

# An Empirical Study of Nifty 50 Option Time Spreads

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## Abstract

The objective of this study was to identify and test preliminary rules for trading call option time spreads and then to assess opportunities for further research to improve on those rules. To do so, the theoretical and empirical properties of near-the-money time spreads were used to develop four rules for profitably trading in India's Nifty 50 (NSE 50) call options. Day-end pricing for 2015–2019 included periods of rising, falling, and stable volatility. The resulting four rule algorithm produced positive results on out-of-sample data and outperformed a buy and hold strategy. As the general procedure followed for rule development was not country specific, it was applied to options on China's SSE 50 index, where the algorithm was found to outperform a hold-to-expiry strategy in every year tested. These related studies of NSE 50 and SSE 50 option time spreads provide a helpful addition to the growing knowledge about the developing derivatives markets in India and China. Opportunities for further research are described.

**Keywords :** SSE50 options, Nifty 50 options, time spreads, calendar spreads, horizontal spreads

**JEL Classification :** G10, G11, G13, G14, G15

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Time spreads, also known as calendar or horizontal spreads, are members of a large variety of marketplace transactions occurring in both option and futures markets. Most spreads, including time spreads, are of interest primarily to practitioners rather than scholars. Accordingly, the formal properties of these trades are little studied and less understood than common derivative investment strategies. In this paper, we limit our analysis to option time spreads formed by the sale of an index call having the shortest available time to expiry (front month) combined with the simultaneous purchase of a single call on the same index having the next-nearest time to expiry (back month). Both calls have the same strike price, chosen to be nearest the day-end spot market price, thereby forming a nearest-the-money (NTM) spread.

The primary trading objective of forming NTM spreads is to achieve a risk-adjusted rate of return above the cost of borrowing to purchase the spread. The profit from such a spread arises from the faster decay of the short option time premium against the relatively slower decay for the long call. The risk in holding a back month call is

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mostly offset by selling a front month call and the combination is largely market neutral. These features make option time spreads highly attractive for conservative investors.

To effectively identify NTM spreads with potentially superior returns, we first formally analyze the properties and behavior of a pure at-the-money (ATM) spread. Once understood, the spread's behavioral findings are used with in-sample data on Nifty 50 (NSE 50) options to develop rules for entering and exiting transactions. The empirical rules so developed are then tested with out-of-sample data.

Separately, a test of the algorithm generality and robustness is made by applying it to out-of-sample SSE 50 ETF options listed on the Shanghai Stock Exchange. The results appear surprisingly similar to those for NSE 50 options. With only a very slight modification based upon SSE 50 behavior, the algorithm is also applied to NSE 50 data with results again similar in both markets.

The result of this study is not a refined set of trading rules immediately available for implementation. Rather, it offers an encouraging direction for future rule development based upon both theoretical and empirical considerations. Promising next steps for algorithm improvement are offered in the next to last section.

## Literature Review

Scholarly studies on time spreads fall into two categories, one relating to options and one to futures. For completeness, searches in either category must cover alternative terms used to describe this transaction, including “calendar” and “horizontal” spreads. In none of the categories, we found an extensive literature primarily due to the deceptive simplicity of these transactions and the preference of scholars for more complex academic topics.

An independent search for studies on option time spreads revealed no new additions to those identified and referenced recently by Slivka and Wang (2019). Their study reported on time spreads formed with China's options on the SSE 50 ETF. A two-factor calendar spread option pricing model on corn futures was studied by Seok, Brorsen, and Niyibizi (2018). A trading system for swaption calendar spreads was developed by Koshiyama, Firoozye, and Treleven (2019). Calendar spreads on crude oil futures options were modeled and tested by Schneider and Tavin (2018) and magazine articles on currency and Eurodollar option time spreads were described by Cretien (2012, 2013). However, no other studies on equity option time spreads were found in global markets, including India, making it likely that the current work is the first of its kind, thereby adding to a better understanding of this understudied market transaction.

