Time Spreads in China SSE 50 Options

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Abstract

Using day-end pricing data from a comprehensive database not readily available outside of China, an algorithm to trade near-the-money call option time spreads on China's SSE 50 ETF was developed and tested. Analysis of in-sample data suggested profitable trading rules that, when applied to limited out-of-sample data, failed to produce superior similar results. A likely explanation for this was offered and further testing was planned. To our knowledge, there are no known related studies of SSE 50 option time spreads ; so, this work provides a helpful addition to the growing knowledge about the developing China market.

Keywords : SSE 50 options, time spreads, calendar spreads, horizontal spreads

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

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Some authors have reported that China's SSE50 ETF options are frequently overvalued (Hilliard & Xhang, 2017 ; Pan & Song, 2017 ; Tongtong, Susheng, Ke, Dandan, & Mingzhu, 2017). If correct, this overvalued feature of the China options market can make strategies for selling calls exceptionally attractive. Trading volumes for SSE50 ETF options now appear sufficient to allow creation and management of time spreads and related option trading strategies that fit this profile. A second strategy, for example, is covered call writing on the SSE 50 ETF. Each strategy has a return that depends upon the decay of option time premium. If excess premium is present, then it can be captured resulting in an above average return as time premium decays toward zero at expiry. It is the object of this study to create and test an algorithm for profitable formation of SSE 50 time spreads using daily day-end call option prices.

In the literature of financial derivatives, the terms "time spread," "calendar spread," and "horizontal spread" are often used interchangeably. These combinations of two derivatives depend upon the price difference (spread) between two closely related instruments in which one is purchased and one sold simultaneously. Designed and executed properly, the combination's profit arises as the spread evolves over time due to the differential rates at which the individual member prices change.

Such spreads exist in both the options and futures markets. In this study, we narrow the use of the term "time spread" to refer to transactions in which an option on the SSE 50 ETF closest to expiry is sold and a second option with the next closest date to expiry is bought. The ratio of long to short options was always 1 : 1. The longer dated option price exceeds the price of the short option, creating a debit to establish the spread. The debit becomes the maximum potential loss at the first expiration date. Both options have the same strike price. Although these

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spreads can be formed from puts or calls, we have limited our analysis to call time spreads with a one month differential in expiration.

Time spread trading is a conservative option strategy with low risk, normally employed on underlying references (equity, currency, commodities…) that are in a trading range over the life of the spread. The trading objective is to achieve a superior risk-adjusted rate of return that is expected to be above money market rates, while typically also below a long term market return.

Time spreads are of primary interest to traders rather than scholars. The structure of time spreads is deceptively simple and offers only a modest amount of complexity for academic study. For those seeking profitable transactions, however, the simplicity of spreads is highly attractive for ease of implementation and tracking. Such a division of interests very likely accounts for why there are so few journal references to these spreads and why analysis more frequently appears in magazine articles or webpage commentary.

Literature Review

Relevant articles on option calendar spreads include the following :

Seok, Brorsen, and Niyibizi (2018) derived a new two-factor option pricing model for calendar spreads formed using options on futures assuming arithmetic Brownian motion and tested it using corn futures prices. The new model outperformed four other models in estimating payoffs. Koshiyama, Firoozye, and Treleaven (2019) developed a trading recommendation system and applied it to swaption calendar spreads, and found that it performed favorably against four similar benchmark models. Schneider and Tavin (2018) developed and tested a model to price vanilla calendar spreads on crude oil futures options. In magazine articles, Cretien (2013) analyzed and suggested specific calendar spread trades in currency and Eurodollar options (Cretien, 2012).

Despite an extensive literature search, no journal papers or articles were found analyzing option calendar spreads on stock or indexes. In so far, as we can tell, the present study may be the first of that kind and so add to the understanding of this important market transaction.

Data and Methodology

The database for this study consisted of a complete set of daily historical data on every index option listed on the Shanghai Stock Exchange (SSE) from the date of first listing in China on 2/9/2015 – 9/12/2018, that is, some 98,722 option records. Table 1 displays data items from which other important parameters were calculated. Table 2 delineates the time segment for each sample period.

The SSE 50 Index, based on the 50 largest liquid Shanghai Stock Exchange stocks, is China's leading stock market performance measure. The SSE 50 ETF is valued directly from this index and is the most liquid of China's

Table 1. Daily Data (2017 – 2018)

SSE 50 ETF Price Levels, High, Low Close
SHIBOR (1 – 60 days)
Single Option Close, Strike, Expiry

Table 2. In-Sample and Out-of-Sample Data

Period	Start	End
In-Sample	1–Jan–17	31–Dec–17
Out-of-Sample	1–Jan–18	21–Sep–18

ETFs. Options on the SSE 50 ETF track the ETF which, in turn, closely tracks the underlying index. Historical data on the Shanghai Interbank Offered Rate (SHIBOR) is available from the official website at http://www.shibor.org/shibor/web/DataService.jsp. SHIBOR data were interpolated linearly as and when needed to match option maturities.

