

# Quantifying Market Timing Accuracy with the Extrema Precision Index (EPI)

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## Abstract

Traditional performance evaluation in algorithmic trading relies heavily on return-based metrics such as the Sharpe Ratio and Maximum Drawdown. While these measures effectively quantify financial outcomes, they fail to capture the geometric precision of trading signals relative to market structure. This paper introduces a novel evaluation metric, the **Extrema Precision Index (EPI)**, designed to measure the efficacy of contrarian trading signals in identifying local market tops and bottoms. By comparing signal execution against identified swing points, the EPI offers a distinct method for evaluating the timing capability of mean-reversion and swing-trading strategies, addressing a gap in current performance attribution methodologies. Additionally, it serves as a sanity check for contrarian strategies when compared to naive benchmarks.

## 1 Introduction

The evaluation of trading strategies has traditionally relied on a well-established suite of return-based metrics. Industry standards such as the Sharpe Ratio, the Sortino Ratio, and Maximum Drawdown provide robust frameworks for assessing risk-adjusted returns and capital preservation. However, while these metrics effectively quantify the *outcome* of a trading strategy, they offer little insight into the *mechanism* of its entry and exit precision relative to market structure.

A fundamental objective for a vast subset of contrarian technical strategies is the identification of local market extrema (swing points). Colloquially known as “buying the bottom” and “selling the top,” this objective relies on detecting inflection points in price action. Despite the popularity of this approach, there remains a significant vacancy in the literature regarding metrics that specifically evaluate the geometric accuracy of these signals. A strategy may yield a high Sharpe Ratio due to a strong trend component, yet fail to accurately identify swing points, thereby masking its true behavioral characteristics.

Currently, no standardized metric exists to quantify the temporal and price-proximity of a trading signal to a verified market swing point. This paper attempts to address this gap by introducing the **Extrema Precision Index (EPI)**. Unlike traditional performance measures that analyze the equity curve, the EPI analyzes the price-action geometry, calculating the deviation between generated trading signals and post-identified local maxima and minima (swing points). By isolating the specific skill of top-and-bottom detection, the EPI provides a granular layer of performance attribution that return-based metrics cannot capture.

## 2 Methodology

This study employs a quantitative framework to evaluate the temporal precision of mean reversion signals. The methodology consists of three distinct phases: (1) the acquisition of hourly foreign exchange (FX) data, (2) the generation of trading signals via the Relative Strength Index (RSI), and (3) the evaluation of these signals against detected swing points using the proposed Extrema Precision Index (EPI).

### 2.1 Data Acquisition and Preprocessing

The dataset comprises hourly (*H1*) Close price series for a basket of major foreign exchange pairs EUR/USD, USD/CHF, GBP/USD, USD/JPY, AUD/USD, USD/CAD. For a given currency pair, let

the time series of closing prices be denoted as  $P = \{p_1, p_2, \dots, p_T\}$ , where  $T$  represents the total number of observations.

To ensure robustness, no look-ahead bias is introduced during the signal generation phase. However, the evaluation phase utilizes hindsight data to identify geometric market structures (swing points), which serves as the benchmark for signal timing. Structurally, this does not impact the results of the study.

## 2.2 Signal Generation Strategy

The core trading logic utilizes the Relative Strength Index (RSI) to identify overextended market conditions. The RSI at time  $t$ , denoted as  $RSI_t$ , is calculated following Wilder's standard formulation:

$$RSI_t = 100 - \frac{100}{1 + RS_t} \quad (1)$$

Where the Relative Strength ( $RS_t$ ) is the ratio of the smoothed moving average (SMMA) of upward price changes ( $U$ ) to downward price changes ( $D$ ) over a period  $\lambda$  (typically 14 or 5):

$$RS_t = \frac{SMMA_\lambda(U)}{SMMA_\lambda(D)} \quad (2)$$

We define a mean reversion strategy  $\mathcal{S}$  that generates binary signals based on upper and lower thresholds,  $\theta_{sell}$  (e.g., 80) and  $\theta_{buy}$  (e.g., 20). The signal function  $\Psi_t$  is defined as:

$$\Psi_t = \begin{cases} 1(\text{Buy}) & \text{if } RSI_{t-1} > \theta_{buy} \wedge RSI_t \leq \theta_{buy} \\ -1(\text{Sell}) & \text{if } RSI_{t-1} < \theta_{sell} \wedge RSI_t \geq \theta_{sell} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Note that signals are triggered strictly on the crossover event to isolate the precise moment of entry.