## Data and Methodology

The database depicted in Table 1 for this study consisted of a complete set of daily historical data for years 2015 – 2019 on MIBOR, the Nifty 50 index and every index call option listed on the National Stock Exchange of

**Table 1. Daily Data (2015 – 2019)**

NSE 50 Index Levels, High, Low Close		
MIBOR (1 – 60 days)		
NSE 50 Call Option Close, Strike, Expiry		
<b>In- and Out-of-Sample Data</b>		
<b>Period</b>	<b>Start</b>	<b>End</b>
In-Sample	1-Jan-15	31-Dec-18
Out-of-Sample	1-Jan-19	31-Dec-19

India (NSE). Similar data were subsequently collected on SHIBOR, the SSE 50 index and index options listed on the Shanghai Stock Exchange (SSE) from the date of first listing in China on 2/9/2015 – 12/31/2019. The data collected for each country include rising, falling, and stable periods of volatility.

A trial NSE 50 algorithm is developed using in-sample data and then applied to out-of-sample data. Next, the algorithm is applied to SSE 50 data to test its robustness in another market. To facilitate comparisons with the Slivka and Wang (2019) study, the notation and definitions are adopted for the NSE 50 data and appear in Table 2. Conclusions are drawn and opportunities for future research are identified.

**Table 2. NSE 50 Option Time Spread Notations and Definitions**

Notation	Definition
$T1$	Front Month Expiry Date
$T2$	Back Month Expiry Date
$I(0) = I_0$	Index level on Trade Day ( $t = 0$ ).
$I(T1)$	Index level on Expiry Day ( $t = T1$ ).
$C1(T1)$	Front Month call closing price at expiry = $\text{Max}[0, I(T1) - K]$ .
$C2(T2 - T1)$	Back Month call closing price at front month expiry with time remaining of $T2 - T1$ .
$K$	Time Spread (TS) Strike Price.
UBE	On expiry date $T1$ , the maximum Index level at which the profit $P(T1)$ is zero.
LBE	On expiry date $T1$ , the minimum Index level at which the profit $P(T1)$ is zero.
$(UBE - LBE)$	Breakeven Range for TS at expiry.
$D0 = C2(0) - C1(0)$	The initial TS Debit (Cost of purchase).
$P(T1) =$	$PB(T1) = C2(T2 - T1) + (C1(0) - C2(0)) = \text{Profit at Front Month Expiry if } I(T1) < K.$ $PA(T1) = PB(T1) + (K - S) = \text{Profit at Front Month Expiry if } I(T1) > K.$ Represents Profit at Front Month expiry with Index level at $I(T1)$ .
$P(t)$	$C2(t) - C1(t) + (C1(0) - C2(0))$ Represents Profit on Trade Day $t$ with Index level at $I(t)$ .
$PMAX$	Maximum Profit of TS at Front Month expiry.
$\%PMC(t)$	$\% \text{ of } PMAX \text{ captured on Trade Day } t = P(t) / PMAX.$
$RSS$	StandStill Return. Return at expiry with Index level unchanged. $RSS = P(T1) \times (365/T1) / D0$ ; $P(T1)$ calculated using $I(T1) = I(0)$ .
$RIU(t)$	Return if the TS is hypothetically unwound on Trade Day $t = P(t) * (365/t) / D0$ .
$RR(t') = RIU(t')$	Return if the TS is actually unwound on Trade Day $t' = P(t') * (365/t') / D0 = RIU(t')$ .
$RR(T1)$	Return realized at Front Month expiry on Trade Day $T1 = P(T1) * (365/T1) / D0$ .
$RMAX$	Maximum return at Front Month expiry on Trade Day $T1$ . $RMAX = PMAX * (365/T1) / [C2(0) - C1(0)] = PMAX * (365/T1) / D0.$

### Algorithm Trading Rules

The proposed Entry and Exit Rules (Table 3) for trading time spreads follow generally accepted best trading practice. For example, it would be unwise to enter a new time spread if the day-end standstill return is less than the cost of borrowing. Also, options approaching expiry typically exhibit day-end price abnormalities in their

