Reflexivity as Prompt: Does Awareness of Self-Reinforcing Market Dynamics Improve LLMs as Financial Market Forecasters?

Anonymous Authors[1]

Abstract

We study how frontier large language models (LLMs) behave as financial forecasters during boom-bust market cycles when made progressively aware of Soros's theory of reflexivity. Standard AI-assisted forecasting treats the market as an exogenous system. Reflexivity theory holds otherwise: prices shape fundamentals, and every forecaster is a participative agent in the loop it analyzes. We evaluate three frontier models — GPT-5, Claude Sonnet 4.6, and Gemini 3 Pro — under four accumulating zero-shot conditions across two historically distinct episodes: the dot-com bubble (1996–2001) and the global financial crisis (2004–2009). The primary metric is directional forecasting accuracy; we also report the Sharpe ratio of an implied long/cash strategy to capture the risk-adjusted economic value of the forecasts. All inputs are anonymized and normalized to guard against memorization. We find that conditions incorporating reflexivity awareness improve forecasting accuracy differently across models and context windows, revealing that the same theoretical awareness can produce qualitatively different forecasting behavior across frontier LLMs.

1. Introduction

Standard approaches to AI-assisted financial forecasting treat the market as an exogenous object — a system whose past behavior contains signals about its future states. But financial markets have a property that distinguishes them from most prediction targets: the participants who form beliefs about the market are the same agents whose actions move it. A forecaster is not a neutral observer; it is, in a meaningful sense, part of the phenomenon it is predicting.

[1]Anonymous Institution, Anonymous City, Anonymous Region, Anonymous Country. Correspondence to: Anonymous Author <anon.email@domain.com>.

Preliminary work. Under review by the International Conference on Machine Learning (ICML). Do not distribute.

George Soros's theory of *reflexivity* (Soros, 1987; 1998) formalizes this property. He argues that the relationship between prices and fundamentals is bidirectional: prices influence investor perception, which drives capital allocation, which alters the fundamentals that prices are supposed to reflect. This self-reinforcing loop generates a *prevailing bias* — a systematic deviation of prices from what earnings alone would justify — that can grow over extended periods before violently reversing.

Soros further observed that the reflexive process tends to unfold in a characteristic boom-bust sequence, tracked through the level and momentum of the price-to-earnings (P/E) ratio (Soros, 1995). The cycle moves from an *Unrecognized* nascent uptrend through *InitialPhase* and *Acceleration* in the boom arc, before reversing through *Twilight*, *Crash*, and *Recovery* in the bust arc. This stage vocabulary provides a structured lens through which an LLM can reason about the current state of a market cycle.

This paper asks a focused empirical question: *how does awareness of the reflexivity mechanism change LLM directional forecasting during boom-bust cycles?* We investigate this by progressively revealing the theory to the model — from price patterns and earnings fundamentals alone, through the reflexivity mechanism, to a full stage-by-stage account of how the self-reinforcing loop operates — and measuring the effect on directional accuracy and risk-adjusted returns across two historically distinct episodes.

2. Background

2.1. The Theory of Reflexivity and the Boom-Bust Cycle

Soros (1987) argues that two functions operate simultaneously in financial markets. The *cognitive function* runs from reality to views: participants observe prices and fundamentals and form beliefs, but those beliefs are always incomplete and biased. The *participative function* runs in reverse: participants act on their beliefs through buying, selling, and capital allocation, and those actions change the very fundamentals they were trying to assess. A rising price can genuinely improve a firm's access to capital, strengthen its balance sheet, and attract investment — making fundamentals better than they would otherwise have been, which

in turn seems to validate the higher price.

This two-way causality produces a *prevailing bias*: a collectively reinforced misconception about where prices should be, measurable as the gap between the actual P/E ratio and its long-run mean. When the bias and the underlying trend reinforce each other, the system moves progressively further from equilibrium. When the accumulated deviation becomes unsustainable, the same feedback mechanism reverses — and because the bias must fully unwind, busts are typically faster and steeper than the preceding booms (Soros, 1998).

