Trend Following Algorithms on India's Nifty Index

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Abstract

The objective of this technical analysis study was to test the profitability of 80 related trend following algorithms applied to closing prices for India's Nifty index over periods of rising, falling, mixed trend, and nearly trendless markets. Daily closing prices for the Nifty index were divided into four periods covering trading days from 2005 through 2012. Trend following rules were used that employed no leverage and no short positions. Only investments in the Nifty index or in cash at India's MIBOR rate were permitted with no transaction costs or dividends assumed. For each period, all 80 related trend following algorithms were statistically examined for significance against return distributions created using a Levich-Thomas bootstrapping process. We conclude from this technical analysis study that the family of 80 algorithms investigated worked well in a sharply declining market, but far less so, or not at all well in markets that were more gradually rising, mixed trend, or nearly trendless.

Keywords: trend following, algorithms, nifty, technical analysis
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Scholars, students, and practitioners have long applied technical analysis tools to stock markets in developed countries in an effort to devise profitable trading strategies. Applications of technical analysis to developing markets , however, are far fewer in number, despite the possibility of discovering valuable rules that exploit market inefficiencies not found elsewhere. Among developing global stock markets, India provides a challenging opportunity to test traditional technical analysis trading rules found useful in more developed markets.

Objectives of the Study

- To test the profitability of 80 related trend following algorithms applied to closing prices for the Nifty index over periods of rising, falling, mixed trend, and nearly trend less markets.
- To limit algorithms to only cash or long positions in the index.
- To assume no dividends or transaction costs.
- To statistically test returns using a bootstrapping process.

Review of Literature

Technical analysis studies of Indian stock markets have thus far produced mixed conclusions. In a purely efficient market, technical trading rules should produce no excess profits. Some studies of Indian markets, however, suggest prices do not satisfy the efficient market hypothesis. For example, Kakani and Sundhar (2006) applied moving average rules to both the S&P CNX Nifty and the BSE Sensex indexes over a 15-year period (1991 - 2005) and found excess returns after transaction costs. Mitra (2002) also found excess returns when applying moving average crossover and filter rules to four important Indian stocks during the period from 1995-1999 . The findings of these

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authors suggest that the Indian markets did not conform to the efficient market hypothesis during the study periods. On the other hand, Ratner and Leal (1999) found that 10 variable length moving average trading rules applied to closing levels of India's BSE index in the period from 1982 - 1995 produced no significant positive returns.

In this paper, trend following algorithms were applied to daily closing prices on India's S&P CNX Nifty stock index, the same index upon which quotes are offered on India's only stock index futures contracts. Closing levels of the Nifty index were divided into four periods spanning the years 2005 - 2012. Eighty-related trend following algorithms were defined and applied to each period to generate daily returns. All algorithms were tested for significance against return distributions generated using a Levich-Thomas bootstrapping process. The results in rising, falling, mixed trend, and nearly trendless markets are discussed.

Research Methodology

- **Data Selection :** Daily closing Nifty index levels and overnight MIBOR rates were divided into four periods for testing. The periods appear in Table 1 along with a gradient that measures the number of index points per trading day that the Nifty index rose or fell during the period.

Table 1. Data Periods For Daily Closing Levels of Nifty Index and Overnight MIBOR Rates

Period	Trend	From	To	Gradient
Period1	Downtrend	8-Jan-08	27-Oct-08	-18.91
Period2	Uptrend	22-Apr-09	5-Nov-10	7.71
Period3	No Trend	25-May-11	28-Sep-12	0.91
Period4	Mixed Trends	12-Oct-05	31-Dec-12	1.85

Source: Authors' Research

- **Algorithm Descriptions :** Trend following algorithms constructed for use in this study employ a binary strategy in which a hypothetical investor places all funds daily either in cash or in the Nifty index and uses no leverage. As India has an underdeveloped market for securities lending, shorting stocks is extremely difficult ; so for these algorithms, the investor is never short. Cash investments earn interest at the overnight MIBOR rate. Transaction costs and dividends are assumed to be zero in all calculations. An investment in the Nifty index is made once a positive trend is detected and then sold for cash when a subsequent negative trend is detected. Each algorithm is identified by the notation EMA (k, m, n) which uses the following rules :

- **Definition :** EMA(k) is the exponential moving average for k days where k = 10, 20, 50, 100, 200.

