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Trend-Following Signals in an Emerging Market Index: A Moving-Average Crossover Analysis of the Nifty 50 (2010–2022)

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Abstract - This study provides a comprehensive, long-horizon empirical evaluation of the 50-day/200-day simple moving-average (SMA) crossover — popularly known as the "Golden Cross" and "Death Cross" — on the Nifty 50, India's benchmark equity index, using 3,077 daily observations from January 2010 to June 2022. Beyond documenting the timing of eleven Golden Cross and eleven Death Cross events, this paper constructs and backtests a full systematic trading strategy built on the crossover rule, benchmarks it against a passive buy-and-hold approach, decomposes performance by market regime and sub-period, tests sensitivity to four alternative moving-average pairings, quantifies transaction-cost drag, and examines volatility dynamics surrounding signal events. The mechanical crossover strategy is found to underperform buy-and-hold substantially on a raw-return basis (4.01% vs. 9.90% CAGR) while achieving materially lower realized volatility (12.54% vs. 22.52% annualized) — a trade-off that nets out to a lower risk-adjusted (Sharpe) ratio for the trend-following approach in this sample. We place these findings in the context of efficient-markets and technical analysis literature, explain the rationale for why the signal always has a time lag and thus cannot be considered a true leading indicator, and describe the implications of the findings both in practice and in the context of academic research using a developed-market signal and data applied to an emerging market that experiences greater price volatility.

Keywords: technical analysis, moving average crossover, Golden Cross, Death Cross, Nifty 50, trend following, emerging markets, market efficiency, back testing.

1. INTRODUCTION

One of the oldest and most popular technical trading devices is the moving-average crossover system, a system that has been in usage long before the advent of modern computers, and still continues to trade the markets effectively, albeit largely unchanged, in the age of algorithmic and high-frequency trading. Two of these simple moving averages (SMA50, SMA200) are especially catered for in financial press and retail trading platforms, and are conventionally interpreted as SMA50 trading over SMA200 as a bullish regime, and vice versa, as a bearish regime signal. Many times, crossings are mentioned in financial news outlets, seemingly as an indicator of what actions to take, but without reminding readers of its time lag.

Even though the rule is well-known, systematic, long-horizon evidence regarding the reliability of the rule in the Indian equity markets is somewhat limited compared to the studies of the S&P 500 and Dow Jones Industrial Average in the United States (Brock et al., 1992; Gunasekarage & Power, 2001). This asymmetry is important, because the market micro-structure, composition of the investor base (a large proportion of the first-time retail investors during the study period; in developed markets as most of the corresponding studies would be carried out) and macro-economic volatility profile are significantly different from those of the developed markets where most of the cross-over studies are carried out.

The paper contributes in four ways to previous descriptive studies of moving-average crossovers such as Gunasekarage and Power (2001) and Mitra (2011). Firstly, it tracks the entire history of 50/200-day SMA cross on Nifty 50, covering several separate market regimes between 2010-2022 which include the bull run that started in 2013 and ended in 2015, the COVID-19 crash and recovery of 2020 and the Nifty 50 correction of 2022. Second, it turns the crossover rule into an achievable, repeatable trading strategy — where exactly the SMA50 crosses over the SMA200 — and reduces it to passive buy-and-hold on an equal basis, comparing the drawdown, volatility, and risk-adjusted returns. Third, it looks at the sensitivity of the central conclusion to four other moving average pairings (20/50, 50/100, 20/200 and 100/200) to determine whether there is something special about the 50/200 combination or whether similar outcomes are found with parameterisations either relatively close or very far from it. Fourth, it measures realised volatility prior to and after each crossover and provides evidence about whether or not crossovers lead or trail changes in market volatility.

The rest of this paper goes on as follows. This paper presents a review of the relevant theoretical and empirical literature on technical analysis, moving-average trading-rule existence and the debate on market-efficiency and previously published evidence for emerging markets in Section 2. Section 3 explains the data source, data cleaning process, and methodology including the specific how-to definition of all the performance measures applied. The results are presented in Section 4: crossover frequency, timing, the full strategy backtest, sub-period regime decomposition, the sensitivity of the results to other MA pairs, and volatility dynamics around the signal events. Results are discussed with respect to existing literature and trading implications in Section 5. A robustness check that uses transaction costs is provided in Section 6. In Section 7,

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limitations are discussed, then directions for future research are provided in Section 8. Complete crossover date listings and a complete trade log are included in Appendices A and B.