**Table 3. NSE 50 Call Option Time Spread Algorithm**

Entry Rule for each Trade Day $k$ :	If at a day-end, $RSS > MIBOR$ and the number of days to front month expiry is greater than or equal to 5, then buy one and only one Time Spread ( $TS$ ) for that day $k$ .
Exit (Unwind) Rule:	Unwind that $TS$ on the first Trade Day that meets an Exit (unwind) Rule.
	1. If on a subsequent Trade Day $t$ , $RIU(t) > \text{Initial } MIBOR$ and $\%PMC(t) \geq X\%$ , then unwind the $TS$ . $10\% < X < 100\%$ .
	2. If on a subsequent Trade Day $t$ , the NSE 50 index level is outside the Breakeven Range, then unwind the $TS$ .
	3. There is a mandatory unwind 1 Trade Day prior to expiry.

last five trading days, making spread performance calculations unreliable. Establishing a new position having less than 5 days to expiry also provides little time for meaningful absolute profit capture. The Entry Rule, therefore, requires the standstill return to be at or above the spot MIBOR rate and the number of days to expiry at or above five.

Typically unreliable pricing on the very last option trading day leads to Exit Rule 3, mandating unwind with one day remaining to expiry. Should the index move to a level outside the breakeven range (Figure 1), then the spread has an increased chance of resulting in a negative return and the position should be unwound (Exit Rule 2). Exit Rule 2 acts like a stop loss order. Finally, if  $\%PMC$ , the percentage  $X$  of maximum possible expiry-based profit is captured on any trading day, then the spread has met its target objective and should be unwound (Exit Rule 1). The optimal range for a value of  $X$  can be determined empirically by calculating the algorithm profit resulting from application of the Rules in Table 3 as  $X$  is varied between 0% and 100%. In this study, values of  $X$  were chosen to be 10%, 25%, 50%, 75%, and 100% and profit profiles calculated for each year of collected data.

Discussed later, a second Entry Rule (Rule 4) is added to the algorithm to account for NTM spread behavior in changing volatility markets. The necessity for such a rule is best understood by examining the profit profile of a pure ATM time spread.

Finally, there are seven transaction costs incurred in executing a NSE 50 round-trip time spread. On each option purchase or sale, these costs consist of brokerage, Securities Transaction Tax (STT), Goods and Services Tax (GST), Stamp Duty, NSE transaction charge, NSE Clearing charge, and a Securities and Exchange Board of India (SEBI) charge. In our study, the typical round-trip total cost per option pair (Front and Back Month) was between ₹ 1.25 and ₹ 2.00. In all but 2015, algorithm profits were positive, net of such transaction costs.

## Data Analysis, Results, and Discussion

### *At-The-Money Time Spread Profile*

Most fundamental features of a NTM time spread can be understood by the analysis of an at-the-money (ATM) spread. For this purpose, notation and definitions in Table 2 are used to create the profit profile in Figure 1 using illustrative 2017 NSE 50 spread parameters determined in 2017, a year of trendless volatility (see Table 4).

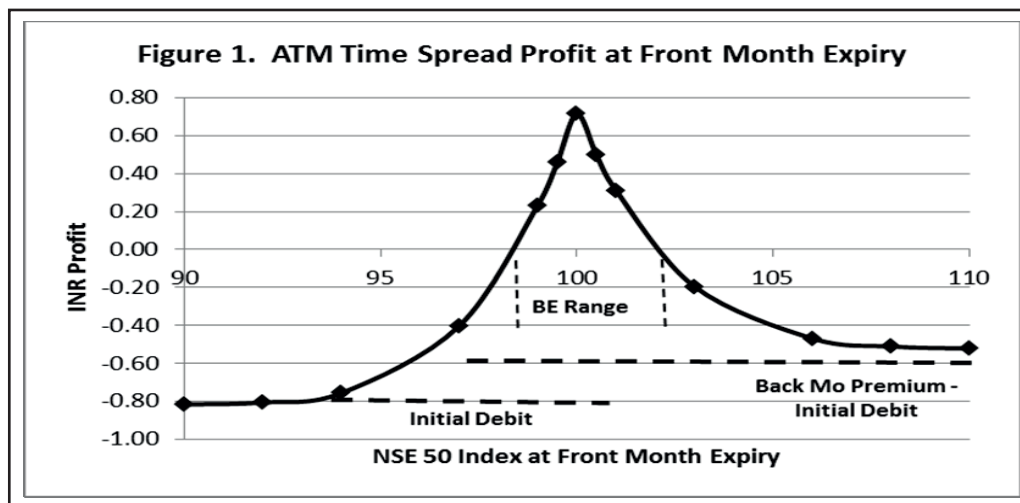
The resulting ATM profit profile at front month expiry (Figure 1) has a profit maximum at the strike price, a breakeven range, and lower bounds on the profit as the index moves deep in or deep out-of-the-money. The profit profile is asymmetric, which is reflected in other spread properties.