- **Algorithm:** Definitions and crossover rules :

1) The Nifty closing level is observed for m consecutive days, where m = 2, 3, 4, 5.

2) From a cash investment position:

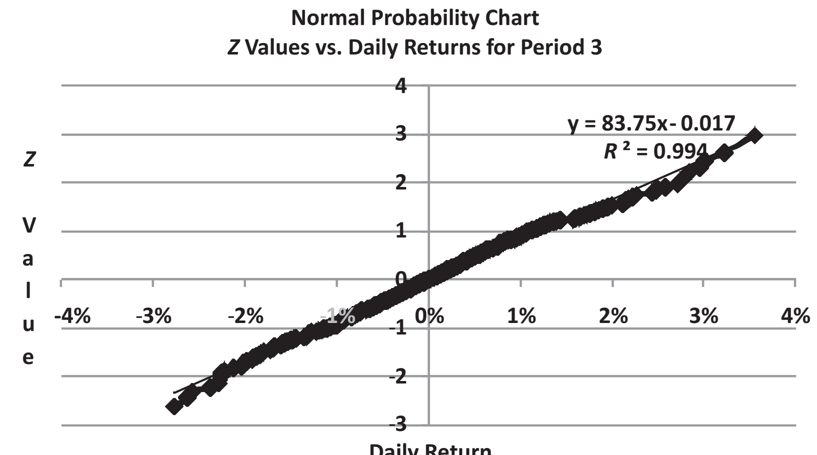
- Buy Nifty if consecutive closing index levels C_j for j = 1 to m are all above EMA with fixed k.
- Occurrence of this event is taken to identify a positive price trend.
- Otherwise, no action is taken.

3) From a Nifty investment position:

- Sell Nifty if consecutive closing levels C_j for j = 1 to n are all below EMA for fixed k.
- n = 2, 3, 4, 5
- m and n are independent and k is greater than or equal to m or n.
- Occurrence of this event is taken to identify a negative price trend.
- Otherwise, no action is taken.

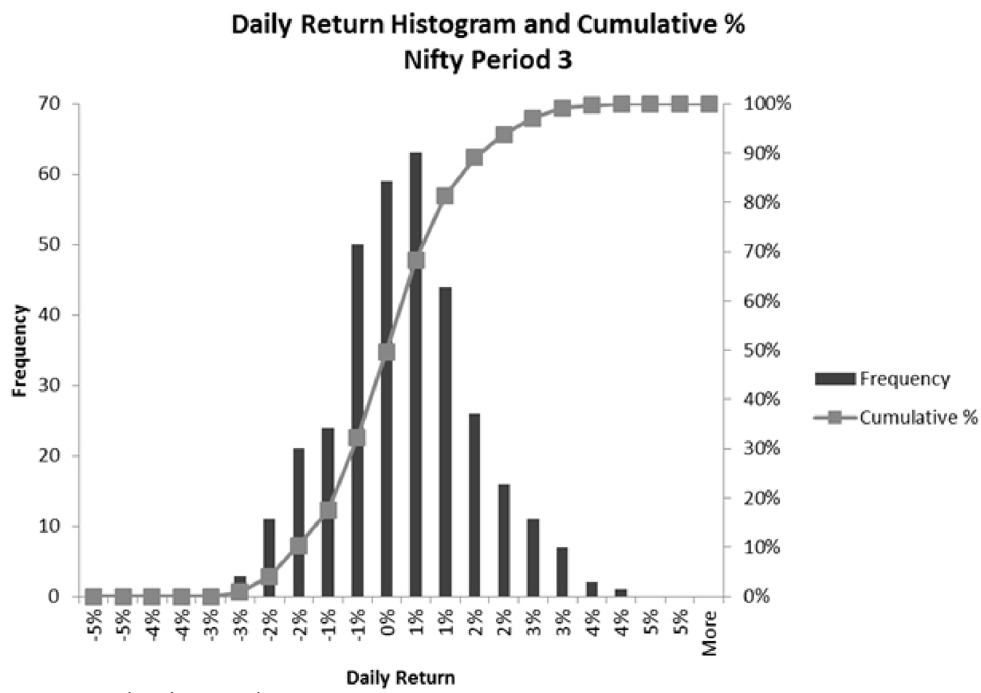
These rules give rise to a family of 80 algorithms in which for each k, there are Nifty purchases and sales that satisfy

Figure 1. Normal Probability Chart for Daily Returns in Period 3



Source: Authors' Research

Figure 2. Period 3 Daily Return Histogram and Cumulative %



Source: Authors' Research

choices for *m* and *n*. These strategies, carrying the notation EMA (*k,m, n*), can be conveniently arranged in the matrix form for any statistic in tables formatted like that of Table 4.