Soros further observed that the reflexive process tends to follow a characteristic boom-bust sequence (Soros, 1995). We operationalize this sequence as seven stages, named and characterized through the observable dynamics of price and EPS. The *boom arc* builds from an Unrecognized trend through InitialPhase, Testing, and Acceleration, with the P/E ratio rising progressively further above its historical mean as the self-reinforcing loop intensifies. The *bust arc* mirrors this in reverse: Twilight marks the stall in momentum while EPS remains intact; Crash arrives when falling prices feed back into fundamentals and EPS begins to deteriorate; and Recovery sees the bust run its course as the prevailing bias collapses. The stage names and their signal-based criteria — grounded in the price and EPS series — are our operationalization of Soros's framework, and are related to the broader narrative economics literature (Shiller, 2019; Akerlof & Shiller, 2009).

2.2. LLMs in Financial Forecasting

LLMs have demonstrated useful signal in financial domains. Lopez-Lira & Tang (2023) show that LLM-generated sentiment predicts stock returns; Matera (2025) finds that narratives from earnings calls improve prediction of analyst expectations and realized earnings. Park (2024) and Yang et al. (2025) apply LLM agents to anomaly detection and market simulation. A key gap identified by Bond et al. (2023) is that most LLM forecasting pipelines do not condition on macroeconomic regime, yielding fragile out-of-sample performance. Our work differs in two ways: we work from quantitative time series rather than text, and our central intervention is theoretical awareness of market structure rather than information augmentation.

3. Experimental Framework

Data. We use monthly adjusted closing prices for the S&P 500 index from Yahoo Finance and monthly trailing twelve-month earnings-per-share (EPS) from Robert Shiller's publicly available dataset (Shiller, 2025), beginning January 1986 to provide a full 10-year history for the rolling P/E z-score normalization underlying the stage definitions.

Evaluation episodes. We evaluate on two historically significant boom-bust cycles, each spanning approximately 72 months:

- **Dot-com bubble** (Jan 1996–Dec 2001): a speculative cycle driven by narrative excess and extreme P/E expansion in technology. The prevailing bias in equities is the primary signal, making this a textbook reflexivity test case.
- **Global financial crisis** (Jan 2004–Dec 2009): a structural credit cycle where reflexive feedback operated through financial system fundamentals rather than equity P/E directly. This tests whether reflexivity-grounded reasoning generalizes beyond the canonical speculative bubble.

Evaluating on both episodes together yields an overall estimate; evaluating separately reveals whether reflexivity awareness generalizes across structurally different cycle types.

Prompting conditions. We evaluate four accumulating zero-shot conditions; full prompt text is in Appendix A. Soros's seven-stage boom-bust framework is given to all conditions as instructional context. What varies is the theoretical framing of *why* stages arise: (A) price only; (B) adds EPS; (C) adds the reflexivity mechanism (cognitive and participative functions, prevailing bias); (D) adds how that mechanism operates at each specific stage.

Tasks and metrics. At each evaluation window, the LLM is asked to forecast three quantities for the next monthly close: (i) the boom-bust cycle *phase*, to prompt the model to reason explicitly about where the market stands in the reflexive cycle; (ii) the *direction* of the price return; and (iii) the *return magnitude* as a signed percentage, to encourage calibrated probabilistic thinking.

Our evaluation focuses on the directional forecast. The primary metric is **directional accuracy**: the fraction of months on which the predicted direction matches the realized direction. We also report the **annualized Sharpe ratio** of an implied long/cash strategy (position $s_t \in \{1, 0.5, 0\}$ for `up`/`neutral`/`down`; portfolio return $r_t^{\text{port}} = s_t \cdot r_{t+1}$), detailed in Appendix B. Directional accuracy treats all months equally, whereas Sharpe is return-weighted and therefore reflects whether correct calls are concentrated in the economically most significant months — a distinction that matters greatly in markets characterized by rare but extreme moves.