In general, at front month expiry, using the notation in Table 3:

$$P(T1) = \text{Time Spread Profit} = \text{Current Debit} - \text{Initial Debit}.$$

**Table 4. Typical 2017 NSE 50 ATM Option Time Spread  
Parameters at Inception**

Parameter	Value
Calendar Days to Front Month Expiry	18
Calendar Days to Back Month Expiry	48
Average Return Volatility	10.90%
Average MIBOR	6.31%
Initial Debit	0.817



The maximum profit occurs at the spread strike price.

$$\text{MAX Profit} = C2(T2 - T1) - Do$$

The back month call value at this time can be reasonably estimated using the front month implied volatility at spread inception.

The profit below strike is  $PB$ , which has a maximum loss of  $(-1.0) Do$  because the lower bound value for the back month call is :

$$S - K \exp(-rT).$$

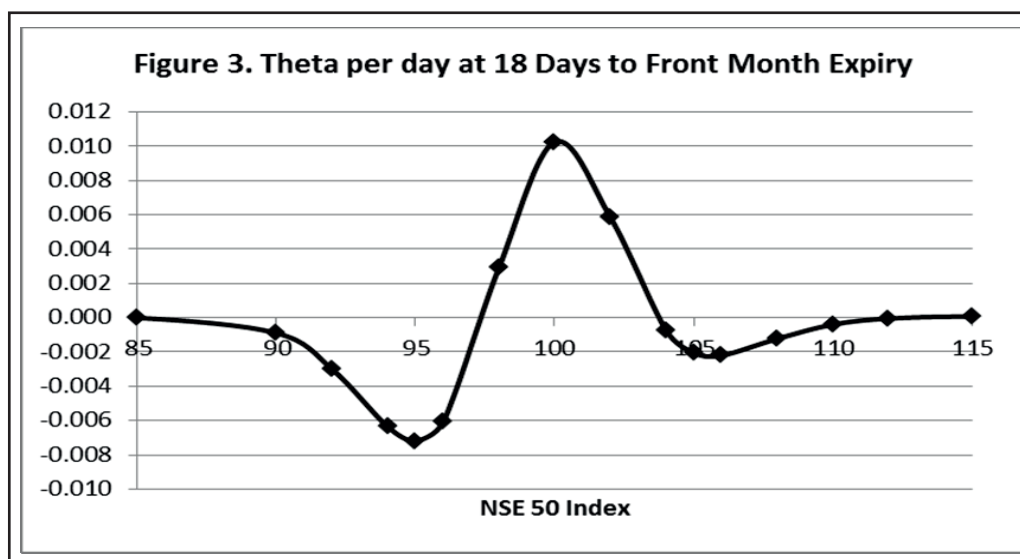
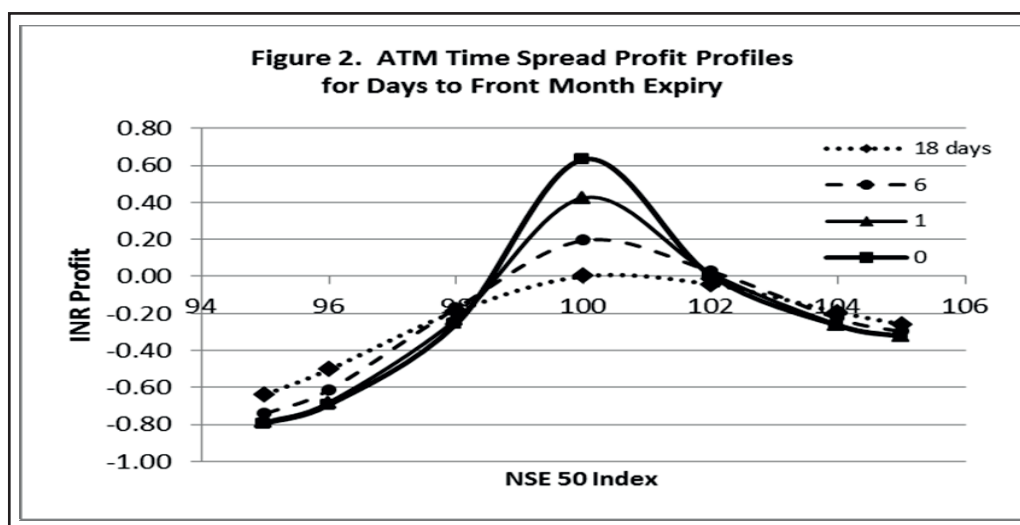
The maximum loss above strike is therefore :