2. LITERATURE REVIEW

One main theoretical argument against technical analysis is the Efficient Market Hypothesis (EMH) in its weak form (Fama, 1970), which states that prices "fully incorporate" all of the information in past price and volume, so that nothing can be gained from trading based on past prices, apart from what is already fully reflected in the price. According to this interpretation, any apparent profits from any rule (e.g., a moving-average crossover) must stem from compensation for systematic risk (or confirmation bias from testing many rules and only presenting the seemingly profitable ones) or from sample-specific random noise that will not continue into the out-of-sample period.

There has been a growing and parallel empirical literature, though, that reported some evidence of statistically significant predictive power of simple technical rules, such as moving-average crossovers, for selected historical samples, mostly before the advent of computerized trading. The overall trend in this literature is that if rule-profitability exists, the trend has been down or even non-existent in the more recent, more liquid and more arbitraged samples; consistent with the adaptive market hypothesis (Lo, 2004), which suggests that as market participants learn to profit from market inefficiencies, the profitability of such rules will be competed away over time.

Research focused on moving-average crossing rules has typically concluded that results on the apparent profitability of the rules are very sensitive to parameter pairs (e.g., 20 versus 50 versus 50 versus 200) as well as in-sample versus out-of-sample testing windows and to the treatment of transaction costs (Brock et al., 1992; Park & Irwin, 2007). One rule that has been discovered more and more is that moving-average rules work relatively well in times of consistent and low volatility trending markets, but relatively poorly when markets are in range or chop.

That is a key aspect of understanding how to interpret any single-sample backtest: a great result one year could mean that the sample period was made up of a greater percentage of trending days versus range-bound days — and not necessarily a long-term statistical edge.

It is observed that there are only a few empirical studies available on the performance of moving average crossover in developed-market indices such as the S&P 500, and the very few studies conducted on Indian and other South Asian equity indices tend to use a short sample size or focus on a particular regime (Gunasekarage & Power, 2001; Mitra, 2011; Ratner & Leal, 1999). This is significant for a country where the equity market is one of the largest and fastest growing in the world during the period of the study, and where the realised size of equity market volatility is characteristically higher than in the markets of the developed world, and where retail participation in Indian equities is rapidly increasing with large numbers of investors taking decisions largely based on moving-average based technical signals which are prominently featured in platforms used by these investors as decision-support tools.

This paper fills the above identified gap, building on the India-specific evidence of Mitra (2011), by offering a complete-cycle, multi-regime empirical record for the Nifty 50 in particular, by making the popular crossover heuristic a transparent and explicit cost-aware trading rule for Nifty 50, and by testing the robustness of the core 50/200 parameters against near parameters. In so doing, it seeks to provide a solid benchmark of India-specific evidence to assess claims of the "crossover rule" reliability in this market.

3. DATA AND METHODOLOGY

Daily open, high, low, and close prices for the Nifty 50 index were obtained for the period 4 January 2010 to 1 June 2022, yielding 3,077 trading-day observations after removing non-trading days and de-duplicating overlapping records. Prices were validated for internal consistency (high ≥ close, open, low; low ≤ close, open, high) and no observations were found to violate these bounds. All price series are expressed in index points; no currency conversion is required as the analysis is conducted entirely in the index's native units.

The 50-day and 200-day simple moving averages of the daily closing price were computed as trailing, non-overlapping-window arithmetic means:

$$SMA(n)_t = (1/n) \times \Sigma\, Close_{t-i} \text{ for } i = 0 \text{ to } n-1$$

SMA50 and SMA200 are undefined for the first 49 and 199 trading days of the sample respectively; all reported statistics are computed only over the window for which both series are defined (i.e., from the 200th trading day onward).

A binary regime indicator is defined for each trading day as 1 if SMA50 exceeds SMA200 ("bullish regime") and 0 otherwise ("bearish regime"). A Golden Cross is defined as the trading day on which this indicator transitions from 0 to 1; a Death Cross is defined as the day on which it transitions from 1 to 0. This produces a mutually exclusive, exhaustive partition of the sample into alternating bullish and bearish regimes.