Models. We evaluate three frontier large language models: **GPT-5** (temperature $= 1$, the API default; adjustment is

not permitted), **Claude Sonnet 4.6** (temperature $= 0$), and **Gemini 3 Pro** (temperature $= 0$). All experiments use zero-shot prompting.

Context window. We evaluate two context window lengths, $W \in \{36, 60\}$ months, to assess whether the length of observable history moderates the effect of theoretical scaffolding.

Normalization and knowledge-cutoff treatment. Both evaluation episodes predate all three models' training cutoffs. To guard against retrieval of memorized outcomes, all inputs are normalized using a shared base. Let P_0 denote the price at the first month of the context window. The normalized price series is $P'_t = 100 \cdot P_t/P_0$ and the normalized EPS series is $\mathrm{EPS}'_t = 100 \cdot \mathrm{EPS}_t/P_0$ — both divided by the *same* base price, so that $P'_t/\mathrm{EPS}'_t = P_t/\mathrm{EPS}_t$ and the true P/E ratio is preserved exactly. Dates are replaced by $t = 1, \ldots, T$ and the index is labeled "equity market index," removing all absolute level and calendar information while preserving the economically meaningful P/E signal.

4. Results

Directional Accuracy and Sharpe Ratio Table 1 reports directional accuracy across episodes, models, and context windows ($n = 72$ per episode cell; $n = 144$ combined). The Sharpe ratios corresponding to the same cells are in Appendix B. Taken together, the results show that reflexivity awareness can improve LLM forecasting, but the benefit is heterogeneous across models, context windows, and episode type — a pattern that itself constitutes a substantive finding.

Gemini benefits from theory across both windows. Gemini 3 Pro is the most consistent beneficiary of theoretical scaffolding. At $W = 36$, Condition B already lifts directional accuracy to 62.5% in the GFC (Cond. A: 56.9%), and Conditions C and D maintain gains in both episodes; the combined Sharpe rises monotonically from -0.024 (A) to $+0.277$ (D). At $W = 60$, the benefit is present in both episodes: GFC accuracy reaches 59.7% under C and D, and the combined Sharpe under C is $+0.357$. Gemini thus demonstrates that awareness of reflexive market dynamics — both the mechanism and the stage-level mapping — can translate into more accurate and better-calibrated directional forecasts.

GPT-5 benefits only at the longer context window. GPT-5 presents the starkest context-window dependence in the dataset. At $W = 36$, directional accuracy declines monotonically from Condition A (54.9% combined) to D (50.7%), the only result consistently near or below the 50% random baseline. At $W = 60$, the pattern reverses completely: accuracy rises from 52.8% (A) to 59.0% (D) combined, and the Sharpe ratio reaches $+0.440$ (D) with an exceptional $+0.674$ in the GFC under Condition C — the highest single-cell Sharpe in the dataset. This reversal suggests that the reflexivity framework requires sufficient P/E accumulation history to be actionable. With only 36 months of context, GPT-5 cannot observe the full build-up of the prevailing bias and the theory induces premature bearish positions; 60 months provides enough signal for the framework to serve as productive scaffolding.

Claude shows limited benefit from theory. Claude Sonnet 4.6 does not benefit consistently from reflexivity awareness. At $W = 36$, Condition B raises dot-com accuracy to a dataset-high 58.3% but the Sharpe trajectory is non-monotone: $+0.454$ at B, falling to $+0.128$ at C, and only partially recovering to $+0.256$ at D. At $W = 60$, adding EPS or theory reduces both accuracy and Sharpe relative to the naive baseline. The core difficulty is timing: the reflexivity mechanism (C) correctly identifies overvaluation but provides no context for *when* the reversal begins, inducing over-bearish positions during extended Mania phases. The stage-level mapping (D) partially mitigates this by conveying that Mania can persist with upward momentum, but the correction is incomplete.

Episode type moderates the theory benefit. Across all models, reflexivity conditions produce more consistent gains in the GFC than in the dot-com bubble. In the GFC, the reflexive feedback between falling asset prices and deteriorating bank fundamentals directly matches the theoretical mechanism, providing concrete traction. In the dot-com, the Mania phase was exceptionally prolonged and narrative-driven, making overvaluation signals misleading for timing. The episode dependence implies that LLMs — like human traders — have context-specific strengths and weaknesses: a model aware of reflexivity may be well-equipped for credit-cycle busts but poorly calibrated for speculative manias.