Data Analysis and Interpretation

The Anderson-Darling test for normality (Razali & Wah, 2011) was applied to the daily closing returns for each of the four data periods and was found to indicate returns that were not normally distributed except for Period 3. A normal probability chart appears in Figure 1 for Period 3, showing minor deviations from the linear trendline associated with a pure normal distribution. Returns were computed as the natural log differences of successive daily prices. The returns distribution for Period 3 appears in Figure 2 and uses 339 trading days of daily returns. While there are no regulatory

Table 2. Descriptive Statistics on Daily Returns for Period 3

Descriptive Statistics on Daily Returns For Period 3	Value
Mean	0.00019
Standard Error	0.00065
Median	0.00001
Standard Deviation	0.01196
Sample Variance	0.00014
Kurtosis*	0.31310
Skewness	0.14299
Range	0.07723
Minimum	-0.04169
Maximum	0.03555
Sum	0.06414
Count	339

*For a Normal Distribution in Excel, Kurtosis = 0

Source: Authors' Calculations

Table 3. Autocorrelation Coefficients for Four Data Periods With Alpha at 5%

Period	r_1	r_2	r_3
Period1	0.036	0.048	-0.029
Period2	0.016	-0.072	-0.011
Period3	0.032	0.028	-0.011
Period4	0.009	-0.012	-0.002

Source: Authors' Calculations

Table 4. Average Percentage of Trading Days Invested in the Nifty Index for Period 3

	k values for EMA (*k,m,n*) algorithms				
{m,n}	10	20	50	100	200
{2, 2}	50%	51%	54%	59%	64%
{2, 3}	57%	57%	58%	62%	66%
{2, 4}	63%	61%	61%	64%	68%
{2, 5}	68%	65%	63%	66%	70%
{3, 2}	43%	46%	50%	57%	62%
{3, 3}	50%	52%	54%	60%	65%
{3, 4}	57%	56%	57%	62%	66%
{3, 5}	62%	60%	60%	64%	68%
{4, 2}	38%	42%	48%	55%	61%
{4, 3}	45%	47%	51%	58%	63%
{4, 4}	51%	52%	54%	60%	65%
{4, 5}	56%	56%	57%	62%	66%
{5, 2}	33%	39%	46%	53%	59%
{5, 3}	40%	44%	49%	56%	62%
{5, 4}	45%	48%	52%	58%	63%
{5, 5}	51%	52%	55%	60%	65%

Source: Authors' Calculations

Table 5. Original Period 3 Annualized Returns (%)

	k values for EMA (*k,m,n*) algorithms				
{m,n}	10	20	50	100	200
{2, 2}	5.81	7.17	7.69	5.03	3.60
{2, 3}	5.74	3.50	3.80	2.92	-0.11
{2, 4}	7.13	4.23	2.83	0.93	-0.78
{2, 5}	8.46	-0.33	2.31	0.24	-1.87
{3, 2}	9.39	10.37	4.00	0.78	0.98
{3, 3}	7.49	4.93	0.16	-1.32	-2.74
{3, 4}	9.94	3.61	-0.39	-2.74	-3.41
{3, 5}	10.21	-2.89	-0.39	-3.43	-4.50
{4, 2}	9.72	13.31	6.64	3.24	1.55
{4, 3}	4.68	7.97	4.68	0.77	-2.16
{4, 4}	6.55	5.63	3.02	-2.21	-2.84
{4, 5}	6.60	0.26	3.11	-2.90	-3.92
{5, 2}	14.71	16.97	4.13	4.18	1.16
{5, 3}	11.94	13.71	3.24	1.71	-2.56
{5, 4}	12.04	10.38	1.03	-0.57	-3.23
{5, 5}	13.51	6.55	-0.95	-1.26	-4.32

Source: Authors' Calculations

constraints on movements in daily returns, the data shows that the variations were confined to a relatively small range. Descriptive statistics for the daily returns of Period 3 appear in Table 2, where a small negative skew and a modest kurtosis appear. The high R -square in Figure 1 suggests a good fit to a normal distribution with deviations appearing primarily in the distribution tails. Daily return distributions were also tested for the presence of autocorrelation by computing the first three autocorrelation coefficients, rh, for a lag of $h = 1, 2, 3$ days. These coefficients appear in the Table 3 for each data period.