$$K[1 - \exp(-rT)].$$

At inception of the time spread, the profit profile shows only losses vs. the index level, but evolves as front month expiry approaches seen illustrated in Figure 2.

The asymmetric profit profile at front month expiry (Figure 1) is also reflected in time spread profiles for delta, gamma, theta, and other Greeks.

The profile for theta (Figure 3) is positive in a region around the strike price, but negative otherwise. This shape

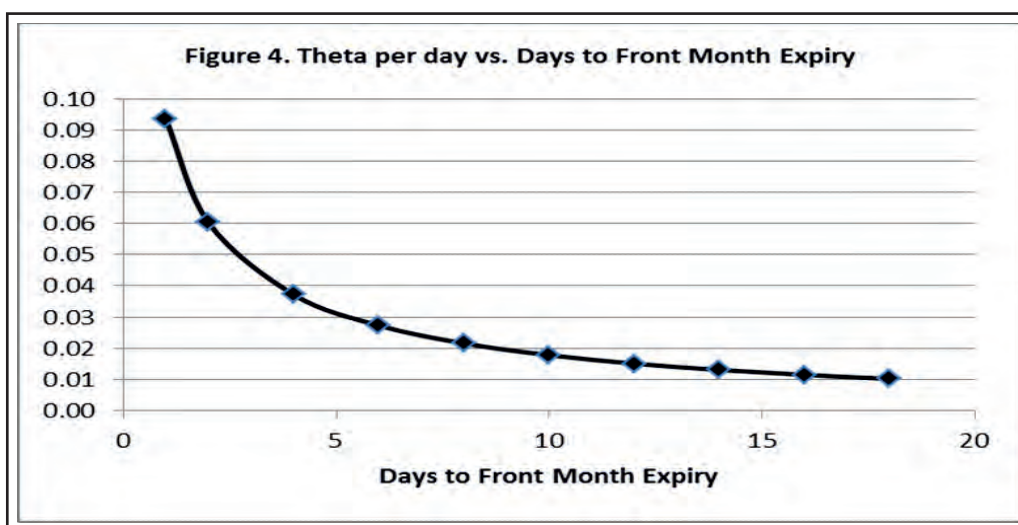


supports unwinding the spread when the index travels outside a breakeven range (Rule 2).

The modest rise in theta 10 or more days to expiry (Figure 4) and its rapid acceleration thereafter also illustrates the value of establishing and holding short term spreads close to front month expiry.

The percentage, %PMC, of maximum expiry date profit reached vs. days to expiry has a similar behavior, accelerating with less than 10 days to front month expiry. Together, the pattern of rise in both theta and the percentage of expiry maximum profit strongly suggest establishing short duration time spreads and holding such spreads as long as possible before front month expiry.