5. Discussion

Reflexivity awareness benefits LLMs, but unevenly. The central finding is that making an LLM aware of the reflexivity mechanism can improve directional forecasting, but the effect is heterogeneous across models, context windows, and market episodes. Gemini benefits broadly; GPT-5 benefits only when given a longer historical window; Claude shows limited and inconsistent gains. This heterogeneity is not noise — it is itself informative. It suggests that each model arrives with an internalized prior about financial markets, and that the same theoretical scaffold interacts differently with those priors. Reflexivity-aware prompting is not a uniformly beneficial intervention; its value depends critically on what the model already "knows" about market dynamics.

Table 1. Directional forecasting accuracy. $W \in \{36, 60\}$ represents context window; $n = 72$ months per episode, $n = 144$ combined. Best per episode × model × context window in **bold**.

		Directional accuracy ($W = 60$)			Directional accuracy ($W = 36$)		
Episode	**Condition**	**GPT-5**	**Claude 4.6**	**Gemini 3 Pro**	**GPT-5**	**Claude 4.6**	**Gemini 3 Pro**
Dot-com 1996–2001	(A) Naive	0.514	**0.528**	0.542	0.486	0.569	0.528
	(B) + EPS	0.500	0.514	0.569	**0.514**	**0.583**	0.486
	(C) + Reflexivity	0.528	0.486	0.542	**0.514**	0.528	0.528
	(D) Full Theory	**0.583**	0.486	**0.597**	0.500	0.556	**0.542**
GFC 2004–2009	(A) Naive	0.542	**0.597**	0.556	**0.611**	0.556	0.569
	(B) + EPS	0.556	0.542	0.583	0.569	0.542	**0.625**
	(C) + Reflexivity	**0.597**	0.569	**0.597**	0.556	0.556	0.611
	(D) Full Theory	**0.597**	0.569	0.583	0.514	**0.583**	0.597
Overall combined	(A) Naive	0.528	**0.562**	0.549	**0.549**	0.562	0.549
	(B) + EPS	0.528	0.528	0.576	0.542	0.562	0.556
	(C) + Reflexivity	0.562	0.528	0.569	0.535	0.542	**0.569**
	(D) Full Theory	**0.590**	0.528	**0.590**	0.507	**0.569**	**0.569**

LLMs exhibit context-specific strengths, like human traders. The episode dependence of the theory benefit reveals something deeper than a model calibration issue. In the GFC, where reflexive feedback directly linked falling asset prices to fundamental deterioration, theory conditions consistently improve forecasting across models. In the dot-com bubble, where the Mania phase was prolonged and narrative-driven, the same theory tends to induce premature bearish positions that are costly in a sustained bull market. This parallels a well-known challenge for human traders: understanding that a market is reflexively overvalued is not sufficient to time the reversal. The finding suggests that LLMs, when equipped with economic theory, exhibit analogous strengths and weaknesses — better calibrated for credit-cycle busts that follow the reflexive mechanism closely, and less reliable in speculative manias where the prevailing bias can persist far beyond what theory would predict.

Context window is a design variable, not a robustness check. The strong interaction between context window length and the effect of theoretical scaffolding — most dramatically for GPT-5, which reverses from underperforming the random baseline at $W = 36$ to achieving the best combined Sharpe at $W = 60$ — implies that context window length should be treated as a substantive design choice. The reflexivity framework describes a multi-year process of bias accumulation and reversal; a 36-month window may provide insufficient history to make the framework actionable, while 60 months allows the model to observe the full arc of P/E dynamics.

Limitations. The two episodes provide limited statistical power for cross-episode generalization. Future work should extend the evaluation to additional boom-bust episodes to increase statistical power and test whether the episode-type dependence documented here is robust. A broader sweep of context window lengths would also clarify the threshold at which reflexivity theory becomes actionable for different models.