For each data period, the null hypothesis that there is no autocorrelation at lag h was accepted for alpha at the 5 % level. The absence of autocorrelation is not surprising, given the normal and near-normal character of return distributions for each period. The procedure for statistical testing and analysis of original period returns was the same for each period in Table 1. Period 3 is used here as an example to illustrate the steps used. For each algorithm, Table 4 shows the average percentage of trading days invested in the index during Period 3. There it appears that while the range was from 33% to 70%, only 15 algorithms spent less than 50% of the time invested in cash, one being EMA(20,5,2), which is of special interest. As discussed later, this return and other algorithm returns appear to benefit from less rather than more time invested in the Nifty.

The Table 5 shows the annualized percentage returns for each algorithm when applied to Period 3 data (original period returns). To test the significance of any single algorithm's original period returns appearing in Table 5, it was necessary to compare its original period returns to its related algorithm returns distribution. Such a distribution does not exist naturally, but can be created with some assurance using a bootstrapping method described by Levich and Thomas (1991). The bootstrapping process creates new randomly arranged price paths for the index, starting and ending at the original period index levels, but with the original returns distribution (Figure 2) held constant. Each algorithm is then applied to these price paths with the assurance that the outcomes are consistent with observed returns distribution in a selected time period. The resulting distribution of algorithm returns (Levich-Thomas returns distribution) allows calculation of a p value to test for excess original period returns.

Generation of the Levich-Thomas price paths requires three steps :

➢ **Step 1 :** Generate 10,000 return paths by sampling without replacement the Period 3 daily returns.

Table 6. Levich-Thomas *p* values for Period 3

	k values for EMA (*k,m,n*) algorithms				
{m,n}	10	20	50	100	200
{2, 2}	40.6%	31.9%	25.64%	32.4%	31.9%
{2, 3}	40.4%	49.3%	43.26%	43.2%	53.5%
{2, 4}	32.7%	45.4%	47.97%	54.1%	58.2%
{2, 5}	25.6%	68.3%	50.89%	57.7%	65.3%
{3, 2}	24.0%	18.9%	43.36%	54.4%	46.5%
{3, 3}	31.9%	42.3%	62.01%	65.3%	68.7%
{3, 4}	21.1%	48.4%	64.64%	72.6%	72.8%
{3, 5}	19.8%	78.3%	64.37%	75.7%	78.5%
{4, 2}	22.1%	10.2%	30.66%	41.3%	43.3%
{4, 3}	45.1%	28.4%	39.57%	54.1%	65.2%
{4, 4}	34.9%	38.2%	47.32%	69.6%	69.3%
{4, 5}	34.6%	64.7%	46.18%	73.2%	75.2%
{5, 2}	7.5%	**3.6%**	42.33%	36.2%	45.8%
{5, 3}	14.7%	9.3%	46.22%	48.8%	66.9%
{5, 4}	14.5%	18.3%	57.31%	61.4%	70.7%
{5, 5}	10.7%	33.9%	66.97%	64.7%	76.8%

Source: Authors' Calculations

Table 7. *Z* Scores for Period 3

	***k* values for EMA (*k,m,n*) algorithms**				
{m,n}	**10**	**20**	**50**	**100**	**200**
{2, 2}	0.24	0.48	0.66	0.47	0.47
{2, 3}	0.24	0.02	0.17	0.18	-0.10
{2, 4}	0.45	0.12	0.04	-0.10	-0.22
{2, 5}	0.64	-0.49	-0.03	-0.21	-0.41
{3, 2}	0.71	0.89	0.18	-0.10	0.09
{3, 3}	0.47	0.20	-0.31	-0.39	-0.48
{3, 4}	0.81	0.04	-0.38	-0.60	-0.60
{3, 5}	0.86	-0.80	-0.38	-0.71	-0.79
{4, 2}	0.77	1.28	0.53	0.23	0.18
{4, 3}	0.12	0.59	0.28	-0.10	-0.38
{4, 4}	0.37	0.30	0.07	-0.51	-0.49
{4, 5}	0.39	-0.38	0.09	-0.62	-0.68
{5, 2}	1.45	**1.77**	0.20	0.35	0.12
{5, 3}	1.05	1.34	0.09	0.03	-0.43
{5, 4}	1.07	0.91	-0.19	-0.28	-0.54
{5, 5}	1.26	0.43	-0.44	-0.38	-0.72