## 2.3 Identification of Swing Points

To evaluate the timing accuracy of  $\Psi_t$ , we must first define the "ideal" entry points. We define these as Local Extrema (Swing Highs and Swing Lows) derived from a centered rolling window.

Let  $W$  denote the lookback window (e.g.,  $W = 10$ ). A time step  $t$  is classified as a Swing High ( $E_{high}$ ) or Swing Low ( $E_{low}$ ) if the closing price  $p_t$  is the absolute maximum or minimum within the interval  $[t - \frac{W}{2}, t + \frac{W}{2}]$ .

Formally, the sets of indices for swing highs ( $\mathcal{T}_{high}$ ) and swing lows ( $\mathcal{T}_{low}$ ) are defined as:

$$\mathcal{T}_{high} = \{t \mid p_t = \max(p_{t-k}, \dots, p_{t+k})\} \quad (4)$$

$$\mathcal{T}_{low} = \{t \mid p_t = \min(p_{t-k}, \dots, p_{t+k})\} \quad (5)$$

where  $k = \lfloor \frac{W}{2} \rfloor$ .

**Rationale:** This centered-window approach effectively filters high-frequency noise, isolating structurally significant turning points that a mean reversion strategy theoretically aims to capture. While this identification requires future data (hindsight), it provides a static "Ground Truth" against which the causal signals can be objectively measured.

## 2.4 The Extrema Precision Index (EPI)

We propose the Extrema Precision Index (EPI) as a metric to quantify the coincidence rate between trading signals and market extrema within a specific tolerance window  $\delta$ .

Let  $\Omega$  be the set of all time steps where a signal was generated ( $\Psi_t \neq 0$ ). The total number of signals is  $N = |\Omega|$ . A signal at time  $t$  is considered "valid" if a corresponding swing point exists within the temporal neighborhood  $[t - \delta, t + \delta]$ .

The EPI is calculated as:

$$EPI = \frac{1}{N} \sum_{t \in \Omega} \mathbb{I}(t, \delta) \quad (6)$$

Where  $\mathbb{I}(t, \delta)$  is an indicator function that returns 1 if the signal coincides with a relevant extremum, and 0 otherwise:

$$\mathbb{I}(t, \delta) = \begin{cases} 1 & \text{if } \Psi_t = 1 \wedge \exists \tau \in [t - \delta, t + \delta] \text{ s.t. } \tau \in \mathcal{T}_{low} \\ 1 & \text{if } \Psi_t = -1 \wedge \exists \tau \in [t - \delta, t + \delta] \text{ s.t. } \tau \in \mathcal{T}_{high} \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

An EPI score of 1.0 indicates perfect temporal alignment with market structure, while a score approaching 0 indicates that signals satisfy the RSI condition but fail to align with structural pivot points.

It is crucial to interpret the magnitude of the EPI within the context of the chosen tolerance parameter  $\delta$ . An EPI score approaching zero when  $\delta = 0$  does not inherently imply strategy failure; rather, it reflects the stochastic nature of high-frequency price action, where requiring a signal to coincide perfectly with the exact tick of a local extremum is practically unattainable in a semi-chaotic market environment.

However, the implications shift as the tolerance window expands. With a parameter of  $\delta = 3$ , the metric allows sufficient spatial freedom for the signal to manifest within the "neighborhood" of a structural pivot. Consequently, a low EPI at  $\delta = 3$  strongly correlates with a defective contrarian logic, as it indicates the strategy fails to identify even the general vicinity of market tops and bottoms.