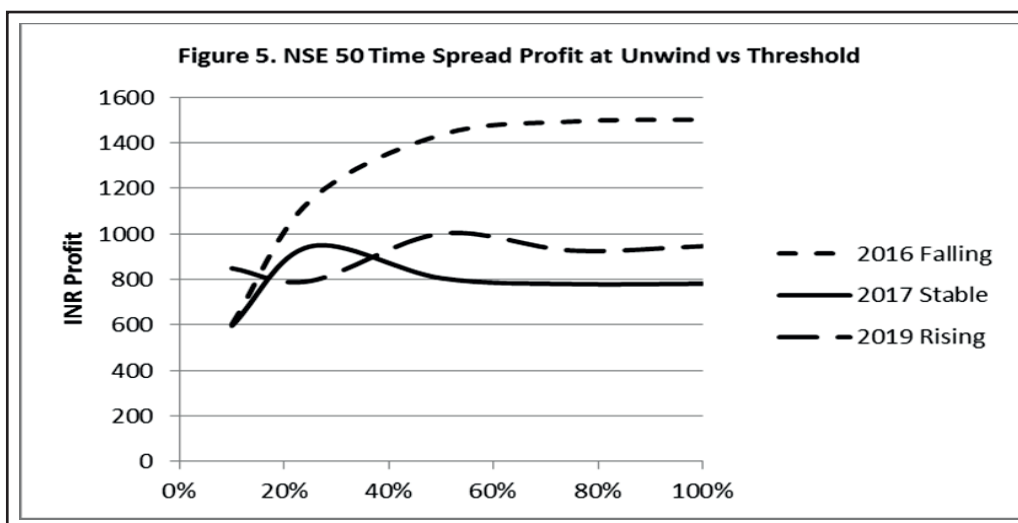
Of special interest (Figure 5) are the yearly total profit profiles for choices of  $X$  in Table 2. For each year in the study period (2015 – 2019), annual profits were computed for %PMC thresholds 10%, 25%, 50%, 75%, and 100%. Theoretical and empirical observations confirm that annual algorithm profits vary with volatility magnitude and trend. This variability leads to a threshold policy range for each trend (Table 5) that brackets or includes the observed maximum profit (Figure 5). Using in-sample data for 2015 – 2018, an approximate mid-range value was assigned to each trend and used for out-of-sample testing.



**Table 5. NSE 50 Volatility Trends and Thresholds**

Year	Trend	Threshold Range	Mid-Range*
2015	Stable	10%–50%	25%
2016	Falling	50%–100%	75%
2017	Stable	10%–50%	25%
2018	Rising	25%–75%	50%
2019	Rising	25%–75%	50%

**Note.** \*See text.



For example, a relatively low (high) volatility during a stable trend period, such as which occurred in 2017 at 9% (2015 at 15%), increases (reduces) spread time spent within the BE Range. At any fixed Threshold  $X$ , the more (less) time spent in the BE Range, the greater (less) is the chance of increasing trade profitability since the time allowed for unwind in 2017 (2015) is lengthened (shortened). As confirmation of this relationship, the percentage

**Table 6. Profit Strategy Comparison for NSE 50 Time Spreads\***

Year	Optimal	NSE Profits	Hold-to-Expiry
2015	260	-494	-1845
2016	1503	1494	865
2017	945	945	-1194
2018	682	682	-541
<b>2019</b>	<b>1001</b>	<b>1001</b>	<b>3312</b>
Total	4391	3629	597

**Note.** \*Profit is in INR.

of 2017 spreads forced to unwind once the index travelled outside the BE Range (43%) was below that of the higher volatility year of 2015 (70%).

For the stable periods in NSE 50 data (2015, 2017), the Threshold Policy Range of % PMC that brackets or includes the optimal threshold was observed to be between 10% and 50%, with an approximate mid-range choice we chose to be 25% (Table 5).

For the in-sample years (2015 – 2018), the trends were defined at a 95% confidence level by acceptance or rejection of the slope of a line regressing annual NSE 50 return volatility vs trade day. Rejection of the slope's null hypothesis began at slope limiting values above (below) 0.0001 (–0.0001), allowing that trend to be labeled rising (falling). Slope values between these two slope limiting values allow the trend to be labeled stable (no trend).