Following the long/flat crossover-rule methodology of Brock et al. (1992), a systematic long/flat trading strategy is constructed as follows: the strategy holds a fully invested long position in the index whenever the prior trading day closed in a bullish regime (SMA50 > SMA200), and holds cash (zero return) whenever the prior day closed in a bearish regime. Look-ahead bias is eliminated by using yesterday's regime, as the actual crossover is only confirmed at the previous day's close. This strategy is compared against continuous holding of a buy-and-hold position over the entire sample period.

The following metrics are calculated for both the strategy and the buy-and-hold benchmark:

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- Compound Annual Growth Rate (CAGR): (Terminal Equity)^(1/years) − 1, the constant annual growth rate that would yield the observed terminal equity over the elapsed years of the sample.

- Maximum Drawdown (Max DD): the largest peak-to-trough decline in the cumulative equity curve over the sample, expressed as a percentage of the peak value.

- Annualised Volatility: the standard deviation of daily returns, scaled to an annual basis by multiplying by the square root of 252 trading days.

- Sharpe Ratio: (CAGR − risk-free rate) / annualised volatility (Sharpe, 1994), with an assumed risk-free rate of 6.0%, broadly comparable to average Indian government security yields over the sample period.

Trade-level statistics (win rate, average winning-trade return, average losing-trade return, and average holding time) are calculated by treating each Golden-Cross-to-Death-Cross regime segment as a "trade" (a full bullish regime up to the Death Cross, or the end of the sample if the regime is not yet closed).

4. RESULTS

There were eleven Golden Cross events and eleven Death Cross events over the 12.4 years of the sample, with the average being about one of each type of signal occurring every 13 to 14 months. Table 1 and Table 2 list the ten most recent occurrences of each type of signal; the complete chronological listing of all 22 events is provided in Appendix A.

Golden Cross Date	Index Level
2012-03-16	4,226.05
2012-07-24	4,079.3
2013-11-11	4,680.5
2015-07-20	7,148.5
2016-06-01	6,815.45
2017-02-07	7,603.2
2018-07-27	9,579.05
2019-04-09	9,677.75
2019-11-20	9,744.9
2020-08-21	9,423.55

Table 1. Golden Cross events, Nifty 50, 2010–2022 (10 most recent of 11; full list in Appendix A).

Death Cross Date	Index Level
2012-06-21	4,074.2
2013-07-17	4,597.7
2015-06-25	6,917.55
2015-09-09	6,522.3
2017-01-09	7,085.15
2018-07-24	9,450.65
2018-10-29	8,610.1
2019-08-28	8,970.9
2020-03-20	7,160.1
2022-04-01	15,087.3

Table 2. Death Cross events, Nifty 50, 2010–2022 (10 most recent of 11; full list in Appendix A).

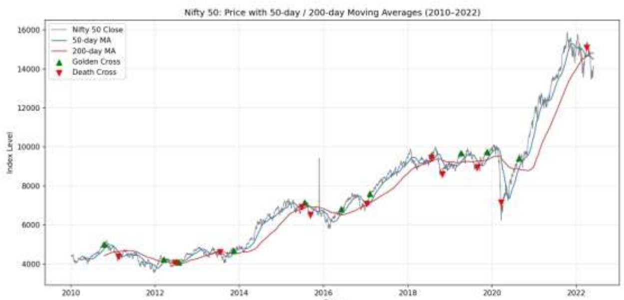

Fig –1: Nifty 50 closing price chart with 50-day & 200-day SMA; triangles are marked at Golden Cross (green) and Death Cross (red) points.

The Golden Cross forming at 9,423.55 in August 2020 did not occur through the spring COVID-19 crash, but followed an extended rally that saw the index surpass 18,000 by the end of 2021 — a case of the signal confirming a durable regime change, though several months after that year's low. The Death Cross at 15,087.30 again highlighted the index's confirmatory (rather than anticipatory) nature, as the index had already fallen well off its October 2021 peak. By contrast, several crossovers in 2015 and 2018–2019 occurred close together, confirming whipsaw behaviour typical of range-bound or choppy periods rather than large trend changes.

