\, v\_V + \omega\_Q\, v\_Q + \omega\_R\, v\_R + \omega\_C\, v\_C) / (\omega\_V + \omega\_Q + \omega\_R + \omega\_C)$$

$$S\_FA,stock\text{^}adj = \rho\_stock\, S\_FA\text{^}stock + (1 - \rho\_stock)50$$

This treatment keeps the model coverage broad without allowing incomplete data to masquerade as high-conviction evidence.

## 11 Cross-Asset Fundamental Extensions

Outside equities, TradeGlass adapts the FA layer to the economic structure of the asset class. The common principle is normalization to [0,100] followed by reliability-aware aggregation.

### 11.1 Crypto fundamental context

Crypto assets require positioning, liquidity, sentiment, dominance, flow, and on-chain or market-structure context rather than traditional balance-sheet ratios. Public notation represents the crypto FA layer as:

$$S\_FA\text{^}crypto = (\Sigma\_(j \in A\_crypto)\ \omega\_j\, q\_j) / (\Sigma\_(j \in A\_crypto)\ \omega\_j)$$

Potential metric families include open-interest change, long/short imbalance, sentiment, exchange-balance pressure, whale or large-holder activity, ETF or institutional flow proxies, dominance, and cycle context. Exact provider mappings and weights remain proprietary.

### 11.2 Foreign-exchange fundamental context

For currency pairs, FA is naturally relative: the base currency is evaluated against the quote currency. The public model can be written as:

$$\Delta r = r\_base - r\_quote, \quad \Delta\pi = \pi\_base - \pi\_quote, \quad \Delta u = u\_base - u\_quote, \quad \Delta PMI = PMI\_base - PMI\_quote$$

$$S\_FA\text{^}FX = \omega\_r\varphi\_r(\Delta r) + \omega\_\pi\varphi\_\pi(-\Delta\pi) + \omega\_u\varphi\_u(-\Delta u) + \omega\_p\varphi\_p(\Delta PMI)$$



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The signs encode economic interpretation: higher relative rates may support the base currency, lower relative inflation and unemployment can improve macro quality, and stronger activity indicators may support relative growth expectations.

### 11.3 ETF and commodity context

For ETFs and commodities, the FA layer can rely on return profile, volatility quality, drawdown behavior, risk-adjusted performance, carry or roll considerations, supply/demand context, and macro sensitivity. A generalized public form is:

$$S\_FA\text{^}asset = \Sigma\_(j \in A\_asset)\ \omega\_j\ \varphi\_j(x\_j;\ \theta\_j)$$

This keeps the architecture consistent across assets while allowing the metric families to reflect the actual drivers of each market.

## 12 Final Blend and Decision Framework

After TA and FA are normalized, TradeGlass combines them into a final Conviction Score. The public reference blend is:

$$S\_TG(a,\tau) = clip\_[0,100](0.70S\_TA(a,\tau) + 0.30S\_FA(a))$$

The adversarial dynamics layer can then adjust the blended score when observed market behavior suggests asymmetric information, fragile participation, liquidity stress, or structurally unsafe execution conditions.

$$S\_adj(a,\tau) = clip\_[0,100](S\_TG(a,\tau) - P\_risk\text{^}*(a,\tau))$$

The model then applies reliability and risk interpretation before producing a directional state. A generalized display-adjusted score can be expressed as:

$$\rho\_total = \rho\_TA \cdot \rho\_FA \cdot \rho\_data$$

$$S\_display = \rho\_total\ S\_adj + (1 - \rho\_total)50$$

The final state is determined by the adjusted score and the active risk gate:

$$D\_final = \{\ Long\ if\ S\_display \geq \Theta\_L\ and\ G{=}1;\ Short\ if\ S\_display \leq \Theta\_S\ and\ G{=}1;\ Stand\ By\ otherwise\ \}$$

This structure allows the system to reward strong confluence while preserving a conservative neutral state when evidence is incomplete, contradictory, or structurally unsafe.