A rise (fall) in the optimal profit threshold is likely to occur if volatility is falling (rising) as it did moderately in 2016 (2019), since the index spends more (less) time inside the BE range, allowing more (less) opportunity for an increase in profitability at the higher thresholds (Figure 5). The mid-range algorithm choice for the observed 2016 (2019) profile of profit at unwind (Figure 5 and Table 5) is 75% (50%). With falling (rising) volatility, the optimal threshold for 2016 (2019) is understandably greater (lesser) than for 2019 (2016). In the relatively stable environments of 2015 and 2017, the mid-range threshold was comfortably set at 25% (Table 5).

Finally, to qualify a spread for initial trading, Rule 4, assigning a mid-range value for each trend, was added to Rule 1.

The algorithm results are compared in Table 6 with two other strategies : an optimal and a hold-to-expiry strategy. An optimal strategy assumes perfect foreknowledge of the best threshold choice each year to produce a maximum achievable profit. A hold-to-expiry strategy assumes spread unwind occurs at closing prices on the last trading day. For all in-sample years, the algorithm produces a positive return, performs better than a hold-to-expiry strategy in 4 of 5 years, and understandably matches the optimal strategy for all but one year. For 2019, the only out-of-sample year, the algorithm matches the optimal choice but does not better the hold-to-expiry strategy. Over the entire sample period, the algorithm captures 83% of the maximum (optimal) possible profit.

### **Application to SSE 50 Options**

When data for 2020 and other out years is available, the NSE 50 algorithm can be directly tested and further improved. Meanwhile, additional proof of Rules efficacy can be tested over the same period (2015 – 2019) in a non-rigorous but suggestive manner by algorithm application to data from options in another market. For that purpose, China's SSE 50 options are suitable, having high liquidity and also being listed in another Asian market.

Two tests were conducted using NSE 50 data. First, the NSE 50 mid-range thresholds (Rule 4) were applied directly without modification to SSE 50 data. The algorithm thus applied captures 56% of the optimal maximum

**Table 7. Profit Strategy Comparison for SSE 50 Time Spreads\***

Year	Optimal	SSE Profits	Hold-to-Expiry
2015	0.627	0.306	-0.405
2016	0.089	0.089	0.293
2017	0.069	0.028	0.163
2018	0.287	0.206	-0.030
<b>2019</b>	<b>0.238</b>	<b>0.105</b>	<b>0.491</b>
Total	1.310	0.733	0.512

**Note.** \* NSE 50 algorithm applied to SSE 50 data. Profit in INR.

**Table 8. NSE 50 and SSE 50 Mid-Range Thresholds**

Trend	Years		Mid-Range Threshold	
	NSE 50	SSE 50	NSE 50	SSE 50
Stable	2015, 2017	2015	25.0%	10%
Falling	2016	2016, 29019	75%	50%
Rising	2018, 2019	2017, 2018	50%	25%

**Table 9. Profit Strategy Comparison for NSE 50 Time Spreads\***

Year	Optimal	NSE Profits	Hold-to-Expiry
2015	260	260	-1845
2016	1503	1436	865
2017	945	597	-1194
2018	682	559	-541
<b>2019</b>	<b>1001</b>	<b>793</b>	<b>3312</b>
Total	4391	3645	597

**Note.** \* SSE 50 algorithm applied to NSE 50 data. Profit in INR.

profit, produces a positive profit in every year, and over the study period, outperforms a hold-to-expiry strategy (Table 7). While certainly not a substitute for future NSE 50 out-of-sample data, this independent result suggests that the NSE 50 Rules might be more robust and reliable than originally thought.