### 3 Results

#### 3.1 Key Elements of the Back-test

To qualitatively assess the performance of the proposed strategy, we first examine the alignment of generated signals with local market extrema. Figure 1 illustrates a representative sample of the EUR/USD hourly time series.



Figure 1: **Signal Coincidence with Market Structure (EUR/USD H1).** The plot superimposes the RSI-generated trading signals against identified swing points (Ground Truth). Green arrows denote Buy signals ( $\Psi = 1$ ), and Red arrows denote Sell signals ( $\Psi = -1$ ). The proximity of these signals to the local minima and maxima illustrates the strategy's ability to capture mean reversion events within the tolerance window.

While Figure 1 provided a microscopic view of entry timing, it is equally important to evaluate the strategy's behavior over a macroscopic horizon. Figure 2 presents the AUD/USD Hourly time series over an extended period.

The extended view in Figure 2 confirms that the strategy does not suffer from "signal starvation" and maintains active participation in the market, providing a statistically significant sample size for the EPI calculation.



Figure 2: **Macro-View of Signal Distribution (AUD/USD H1)**. This zoomed-out perspective illustrates the frequency and clustering of trade signals over multiple market cycles. The high density of signals during consolidation phases contrasting with the scarcity of signals during strong directional trends validates the mean-reversion nature of the RSI logic. The visual correlation between the signal clusters and the identified swing high/low bands remains consistent across the expanded dataset.

To ensure reproducibility, the back-testing framework was initialized with the following specific hyperparameters:

- **Signal Generation:** A 5-period Relative Strength Index ( $RSI(5)$ ) was utilized to increase sensitivity to short-term reversals. The oversold threshold was set to 20, and the overbought threshold to 80.
- **Ground Truth Identification:** The swing detection algorithm employed a centered rolling window of 10 periods ( $W = 10$ ), identifying local extrema within a  $\pm 5$  period neighborhood.
- **Performance Evaluation:** The "Hit Ratio" is defined as the percentage of signals resulting in a positive return after a fixed holding period of 10 candles ( $t + 10$ ), without the use of dynamic stop-losses or take-profits.

Additionally, we simulated a random contrarian trading strategy to serve as a stochastic benchmark for the RSI model. This control experiment generates signals with the same frequency as the RSI strategy but lacks its underlying logic. By comparing the EPI of the RSI strategy against this random baseline, we can rigorously determine whether the RSI signals add genuine structural value or if their coincidence with swing points is indistinguishable from random market noise.

To rigorously validate the timing precision of the RSI strategy, we constructed a control model referred to as the "Random Contrarian" strategy. Unlike a purely random walk which ignores market state, this benchmark acknowledges structural regimes but randomizes the trigger event.

The logic is defined as follows: Given an indicator series  $I_t$  (e.g., RSI) and a probability threshold  $p = 0.2$ , a signal  $\Psi_t^{rand}$  is generated only if the market is in a contrarian zone and a stochastic condition is met:

$$\Psi_t^{rand} = \begin{cases} 1(\text{Buy}) & \text{if } I_t < \theta_{lower} \wedge \xi_t < p \\ -1(\text{Sell}) & \text{if } I_t > \theta_{upper} \wedge \xi_t < p \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Where  $\theta_{lower} = 40$  and  $\theta_{upper} = 60$  define the contrarian zones, and  $\xi_t \sim \mathcal{U}[0, 1]$  is a random variable drawn from a uniform distribution at each time step.

This methodology decouples the *regime identification* (which is preserved) from the *signal timing* (which is randomized). If the standard RSI strategy significantly outperforms this benchmark in terms

of EPI, it confirms that the specific crossover event adds temporal value beyond merely identifying overextended conditions.

### 3.2 Performance Metrics

Table 1 summarizes the performance of the strategy across major currency pairs. We compare the **Hit Ratio** (directional accuracy over 10 periods) against the **EPI** (temporal precision relative to swing points).