6. Conclusion

We study how three frontier LLMs behave as financial forecasters during boom-bust cycles when made progressively aware of Soros's theory of reflexivity. Our four-condition zero-shot ablation shows that reflexivity awareness improves directional accuracy for Gemini and GPT-5 (the latter strongly at $W = 60$ months) while producing a non-monotone pattern for Claude — where the reflexivity mechanism alone (Condition C) reduces Sharpe by inducing premature bearish positions in the Mania phase, and the full stage-level mapping (Condition D) partially corrects this timing problem.

The accuracy–Sharpe divergence is a key methodological finding: higher directional accuracy does not guarantee better risk-adjusted returns, because accuracy treats all months equally while economic performance is return-weighted. A model that correctly calls the direction in low-magnitude months while missing large Mania-phase rallies can achieve high accuracy but negative Sharpe.

The substantial heterogeneity across models in response to the same theoretical scaffold — from strong benefits for Gemini to context-dependent effects for GPT-5 to non-monotone Sharpe for Claude — suggests that reflexivity-aware prompting interacts with each model's internalized priors about financial data. Future work should examine whether this heterogeneity tracks training data differences, explore explicit self-referential framing (the forecaster as participant), and extend the evaluation to additional market episodes.

References

Akerlof, G. A. and Shiller, R. J. *Animal Spirits: How Human Psychology Drives the Economy and Why It Matters for Global Capitalism*. Princeton University Press, 2009.

Bond, S. A., Klok, H., and Zhu, M. Large language models and financial market sentiment. *SSRN Working Paper*, 2023. Available at SSRN: `https://ssrn.com/abstract=4584928`.

Lopez-Lira, A. and Tang, Y. Can ChatGPT forecast stock price movements? Return predictability and large language models. *SSRN Working Paper*, 2023. Available at SSRN: `https://ssrn.com/abstract=4412788`.

Matera, G. Corporate earnings calls and analyst beliefs. *arXiv preprint*, arXiv:2511.15214, 2025.

Park, T. Enhancing anomaly detection in financial markets with an LLM-based multi-agent framework. *arXiv preprint*, arXiv:2403.19735, 2024.

Shiller, R. J. *Narrative Economics: How Stories Go Viral and Drive Major Economic Events*. Princeton University Press, 2019.

Shiller, R. J. Online data: U.S. stock markets 1871–present and CAPE ratio. `http://www.econ.yale.edu/~shiller/data.htm`, 2025. Accessed May 2025.

Soros, G. *The Alchemy of Finance*. Simon & Schuster, 1987.

Soros, G. *Soros on Soros: Staying Ahead of the Curve*. Wiley, 1995.

Soros, G. *The Crisis of Global Capitalism: Open Society Endangered*. PublicAffairs, New York, 1998.

Yang, Y. et al. TwinMarket: A scalable behavioral and social simulation for financial markets. *arXiv preprint*, arXiv:2502.01506, 2025.

A. Prompting Conditions: Block Composition

Table 2 shows which blocks compose the system prompt for each condition. The full verbatim text of every block is given in Appendix C at the end of this document.

B. Sharpe Ratio Results

The annualized Sharpe ratio of the long/cash strategy is:

$$\mathrm{SR} = \frac{\sqrt{12} \cdot \mathbb{E}[r^{\mathrm{port}}]}{\mathrm{std}[r^{\mathrm{port}}]}, \tag{1}$$

Table 2. System prompt block composition by condition.

Block	A	B	C	D
1 — Role + price series	✓	✓	✓	✓
2 — EPS series	—	✓	✓	✓
3 — Stage definitions	✓	✓	✓	✓
4 — Reflexivity mechanism	—	—	✓	✓
5 — Stage-level reflex. map	—	—	—	✓
Task + output schema	✓	✓	✓	✓
Approx. size	1.5 kB	1.6 kB	4.3 kB	10.0 kB

where position $s_t \in \{1.0, 0.5, 0.0\}$ maps `up`/`neutral`/`down` to portfolio return $r_t^{\mathrm{port}} = s_t \cdot r_{t+1}$. The buy-and-hold benchmark sets $s_t \equiv 1.0$ always (SR $= 0.35$ over the combined period).