## 13 Calibration, Reliability, and Model Governance

A public methodology should be stable enough to earn trust but flexible enough to improve as data coverage, market structure, and empirical research evolve. TradeGlass should therefore treat this document as a versioned methodology summary rather than a static permanent specification.

The following principles govern public-safe model communication:

- Publish the model architecture, not the full production calibration.
- Distinguish Conviction Score from guaranteed probability of success.
- Keep asset-class methodology consistent while allowing metric families to differ by market.
- Use reliability discounts when data is missing, stale, inconsistent, or economically non-comparable.
- Version public methodology documents whenever public-facing logic materially changes.

Mathematically, model calibration can be summarized as the selection of parameter sets that map raw evidence into stable normalized conviction:

$$\Theta^* = argmin\_\Theta\ L(S\_TG(X,F;\Theta),\ Y) + \Omega(\Theta)$$

where L is a research loss function and $\Omega(\Theta)$ is a regularization or stability penalty. This equation is included as a conceptual description, not a disclosure of the internal research target, training procedure, or validation framework.

## 14 Responsible Use Statement

TradeGlass is a market-analysis and decision-support framework. It is not a guarantee of future performance, not personalized financial, legal, tax, or investment advice, and not a substitute for independent judgment. Markets are uncertain, liquidity conditions can change rapidly, and model outputs can be wrong or become stale when data changes.

The Conviction Score should be interpreted as a structured evidence summary. Users remain responsible for position sizing, risk management, suitability, and compliance with applicable rules. No methodology can eliminate market risk.

Public descriptions of TradeGlass should avoid claims such as guaranteed profit, certain prediction, risk-free trading, or assured win rate. The accurate claim is that TradeGlass synthesizes multiple forms of evidence into a normalized technical-and-fundamental conviction framework.



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# Appendix A Public Equation Summary

| Concept | Public equation |
| --- | --- |
| Master blend | $S_{TG}(a,\tau) = \mathrm{clip}_{[0,100]}(0.70S_{TA}(a,\tau) + 0.30S_{FA}(a))$ |
| Base technical score | $S_{base} = \Sigma_{(j\in J_{TA})} w_{(\tau,j)}s_j + D$ |
| Technical total | $S_{TA} = \mathrm{clip}_{[0,100]}(S_{base} + B_{MTF} + B_{struct} + I_{pattern} - P_{risk})$ |
| Factor normalization | $s_j = 50 + 50e_j, \quad e_j \in [-1,1]$ |
| MTF confirmation | $A_{MTF} = \Sigma_{(h\in H(\tau))} \beta_{(\tau,h)}\psi(d_\tau,d_h)\rho_h$ |
| Structural bias | $B_{struct} = \mathrm{clip}_{[-\kappa,\kappa]}(\Sigma_{(r\in R)}\gamma_r 1_r)$ |
| General FA | $S_{FA} = (\Sigma_{(j\in A_a)}\omega_j q_j)/(\Sigma_{(j\in A_a)}\omega_j)$ |
| Stock FA | $S_{FA}^{stock} = 0.35V + 0.30Q + 0.25R + 0.10C$ |
| Valuation | $V = \mathrm{mean}(\varphi_{PE}, \varphi_{PB}, \varphi_{PS}, \varphi_{EV/EBITDA}, \varphi_{PEG}, \varphi_{FCFYield})$ |
| Quality | $Q = \mathrm{mean}(\varphi_{GM}, \varphi_{OM}, \varphi_{ROE}, \varphi_{ROIC}, \varphi_{FCFMargin})$ |
| Financial risk | $R = \mathrm{mean}(\varphi_{DE}, \varphi_{ND/EBITDA}, \varphi_{IC}, \varphi_{CR}, \varphi_{DebtMaturityRisk})$ |
| Catalyst | $C = \Sigma\zeta_i\varphi_i, \quad \Sigma\zeta_i = 1$ |
| Reliability discount | $S_{display} = \rho_{total}S_{TG} + (1-\rho_{total})50$ |
| Decision state | Long if $S_{display} \geq \Theta_L$ and G=1; Short if $S_{display} \leq \Theta_S$ and G=1; Stand By otherwise |

Game-theoretic market interpretation:

Markets are treated as strategic, incomplete-information systems.