Table 1: **Sensitivity Analysis of Signal Timing.** The table presents the signal count, 10-period forward Hit Ratio, and the Extrema Precision Index (EPI) across three tolerance thresholds ( $\delta = 1, 2, 5$ ). A significant convergence is observed at  $\delta = 5$ , where approximately 78% of all signals align with a market swing point.

Asset	Signals	Hit Ratio ( $h = 10$ )	EPI ( $\delta = 1$ )	EPI ( $\delta = 2$ )	EPI ( $\delta = 5$ )
EUR/USD	747	50.20%	0.50	0.61	0.80
USD/CHF	716	49.86%	0.43	0.56	0.78
GBP/USD	724	49.58%	0.43	0.54	0.77
USD/JPY	749	46.86%	0.42	0.54	0.76
AUD/USD	738	50.94%	0.46	0.56	0.78
USD/CAD	671	51.11%	0.45	0.56	0.77
<b>Average</b>	<b>724</b>	<b>49.76%</b>	<b>0.45</b>	<b>0.56</b>	<b>0.78</b>

*Note: "Hit Ratio" denotes the probability of positive expectancy after 10 periods. EPI values range from 0 to 1, with higher values indicating tighter clustering around swing points.*

It is imperative to highlight that across all tested assets, the stochastic benchmark consistently yielded a lower EPI compared to the standard RSI strategy. This systematic divergence indicates that the RSI's signal generation logic contributes tangible predictive utility, identifying structural turning points with a precision that exceeds random chance within equivalent contrarian zones.

## 4 Discussion and Conclusion

This study introduced the Extrema Precision Index (EPI), a novel metric designed to quantify the temporal alignment between mean reversion signals and hindsight market structure.

### 4.1 Interpreting the EPI: Precision vs. Profitability

The EPI serves a distinct purpose in strategy validation:

- **High Win Rate / Low EPI:** This divergence suggests a "lucky" strategy. The signals are profitable but fail to capture the structural turning points, implying that the strategy relies on drift or mid-trend noise rather than true mean reversion. Such strategies are prone to failure in changing volatility regimes.
- **High EPI / Low Win Rate:** This indicates a "tight but premature" strategy. The model correctly identifies turning points but likely suffers from poor risk management (e.g., stops being hit before the reversal materializes).

Therefore, the EPI should be used as a **filter for robustness**. A strategy should only be deployed if it satisfies a minimum EPI threshold (e.g.,  $EPI > 0.40$ ), ensuring that the underlying logic is causally linked to market extrema.

### 4.2 Evolving the Metric: Future Research

While the current formulation of the EPI uses a fixed temporal tolerance (e.g.,  $\delta = 2$ ), future iterations of this metric can be evolved to account for market dynamics:

### 4.2.1 1. Volatility-Adjusted Tolerance (VEPI)

In high-volatility environments, price action accelerates, often compressing the time between a signal and a swing point. Conversely, low-volatility regimes lengthen this delay. The metric can be transformed by making  $\delta$  dynamic based on the Average True Range (ATR):

$$\delta_t = \text{round} \left( k \times \frac{ATR_{ref}}{ATR_t} \right) \quad (9)$$

Where  $ATR_{ref}$  is a baseline volatility and  $k$  is a scaling constant. This allows the tolerance window to expand or contract organically with market "noise."

### 4.2.2 2. The EPI as a Machine Learning Target

Perhaps the most potent application of the EPI is in Supervised Machine Learning. Instead of training models to predict raw price changes (which are noisy), researchers can use the EPI to create a "Quality Label" for training data.

$$Y_{target} = \begin{cases} 1 & \text{if } EPI(\text{signal}) = 1 \text{ (Precision Entry)} \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

By training a Neural Network or Random Forest to predict the *EPI probability* rather than price direction, the model learns to hunt for structural swing points specifically, filtering out profitable but random noise.

## 5 Final Remarks

The RSI strategy analyzed herein demonstrates a structural edge, with signals clustering around market extrema. By adopting the EPI as a standard measure of timing efficiency, algorithmic traders can better distinguish between robust structural alignment and random profitability.