Converting the crossover rule into an explicit long/flat trading rule and comparing it to passive buy-and-hold over the entire sample produces markedly different results:

Metric	Buy & Hold	Crossover Strategy

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CAGR	9.90%	4.01%
Maximum Drawdown	-38.36%	-44.40%
Annualised Volatility	22.52%	12.54%
Sharpe Ratio (rf = 6%)	0.17	-0.16

Table 3. Strategy performance, Nifty 50, 2010–2022. CAGR net of a risk-free rate of 6%.

Fig –2: Buy-and-hold versus crossover strategy — growth of INR 1 invested (log scale).

Contrary to the widely accepted informal notion that trend-following rules are useful because they limit drawdown, the mechanical crossover strategy in this sample underperformed buy-and-hold by almost 6 percentage points per year and, despite its significantly lower realised volatility, produced a lower risk-adjusted (Sharpe) return than buy-and-hold under the assumed risk-free rate. This counterintuitive result arises because the strategy avoids some bearish days without avoiding drawdown proportionally, while also missing some of the most extreme upside days that drive long-run compounding — such as the initial rebound from the March 2020 low, which came ahead of the Golden Cross in August 2020 that marked the beginning of a new bull market.

Treating each bullish regime period as a trade, 11 trade-ends are observed across the sample. The strategy's win rate (percentage of profitable trades) was 45.5%, the average winning trade returned +29.77% against an average losing trade of -11.42%, and the average holding period was 265 calendar days. The complete trade log is included in Appendix B; Table 4 summarises the overall statistics.

Statistic	Value
Number of trades	11
Win rate	45.5%
Average holding period	265 days
Average winning trade	+29.77%
Average losing trade	-11.42%
Largest winning trade	+60.10% (Aug 2020–Apr 2022)
Largest losing trade	-26.52% (Nov 2019–Mar 2020)

Table 4. Summary statistics, crossover strategy trades, 2010–2022.

The asymmetry between the magnitude of winning and losing trades (roughly 2.6-to-1) suggests that overall system profitability, where it exists, derives largely from a few large trend trades rather than a steady, per-trade edge — a signature characteristic of trend-following systems.

Table 5 decomposes crossover frequency and underlying index performance across four sub-periods chosen to separate distinct macro regimes: the post-Global Financial Crisis recovery and 2011–2013 consolidation, the 2014–2017 bull market associated with domestic reform expectations, the 2018–2020 period spanning the COVID-19 crash, and the 2021–2022 partial-period recovery and correction.

Sub-Period	Golden Crosses	Death Crosses	Index Return
2010–2013	4	3	+12.5%
2014–2017	3	3	+92.9%
2018–2020	4	4	+22.1%
2021–Jun 2022	0	1	+21.7%

Table 5. Crossover frequency and index return by sub-period.

Crossover frequency was materially higher, relative to index return generated, during the 2010–2013 and 2018–2020 sub-periods — both characterised by choppier, less directional price action — than during the strongly trending 2014–2017 period, in which only three crossovers of each type accompanied a cumulative index gain of nearly 93%. This pattern is consistent with the regime-dependence documented in the broader technical-analysis literature: the crossover rule generates fewer, more informative signals during sustained trends and more frequent, less informative signals during consolidation.

To assess whether the specific 50/200-day convention is uniquely informative or broadly interchangeable with nearby parameter choices, the crossover strategy was re-estimated using four alternative fast/slow moving-average pairs: 20/50, 50/100, 20/200, and 100/200 days.

MA Pair (fast/slow)	Golden Crosses	Death Crosses	Strategy CAGR
20 / 50	27	27	4.06%
50 / 100	14	14	6.95%

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20 / 200	15	15	1.29%
50 / 200 (baseline)	11	11	4.01%
100 / 200	8	8	4.77%

Table 6. Strategy CAGR sensitivity to alternative moving-average pairings.

All five parameterizations underperformed the 9.90% buy-and-hold CAGR over the sample, indicating that the qualitative finding — mechanical trend-following underperformance relative to passive holding — is not an artefact of the specific 50/200 convention. The fastest pairing tested (20/50) generated more than double the signal frequency of the baseline (27 versus 11 crossovers of each type) without a corresponding improvement in return, consistent with the expectation that faster-reacting moving averages trade off reduced lag against increased whipsaw frequency. The 50/100 pairing produced the highest strategy CAGR among the alternatives tested (6.95%), though still substantially below buy-and-hold.