Source: Authors' Calculations

↳ **Step 2 :** Generate a price path for each of the 10,000 return paths.

↳ **Step 3 :** Apply the EMA (*k,m,n*) algorithm to each of the price paths to generate the distribution of annualized returns (Levich-Thomas return distribution) for that algorithm.

To reduce the standard error of the mean of the Levich-Thomas return distribution to 1% requires 10,000 price paths. For *t* - tests having a sample size of 10,000, the *t* and *z* values will be virtually the same, so for statistical testing, we use the *z* score. Algorithm returns passing the significance test for alpha at 5% can be recognized as promising and

Table 8. Test Results for Period 3 Using *p* Values Less than 5%

	***k* values for EMA (*k,m,n*) algorithms**				
{m,n}	**10**	**20**	**50**	**100**	**200**
{2, 2}	Reject	Reject	Reject	Reject	Reject
{2, 3}	Reject	Reject	Reject	Reject	Reject
{2, 4}	Reject	Reject	Reject	Reject	Reject
{2, 5}	Reject	Reject	Reject	Reject	Reject
{3, 2}	Reject	Reject	Reject	Reject	Reject
{3, 3}	Reject	Reject	Reject	Reject	Reject
{3, 4}	Reject	Reject	Reject	Reject	Reject
{3, 5}	Reject	Reject	Reject	Reject	Reject
{4, 2}	Reject	Reject	Reject	Reject	Reject
{4, 3}	Reject	Reject	Reject	Reject	Reject
{4, 4}	Reject	Reject	Reject	Reject	Reject
{4, 5}	Reject	Reject	Reject	Reject	Reject
{5, 2}	Reject	**ACCEPT**	Reject	Reject	Reject
{5, 3}	Reject	Reject	Reject	Reject	Reject
{5, 4}	Reject	Reject	Reject	Reject	Reject
{5, 5}	Reject	Reject	Reject	Reject	Reject

Source: Authors' Calculations

Table 9. Test Results for Period 3 Using *z* Scores with Alpha at 10%

	***k* values for EMA (*k,m,n*) algorithms**				
{m,n}	**10**	**20**	**50**	**100**	**200**
{2, 2}	Reject	Reject	Reject	Reject	Reject
{2, 3}	Reject	Reject	Reject	Reject	Reject
{2, 4}	Reject	Reject	Reject	Reject	Reject
{2, 5}	Reject	Reject	Reject	Reject	Reject
{3, 2}	Reject	Reject	Reject	Reject	Reject
{3, 3}	Reject	Reject	Reject	Reject	Reject
{3, 4}	Reject	Reject	Reject	Reject	Reject
{3, 5}	Reject	Reject	Reject	Reject	Reject
{4, 2}	Reject	Reject	Reject	Reject	Reject
{4, 3}	Reject	Reject	Reject	Reject	Reject
{4, 4}	Reject	Reject	Reject	Reject	Reject
{4, 5}	Reject	Reject	Reject	Reject	Reject
{5, 2}	**ACCEPT**	**ACCEPT**	Reject	Reject	Reject
{5, 3}	Reject	**ACCEPT**	Reject	Reject	Reject
{5, 4}	Reject	Reject	Reject	Reject	Reject
{5, 5}	Reject	Reject	Reject	Reject	Reject

Source: Authors' Calculations

were observed again in each subsequent data period. The Table 6 contains the *p* values calculated from applying algorithms to the Levich-Thomas bootstrapped price paths for Period 3. If the *p* value for an algorithm is less than the critical alpha level of significance, then we accept the hypothesis that the algorithm did extract significant returns from the original price data and reject it otherwise. Using a *p*-value of 5%, the Table 8 shows that EMA (20,5,2) was the only algorithm accepted as producing significant returns for the Period 3.