In a second test, an independent SSE 50 Rule 4 (Table 8) was created using 2015 – 2019 data combined with NSE 50 Rules in Table 3 and applied to NSE 50 data for a second test of algorithm usefulness. Volatility trends were identified in a similar manner as for Nifty data. SSE 50 threshold ranges for a rising (falling) trend shifted vs. NSE 50 (Table 8), yet the resulting SSE 50 algorithm, when applied to NSE 50 data (Table 9), captures 83% of the optimal maximum profit, produces a positive profit in 4 of the 5 sample years, and over the 5 year study period, substantially outperforms a hold-to-expiry strategy. These second test results separately suggest the usefulness of the algorithm construction rules.

## Summary and Conclusion

Reflecting trading best practices, an algorithm to select profitable nearest-the-money time spreads in NSE 50

(Nifty) call options was developed and tested using day-end prices during 2015 – 2019. Four trading rules provided entry and exit criteria applied to in- and out-of-sample data. To qualify for unwinding spreads, a threshold  $X$  for capture of each spread's maximum attainable profit was varied between 10% and 100%. The resulting annual profit across all spreads was found to vary with the trend in volatility, allowing identification of an optimal threshold  $X$  for each trend, whether rising, falling, or stable. The algorithm, applied with best choice thresholds, produced positive profits in every year of the study and outperformed a buy and hold-to-expiry strategy in 4 of 5 years tested.

The NSE 50 algorithm was also applied without modification to 2015 – 2019 data on China's SSE 50 call options and also found to produce positive profits, outperforming a buy and hold-to-expiry strategy in all 5 years. In a separate exercise using the same procedure employed to develop the NSE 50 algorithm, a SSE 50 algorithm was created for application to NSE data. The resulting SSE 50 algorithm produced positive profits and outperformed a hold-to-expiry over the 5 year study period. These results from both NSE 50 and SSE 50 analysis raise the possibility that a general algorithm used in two markets may also have beneficial application in other markets.

## **Research Implications, Limitations of the Study, and Opportunities for Further Research**

The present study is intended to identify candidates for NSE 50 time spread trading rules that result in outperforming a buy and hold-to-expiry strategy. Analysis of suitable SSE 50 candidates for the study period 2015 – 2019 result in a profitable algorithm, which is applied with similar success to time spreads on China's SSE 50 options. These results form a promising basis for future algorithm development.

The surprising compatibility of the NSE 50 algorithm rules, when applied in the SSE 50 market and vice versa, raises the question of whether the general approach used here for algorithm construction might also produce attractive results in other global markets. The empirical identification for best choice of unwind threshold is similar in the two markets for this study, while the general properties of time spreads are common to all option markets. These characteristics provide encouragement to investigating such a research topic.

Further improvement of the NSE 50 algorithm will require additional research and rule modification. Trend identification should be dynamic, requiring the slope of a rolling average volatility to be calculated. The length of a trend should not be artificially defined by dates of a calendar year as in this study. Also, periods with small mid-range best choices for  $X$  allow for more frequent reinvestment of capital from unwound trades which potentially can alter the best choice for  $X$ .

The following additional areas of research are of interest for future study that could lead to improved algorithm performance :

✎ Day-end option prices offer only one spot value for estimation of time spread profitability and that spot value is often made more uncertain by traders adjusting positions to avoid overnight risk. The use of higher frequency, intraday pricing minimizes these issues and allows for multiple opportunities to establish promising spreads.

✎ Time spreads formed using front month and second (vs. first) back month contracts may have overall better profitability due to differences in theta.

✎ Reverse time spreads or time spreads using put options may also present new profit opportunities.

## Authors' Contribution

Dr. Ronald Slivka conceived the study of time spreads in the India and China markets after observing the absence of substantive research on this topic in either market. He developed the qualitative and quantitative research design for this topic and directed the daily work. Messrs. Liang and Xue conducted thorough, global literature searches for time, calendar, and horizontal option spreads using key words and summarized relevant findings. Together, Dr. Slivka and Messrs. Liang and Xue agreed on coding objectives in Python that were developed and implemented by Liang and Xue. Data analysis by Dr. Slivka and extensive further computations by Liang and Xue led to valuable improvements in trading rules for each market. Dr. Slivka wrote the manuscript in consultation with both co-authors.

## Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter, or materials discussed in this manuscript.

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