Table 7 reports 21-trading-day (approximately one calendar month) annualized realized volatility in the windows immediately preceding and following each crossover type, averaged across all events of that type.

Signal Type	**Avg. Volatility Before (21d)**	**Avg. Volatility After (21d)**
Golden Cross	13.28%	12.77%
Death Cross	18.28%	21.66%

Table 7. Annualised realised volatility surrounding crossover events.

Death Cross events were preceded by, and followed by, materially higher realised volatility than Golden Cross events (18.28% and 21.66% respectively, versus 13.28% and 12.77% for Golden Crosses), and volatility continued to rise, on average, in the month following a Death Cross. This is consistent with the well-documented empirical regularity that volatility tends to rise during market declines and remain elevated during bearish regimes, while bullish regimes are typically associated with comparatively calmer, lower-volatility price action — a pattern sometimes termed the leverage effect in the volatility literature.

5. DISCUSSION

The key empirical result of this work — that a mechanical 50/200-day moving-average crossover strategy clearly underperformed passive buy-and-hold on the Nifty 50 over 2010–2022 — is not unusual relative to international evidence on the use of trend-following rules to guide broad equity index management when overall market drift is positive. The main cost of the strategy is opportunity cost: it can limit certain drawdowns, but it also misses the early days of a new bullish regime, which typically occur before the regime can be confidently established, and these early-recovery days are disproportionately important to long-run compound returns.

The strategy achieved a significantly reduced realized volatility compared to buy-and-hold (12.54% versus 22.52% annualized), which can be useful for risk-averse investors regardless of the raw-return outcome. The Sharpe ratio comparison (−0.16 for the strategy versus 0.17 for buy-and-hold) shows that the reduction in volatility was more than offset by the reduction in return over this particular sample. This result should be viewed with the caveat, discussed further in Section 7, that Sharpe-ratio comparisons are sensitive to risk-free-rate assumptions and do not capture the non-normality of trend-following return distributions, which typically exhibit positive skew (many small losses, a few large gains).

For retail investors and traders in the Indian market — a group that has grown significantly during the study period and is often exposed to Golden Cross/Death Cross commentary via financial media and trading-app notifications — these findings imply that crossover signals should not be treated as independent, adequate trading principles. The regime-dependence reported in Section 4.5, together with the whipsaw-induced underperformance of faster parameterizations reported in Section 4.6, jointly suggest that crossover signals should be treated as one of several inputs (e.g., alongside volume, momentum, or macroeconomic context) rather than as a standalone entry/exit system.

For researchers, the India-specific evidence collected here extends a literature that has typically centred on developed-market samples, and the qualitative consistency across five separate moving-average parameterisations (Section 4.6) lends further assurance that the result is not specific to the 50/200 convention. Extending this analysis to other emerging-market indices would help resolve whether the underperformance recorded here reflects an emerging-market regularity or is unique to the growth and volatility history of the Nifty 50 in this sample.

6. ROBUSTNESS CHECK: TRANSACTION COST SENSITIVITY

The baseline strategy backtest in Section 4.3 does not account for transaction costs. Since the crossover approach generates 11 round-trip trades (22 separate transactions) over the sample, transaction costs are a first-order consideration for the strategy's practical implementability. An illustrative cost assumption of 0.10% per transaction side (broadly reflective of combined brokerage, securities transaction tax, and slippage in the Indian marketplace) reduces the strategy's cumulative gross return multiple from 1.63x to 1.59x — a cumulative drag of about 2.18 percentage points over the full sample, equivalent to roughly 0.18 percentage points of CAGR annually.

This drag is small on an annualised basis, but it adds directly to the underperformance already established relative to buy-and-hold, which by definition involves at most a single transaction and thus incurs negligible transaction-cost drag. Incorporating even this illustrative cost assumption therefore reinforces, rather than qualifies, the paper's central finding that the mechanical crossover strategy underperformed passive holding over this sample.