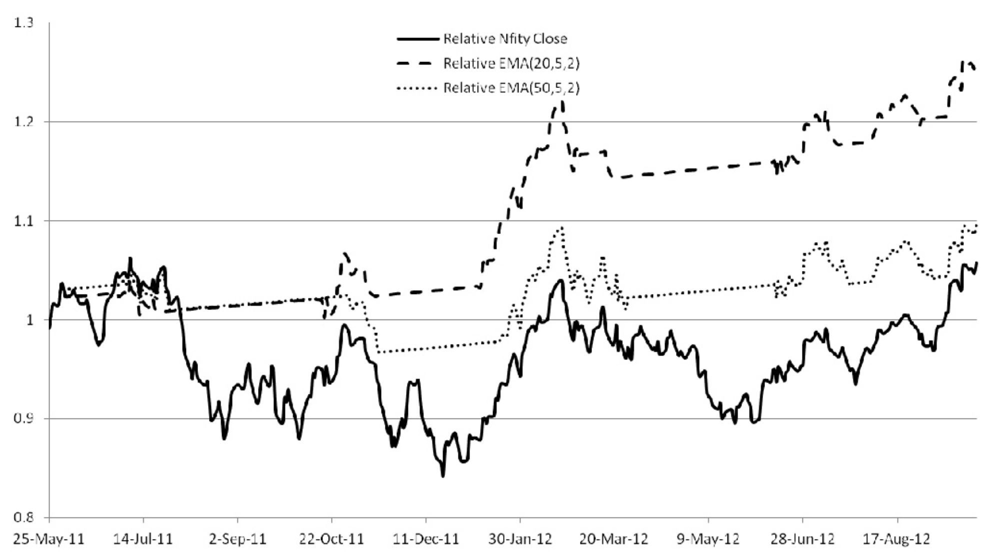
For comparison with standard statistical testing on normal distributions, the mean and standard deviation for Levich-Thomas return distributions were used to compute the algorithm *z* scores for Period 3 and appear in the Table 7. Hypothesis testing results for a one-tailed test at the 5% alpha level appear in the Table 8. If the *z* score for an algorithm exceed the critical *z* for this alpha (1.645), then we accept the hypothesis that the return difference was statistically significant and that the algorithm produced excess original period returns. Only EMA (20,5,2) tested positively at this alpha level, reflecting the same results using the Levich-Thomas *p* values. At an alpha level of approximately 10%, both the *p* values and *z* scores for Period 3 suggest that the two additional algorithms - EMA (20,5,3) and EMA (10,5,2) also have promise (Table 9). The lowest three *p* values in Table 6 occur for exactly the same algorithms accepted in Table 9 using *z* scores with alpha at 10%.

Findings

➯ **Period 3 :** The pattern of returns in the Table 5 can be explained by noting the behavior of EMA as *k, m,* and *n* change. Increasing *n* degrades returns for fixed values of *k* and *m*, suggesting it is beneficial to exit from the index as soon as sequential closing index levels are found below EMA (*k,m,n*). Increasing *m* raises returns for fixed values of *k* and *n*, suggesting it is beneficial to find sequential closing index levels above EMA (*k, m, n*) for a longer time before investing in the index. Taken together, these two conclusions from Table 5 conform to rules often used by successful traders who are more cautious in entering a rising market and are quick to exit when a turn is thought to occur.

The explanation for changing *k* values is slightly different. Mathematically, EMA values will lag behind spot values in a linearly trending market. The larger the value of *k*, the larger the lag. A trend following algorithm comparing spot vs. EMA in a strictly linearly increasing market will result in being fully invested in the index at all times, thereby delivering an index return. Conversely, spot values vs. EMA in a linearly decreasing market will result in an investment in cash at all times. In a trendless market, the returns will depend upon the ability of an algorithm to participate successfully in sub-periods of rising index levels and remain invested in cash during sub-periods of falling index levels. In Period 3, this occurs most successfully for EMA (20,5,2) and nearby algorithms as shown in the Table

Figure 3. Period 3 Relative Performance for Nifty and Two Algorithms



Source: Authors' Research

5. In fact, EMA (20,5,2) appears to be a local maximum for as *k* is raised or lowered, the returns decline; as *m* is lowered, the returns decline, and as *n* is raised, the returns decline. It also appears that EMA(20,*m*,2) are lesser local maxima for *m* = 2 to 5. The pattern of local maxima appeared in all four data periods.