Public technical/fundamental blend:

$$S_{TG}(a,\tau) = \mathrm{clip}_{[0,100]}(0.70S_{TA}(a,\tau) + 0.30S_{FA}(a))$$

Adversarial risk adjustment:

$$P_{risk}^*(a,\tau) = P_{risk}(a,\tau) + \lambda_{asym} \cdot I_{asym}(a,\tau)$$

$$S_{adj}(a,\tau) = \mathrm{clip}_{[0,100]}(S_{TG}(a,\tau) - P_{risk}^*(a,\tau))$$

Conservative directional gate:

$$D_{final} = \{ \text{Long/Short if adjusted evidence crosses calibrated boundaries and } G(a,\tau)=1\text{; Stand By otherwise} \}$$

# Appendix B Variable Glossary

| Symbol | Meaning |
| --- | --- |
| $a$ | Asset under analysis. |
| $\tau$ | Active analysis interval. |
| $X_{(a,\tau)}$ | OHLCV observation matrix for asset a on interval $\tau$. |
| $F_a$ | Fundamental metric vector for asset a. |
| $S_{TG}$ | Final TradeGlass Conviction Score normalized to [0,100]. |
| $S_{TA}$ | Technical analysis score after factor, timeframe, structure, pattern, and risk adjustments. |
| $S_{FA}$ | Asset-class fundamental analysis score. |
| $\theta$ | Calibration set for a transform or threshold. |
| $\beta$ | Multi-timeframe contribution coefficient. |
| $\gamma$ | Structural or pattern contribution coefficient. |



Prepared by TradeGlass Research. Created under the direction of Davide Aufieri, Founder of TradeGlass.

| Symbol | Meaning |
|---|---|
| $\kappa$ | Maximum absolute adjustment cap. |
| $\omega$ | Fundamental metric weight. |
| $\rho$ | Reliability coefficient. |
| $G$ | Risk gate where 1 permits an output and 0 forces neutral interpretation. |
| V, Q, R, C | Stock FA pillars: valuation, quality, financial risk/liquidity, and catalyst momentum. |

$a$: Asset under analysis.

$\tau$: Active analysis interval or timeframe.

$S_{TA}(a,\tau)$: Normalized technical-analysis conviction score.

$S_{FA}(a)$: Normalized fundamental-analysis context score.

$S_{TG}(a,\tau)$: Public blended TradeGlass conviction score before adversarial risk adjustment.

$S_{adj}(a,\tau)$: Risk-adjusted conviction score after adversarial and structural penalties.

$I_{asym}(a,\tau)$: Information-asymmetry adjustment applied when observable price movement, participation quality, catalyst context, and volatility behavior appear misaligned.

$P_{risk}(a,\tau)$: Aggregate risk penalty for volatility stress, structural instability, poor confirmation, data quality issues, and related risk conditions.

$P_{risk}^*(a,\tau)$: Risk penalty after inclusion of information-asymmetry adjustment.

$G(a,\tau)$: Structural risk gate that determines whether a directional output is allowed or overridden to Stand By.

$B_{struct}(a,\tau)$: Structural regime adjustment derived from observable market conditions such as breakout quality, volatility behavior, confirmation strength, and regime stability.

$\lambda_r(\tau)$: Time-decay or persistence coefficient applied to a structural regime signal.

$\lambda_{asym}$: Calibration coefficient controlling how strongly the information-asymmetry adjustment affects the aggregate risk penalty.

$\Theta_L$, $\Theta_S$: Calibrated public decision boundaries for bullish and bearish directional interpretation.

End of public methodology document.