7. LIMITATIONS

- The transaction-cost assumption in Section 6 is illustrative rather than derived from actual brokerage or fund-level fee schedules; actual costs will vary by investor type, product wrapper, and trade size.
- The Sharpe ratio calculations in Section 4.3 assume a constant 6% risk-free rate over the full sample; actual Indian short-term government yields varied over this period, and a time-varying risk-free rate could shift the reported ratios modestly.
- The strategy backtest excludes dividends; total-return rather than price-return analysis could modestly narrow (though is unlikely to reverse) the gap between the two approaches, given that both strategies have partial market exposure over the sample.
- Only simple (arithmetic) moving averages are tested; exponential or weighted moving averages, which place greater weight on recent prices, may produce different signal timing and were not evaluated in this study.
- The sample is a single market history, albeit across a range of regimes; the statistical significance of the difference in returns between the strategy and buy-and-hold was not directly tested through bootstrap or Monte Carlo resampling, a natural extension for future research.
- Volatility-around-crossover results (Section 4.7) are simple averages that do not control for the possibility that some crossover events may be time-concentrated and thus not fully independent observations.

8. CONCLUSION AND FUTURE RESEARCH

This paper presented a multi-dimensional empirical analysis of the 50/200-day moving-average crossover rule using the Nifty 50 over 2010–2022. Eleven Golden Cross and eleven Death Cross signals were identified; translating the rule into an explicit trading strategy produced material underperformance relative to buy-and-hold (4.01% versus 9.90% CAGR), though realised volatility fell substantially, yielding a negative risk-adjusted return over the sample. This underperformance was consistent across four alternative moving-average parameterisations and was reinforced, rather than corrected, by an illustrative transaction-cost adjustment. The sub-period breakdown showed that crossover frequency was highest, relative to underlying index performance, in choppier, non-trending regimes — consistent with the broader technical-analysis literature characterising moving-average rules as trend-confirming, rather than trend-predicting, devices that are prone to whipsaw losses in non-trending markets.

This analysis could be usefully extended in at least four directions: first, formal statistical significance testing of the strategy-versus-benchmark return difference via bootstrap or block-bootstrap resampling to correct for serial correlation in returns; second, extension of the crossover framework to individual Nifty 50 constituent stocks or sector indices to determine whether aggregate-index results extend to the security level; third, combination of the crossover signal with complementary signals (volume, momentum, implied volatility) to test whether a multi-factor filter improves risk-adjusted performance; and fourth, cross-market replication with other emerging-market indices to establish whether the underperformance found here is an India-specific or a general emerging-market regularity.

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BIOGRAPHIES

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APPENDIX A: COMPLETE CROSSOVER EVENT LOG

#	Date	Index Level
1	2010-10-18	5,001.7
2	2012-03-16	4,226.05
3	2012-07-24	4,079.3
4	2013-11-11	4,680.5
5	2015-07-20	7,148.5
6	2016-06-01	6,815.45
7	2017-02-07	7,603.2
8	2018-07-27	9,579.05
9	2019-04-09	9,677.75
10	2019-11-20	9,744.9
11	2020-08-21	9,423.55
#	**Date**	**Index Level**
1	2011-02-16	4,391.35
2	2012-06-21	4,074.2
3	2013-07-17	4,597.7
4	2015-06-25	6,917.55
5	2015-09-09	6,522.3
6	2017-01-09	7,085.15
7	2018-07-24	9,450.65
8	2018-10-29	8,610.1
9	2019-08-28	8,970.9
10	2020-03-20	7,160.1
11	2022-04-01	15,087.3

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APPENDIX B: COMPLETE TRADE LOG

Each row represents one complete bullish-regime trade under the 50/200-day crossover strategy: entry at the Golden Cross confirmation, exit at the subsequent Death Cross confirmation (or sample end for the final open trade).