Such behavior can be understood by more careful examination of the daily algorithm results. For this comparison, we selected EMA (20,5,2) for inspection. Each algorithm, of course, earned interest at the MIBOR rate when not invested in the Nifty. Compared with EMA (20,5,2), EMA(50,5,2) had delayed entries and delayed exits into rising and falling Nifty sub-periods. These longer delays reduced participation in sub-periods of rising Nifty levels and delayed exits once the index began a decline. By successfully entering rising Nifty sub-periods and exiting to cash before significant Nifty declines, EMA (20,5,2) captured a rise of over 700 index points while EMA(50,5,2) lost a modest 30 index points during Period 3. Despite this outcome, both algorithms outperformed the index by being invested in cash during large sub-period index declines. The relative performance of these two algorithms and the Nifty index are compared in the Figure 3. The Figure 3 depicts the EMA (50,5,2) entry and exit delays during the sub-periods. Neither of the two algorithms, of course, capture the full rise of the index during the sub-periods and nor did they completely avoid the index decline during other sub-periods.

Table 10. Comparison of Annual Returns on Cash, EMA(20,5,2), and Nifty Index

Original Period Returns			
Period	**Cash**	**EMA(20,5,2)**	**Nifty**
Period1	5.27%	-27.69%	-73.32%
Period2	2.85%	11.67%	55.22%
Period3	5.88%	16.97%	4.10%
Period4	5.21%	13.37%	17.39%

Source: Authors' Calculations

➩ **Period 1:** For Period 1, with alpha at 5%, all 80 algorithm original period returns were indistinguishable from their associated Levich-Thomas return distribution means. However, all 80 distribution means were significantly above the realized return on the Nifty alone. These results strongly suggest that all original period algorithm returns exceeded the Period 1 Nifty return, and so, were able to successfully reduce the loss from holding the Nifty alone. The performance of EMA (20,5,2), for example, appears in Table 10 where algorithm returns are compared with investments in pure cash or the Nifty alone.

➩ **Periods 2 and 4:** A similar analysis for Periods 2 and 4 with alpha at 5% revealed that no algorithm likely produced returns significantly in excess of holding the Nifty alone. We conclude from the collective results for all the four periods that the family of 80 algorithms investigated here worked well in a sharply declining market (Period 1), but far less so or not at all in markets that were more gradually rising (Period 2), mixed (Period 4), or nearly trendless (Period 3).

Summary and Conclusion

The objective of this technical analysis was to test the profitability of 80 related trend following algorithms applied to closing prices for India's Nifty index over periods of rising, falling, mixed trend, and nearly trendless markets. Daily closing prices for the Nifty index were divided into four periods covering trading days from 2005 through 2012. Trend following rules were used that employed no leverage and no short positions. Only investments in the Nifty index or in cash at India's MIBOR rate were permitted with no transaction costs or dividends assumed. For each period, all 80 related trend following algorithms were statistically examined for significance against return distributions created using a Levich-Thomas bootstrapping process. We conclude from this technical analysis that the family of 80 algorithms investigated worked well in a sharply declining market, but far less so or not at all in markets that were more gradually rising, mixed trend, or nearly trendless.

Scope for Future Research

The present study suggests several subsequent steps for future research. That all 80 algorithms outperformed the Nifty index in a sharply declining market (Period 1) suggests that their structure is useful in such situations. However, to be employed successfully, downward trends need to be consistently identified by some means. Finding a satisfactory indicator for a downward trend then becomes an important direction for a subsequent research step. In an upward trending market (Period 2), all 80 algorithms underperformed the Nifty index, suggesting a need to detect and more quickly enter sub-period rising trends, while avoiding sub-period downtrends. Once again, a means for reliable trend direction along with a prompt application of a suitable algorithm is needed. The ability to short the index has not been permitted in the algorithms studied here. Introducing this ability may allow for additional revenue generation arising from exploitation of falling prices. Once improved algorithms are constructed, accurate estimates of transaction costs should be used to assess net profitability.

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