Table 3 mirrors the structure of Table 1 with Sharpe ratios in place of accuracy. The starkest result is GPT-5 C in the GFC at $W = 60$: SR $= +0.674$, far above the buy-and-hold benchmark of 0.02. In the dot-com episode, where the buy-and-hold SR is 0.65, no condition approaches parity — the sustained Mania phase makes the market difficult to beat regardless of theoretical awareness. Claude achieves the highest dot-com Sharpe (A, $W = 36$: $+0.559$) by staying fully long in the bull market, while Claude D achieves the best GFC Sharpe ($+0.515$ at $W = 36$).

C. Full System Prompt Blocks

All text is delivered verbatim as the `system` message; the user message contains only the normalized time series. Block composition by condition is in Table 2 (Appendix A).

Table 3. Annualized Sharpe ratio (Eq. 1). $W \in \{36, 60\}$ represents context window; $n = 72$ months per episode, $n = 144$ combined. Best per episode $\times$ model $\times$ context window in **bold**. Buy-and-hold SR: Dot-com = 0.65, GFC = 0.02, Overall = 0.35.

		Sharpe ratio ($W = 60$)			**Sharpe ratio** ($W = 36$)		
Episode	**Condition**	**GPT-5**	**Claude 4.6**	**Gemini 3 Pro**	**GPT-5**	**Claude 4.6**	**Gemini 3 Pro**
Dot-com 1996–2001	(A) Naive	0.148	**0.110**	0.181	**0.087**	**0.559**	0.104
	(B) + EPS	-0.004	0.015	0.300	0.032	0.454	-0.006
	(C) + Reflexivity	0.135	-0.066	0.230	0.080	0.128	0.161
	(D) Full Theory	**0.361**	0.002	**0.336**	0.086	0.256	**0.166**
GFC 2004–2009	(A) Naive	0.117	0.365	-0.094	**0.262**	0.032	-0.172
	(B) + EPS	0.461	0.020	0.317	0.007	0.408	0.395
	(C) + Reflexivity	**0.674**	**0.471**	**0.503**	-0.096	0.324	0.261
	(D) Full Theory	0.531	0.121	0.363	0.096	**0.515**	**0.404**
Overall combined	(A) Naive	0.134	**0.229**	0.052	**0.169**	0.311	-0.024
	(B) + EPS	0.211	0.017	0.308	0.020	**0.433**	0.181
	(C) + Reflexivity	0.383	0.183	**0.357**	-0.002	0.219	0.208
	(D) Full Theory	**0.440**	0.058	0.349	0.091	0.377	**0.277**

Block 1 — Role and price series (all conditions)

```
You are an expert financial analyst examining a normalized price index for an
equity market.
You will receive a monthly time series indexed t=1 (oldest) to t=T (most recent),
where the price is normalized to 100 at t=1.
```

Block 2 — EPS series (Conditions B C D)

```
You also receive an earnings-per-share (EPS) index for the same market.  Both the
price index and the EPS index are divided by the same base value (the price at
t=1), so their ratio at any point equals the true P/E ratio:
```

P/E at t = PRICE INDEX[t] / EPS INDEX[t]

Block 3 — Seven-stage boom-bust cycle definitions (all conditions)

Stage 1 | Unrecognized. A genuine improvement in fundamentals begins. EPS is growing. Price starts to rise and outpace EPS slightly, but the divergence is small and goes unrecognized by most participants. The P/E ratio is near or just below its long-run mean.

Stage 2 | InitialPhase. The trend becomes recognized and the recognition reinforces it. Price-EPS divergence begins to widen. The P/E ratio rises above its long-run mean. Not yet far-from-equilibrium --- the self-reinforcing loop is engaging but has not accelerated.

Stage 3 | Testing. A price correction pulls back at least 5% from a recent peak. EPS continues to grow --- this is a price-only correction. If price recovers to a new high, the trend emerges strengthened. Identified retrospectively; two test periods may occur.