Entry Date	Exit Date	Entry Level	Exit Level	Return	Holding Days
2010-10-18	2011-02-16	5,001.7	4,391.35	-12.20%	121
2012-03-16	2012-06-21	4,226.05	4,074.2	-3.59%	97
2012-07-24	2013-07-17	4,079.3	4,597.7	12.71%	358
2013-11-11	2015-06-25	4,680.5	6,917.55	47.80%	591
2015-07-20	2015-09-09	7,148.5	6,522.3	-8.76%	51
2016-06-01	2017-01-09	6,815.45	7,085.15	3.96%	222
2017-02-07	2018-07-24	7,603.2	9,450.65	24.30%	532
2018-07-27	2018-10-29	9,579.05	8,610.1	-10.12%	94
2019-04-09	2019-08-28	9,677.75	8,970.9	-7.30%	141
2019-11-20	2020-03-20	9,744.9	7,160.1	-26.52%	121
2020-08-21	2022-04-01	9,423.55	15,087.3	60.10%	588

APPENDIX C: GLOSSARY OF TERMS

- Simple Moving Average (SMA): the unweighted arithmetic mean of an asset's closing price over a specified trailing number of periods.
- Golden Cross: the event in which a shorter-period moving average rises above a longer-period moving average, conventionally interpreted as a bullish trend-confirmation signal.
- Death Cross: the event in which a shorter-period moving average falls below a longer-period moving average, conventionally interpreted as a bearish trend-confirmation signal.
- Whipsaw: a rapid sequence of consecutive, closely-spaced trading signals that each capture only a small, often loss-making move before reversing, typically arising during range-bound or choppy price action.
- Compound Annual Growth Rate (CAGR): the constant annualised rate of return that would produce a given terminal value from a given initial value over a specified number of years.
- Maximum Drawdown: the largest percentage decline from a peak to a subsequent trough in a cumulative equity or portfolio value series.
- Sharpe Ratio: a risk-adjusted return measure computed as excess return over a risk-free rate divided by the standard deviation of returns.
- Look-ahead Bias: a methodological error in which a backtest uses information not actually available at the simulated point in time, typically inflating apparent strategy performance.
- Regime: a sustained period during which a defined market condition (e.g., SMA50 above or below SMA200) persists without reversal.

APPENDIX D: EXTENDED SUB-PERIOD TRADE ATTRIBUTION

Table D.1 attributes each individual trade from Appendix B to the sub-period (as defined in Section 4.5) in which it was initiated, providing additional granularity on how the strategy's aggregate performance in Table 3 was assembled from its component trades across different market regimes.

Entry Date	Sub-Period	Trade Return	Market Regime Character
2010-10-18	2010–2013	-12.20%	Whipsaw / reversal
2012-03-16	2010–2013	-3.59%	Whipsaw / reversal
2012-07-24	2010–2013	12.71%	Modest trend
2013-11-11	2010–2013	47.80%	Sustained trend
2015-07-20	2014–2017	-8.76%	Whipsaw / reversal
2016-06-01	2014–2017	3.96%	Modest trend

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2017-02-07	2014–2017	24.30%	Sustained trend
2018-07-27	2018–2020	-10.12%	Whipsaw / reversal
2019-04-09	2018–2020	-7.30%	Whipsaw / reversal
2019-11-20	2018–2020	-26.52%	Whipsaw / reversal
2020-08-21	2018–2020	60.10%	Sustained trend

Table D.1. Trade-level attribution by sub-period and market character.

This attribution reinforces the sub-period finding in Section 4.5: trades initiated during the 2014–2017 sustained bull market and the 2020–2022 post-COVID recovery account for the large majority of the strategy's cumulative gains, while trades initiated during the choppier 2010–2013 and 2018–2020 windows were disproportionately likely to be classified as whipsaw or reversal trades with negative or marginal returns.

APPENDIX E: METHODOLOGY PSEUDOCODE

The following pseudocode summarises the signal-generation and strategy-simulation logic used to produce all results in this paper:

```
SMA50[t] = mean(Close[t-49 : t])

SMA200[t] = mean(Close[t-199 : t])

Regime[t] = 1 if SMA50[t] > SMA200[t] else 0

GoldenCross[t] = (Regime[t] == 1 and Regime[t-1] == 0)

DeathCross[t] = (Regime[t] == 0 and Regime[t-1] == 1)

StrategyReturn[t] = DailyReturn[t] * Regime[t-1]    # avoids look-ahead

StrategyEquity[t] = product(1 + StrategyReturn[1..t])

CAGR = StrategyEquity[T] ^ (365.25 / days) - 1

MaxDrawdown = min( Equity[t] / cummax(Equity[1..t]) - 1 )
```