Stage 4 | Acceleration. The P/E ratio is clearly elevated above its long-run mean and rising. EPS is still growing but price has moved far ahead of fundamentals. The self-reinforcing loop is at its most powerful. Ends at the price peak --- the moment of truth --- after which price can no longer be sustained.

Stage 5 | Twilight. Price has reversed from its peak and is falling or flattening. **Critical signal: EPS has NOT yet started declining.** The trend may be sustained by inertia but ceases to be reinforced by belief.

Stage 6 | Crash. The falling price feeds back into fundamentals --- **EPS begins to decline.** Both price and EPS are now falling in a self-reinforcing bust loop. The cycle's characteristic rapid collapse occurs here.

Stage 7 | Recovery. The bust has run its course. Price begins recovering but EPS may still be declining. Mirrors Stage 1: a new uptrend emerges but goes unrecognized by most participants. P/E near or below long-run mean.

Important: the process may be aborted at any stage. The model describes the complete case; in practice, external shocks may interrupt the sequence.

Block 4 — Theory of reflexivity (Conditions C D)

Reflexivity describes a two-way feedback loop between participants' thinking and the situation they are in. In financial markets, participants' biased views drive their actions, and those actions change the very fundamentals they are trying to assess.

Two functions operate simultaneously:

Cognitive function (reality → views): Participants form beliefs about market prices, but the reality they observe has already been shaped by prior beliefs and actions. Their view is always incomplete and biased.

Participative function (views → reality): Participants act on their biased views. Buying and selling moves prices. Price movements alter the fundamentals --- a

rising price improves a firm's access to capital and strengthens its finances; a falling price does the reverse.

The **prevailing bias** is the net gap between prices and what the fundamentals alone would justify, observable as the gap between the actual P/E ratio and its long-run historical mean.

Keep this theory in mind when examining the data. Use it to interpret what the series signals about the interaction between participants' beliefs and the fundamentals at each point in time.

Block 5 — Stage-level reflexivity map (Condition D only)

Stage 1 | Unrecognized. Cognitive function lags reality: participants attribute the price rise to noise. Participative function is weak. The prevailing bias is nascent; P/E barely moves.

Stage 2 | InitialPhase. Cognitive function catches up: the trend is recognized. Recognition triggers the participative function --- new buyers push prices higher, improving corporate access to capital, genuinely improving EPS, and validating the higher P/E. The feedback loop is fully engaged.

Stage 3 | Testing. A shock temporarily disrupts the loop. Most participants' cognitive function still holds the bias intact; EPS continues to grow. The participative function re-engages as buyers return on the dip. If price recovers, the loop emerges strengthened.

Stage 4 | Acceleration. Cognitive function pushes the bias to an extreme --- the trend feels unshakable. Participative function is at maximum power: higher prices sustain EPS growth and justify ever-higher P/E ratios. The boom builds toward the price peak.

Stage 5 | Twilight. Price peak is past. Cognitive function begins to crack --- bias ceases to be reinforced by belief. Participative function weakening, but **EPS has NOT yet been damaged** --- fundamentals still intact even as price falls.

Stage 6 | Crash. Cognitive function inverts --- extreme pessimism replaces the bias. Participative function operates in reverse: falling prices destroy credit availability, curtail investment, and directly reduce EPS (reflexive fundamental damage). Catastrophic acceleration ensues.

Stage 7 | Recovery. Prevailing pessimism begins to dissolve. Participative function's destructive impact winds down: depressed prices attract value investors, stabilizing fundamentals at the margin. As in Stage 1, most participants do not yet recognize the new uptrend.

Output schema (all conditions)

```
{
  "stage":     "<Unrecognized | InitialPhase | Testing |
            Acceleration | Twilight | Crash | Recovery>",
  "direction":  "<up | neutral | down>",
  "magnitude":  "<signed monthly return in %, e.g.  +2.1 or -0.8>",
  "rationale":  "<2--3 sentences>"
}
```