The following tests of SSE 50 ETF daily returns were made for both the in- and out-of-sample periods.

(i) Jarque - Bera test for normality.

(ii) Augmented Dickey-Fuller (ADF) and KPSS tests for stationarity.

(iii) Engle ARCH test for ARCH effects.

For the in-sample period covering all call options, a nearest-the-moneytime spread was written on each SSE trading day, *k* (trade day) and this *k*th position was held until an agreed algorithm required unwind. The following returns for each time spread *k* were made :

- The initial debit, *D*0, required to establish the time spread.
- Time spread profit at expiry of the front month *P(T1)*.
- Standstill Return *(RSSk)* : The return for the *k*th time spread assuming the SSE 50 ETF makes no change between trade day and expiration at *T1*.
- EFT levels for upper and lower breakeven points *(UBE, LBE)* where *P(T1)* = 0.
- Realized Return *(RRk)* : The return realized if the *k*th time spread is held to expiration.
- Return if Unwound (*k,t'*) : The return realized if the *k*th time spread is unwound on any subsequent trade day, *t'* = *P(t')**(365/*t'*)/*D*0 = *RIU(t')*.
- Maximum profit at front month call expiry, *PMAX*.
- Percent of *PMAX* captured at unwind.

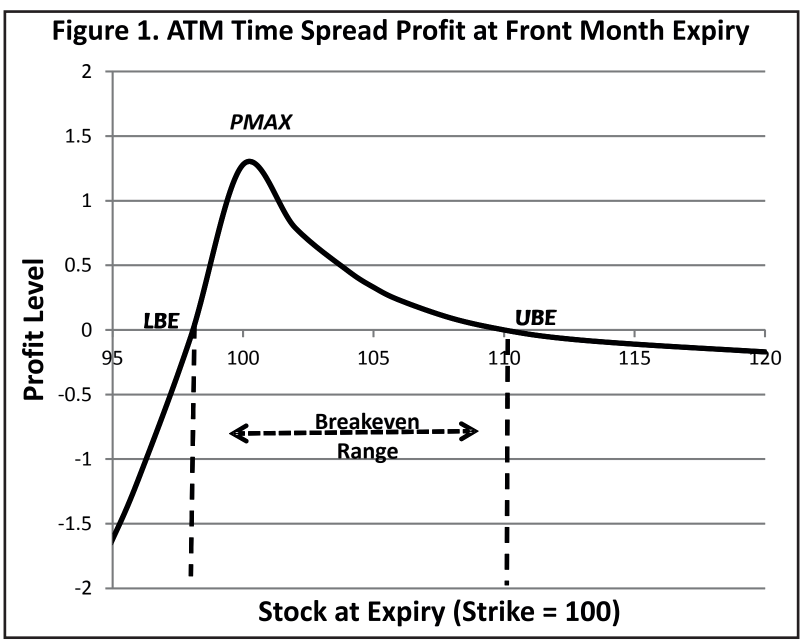


Table 3. SSE 50 Option Time Spread Notations and Definitions

Notation	Definition
$T1$	Front Month Expiry Date.
$T2$	Back Month Expiry Date.
$I(0) = Io$	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 = 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).
$P(T1) =$	$PB(T1) = C2(T2 - T1) + (C1(0) - C2(0))$ = Profit at front month expiry if $I(T1) < K$.
	$PA(T1) = PB(T1) + (K-S)$ = 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.
% $PMC(t)$	% of $PMAX$ 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 $T1$.
	$RMAX = PMAX * (365/T1) / [C2(0) - C1(0)] = PMAX * (365/T1) / D0$.

Using in-sample return results, the best performing entry and exit strategies for writing time spreads was identified. The resulting algorithm was applied to the out-of-sample period and comparisons are made.

The equations needed to compute time spread returns and the associated notations appear in Table 3 along with an illustration in Figure 1 for an at-the-money (ATM) call time spread at front month expiry having a strike price of 100 on an underlying stock price, *S*. Many typical features of an ATM time spread can be understood from this simple example in which the front and back month expiries are assumed, as in our study, to be 30 and 60 days, respectively. The profit profile is characterized by a maximum profit *(PMAX)*, upper and lower breakeven points *(UBE, LBE)* defining a breakeven range, and the lower loss limit, which is the initial cost to establish the spread (initial debit).

Figure 2 illustrates the evolution of such a profit profile from inception to front month expiry. The expiry profit profile rises from a shallow start at inception to a shape at front month expiry containing two breakeven points and a profit maximum. The expiry profit profile rate of growth depends upon the theta differential between front and back month options. The magnitude of the back month theta changes slowly compared with the front month theta and the difference accelerates as expiry approaches. At all points in time, the entire shape of the profile depends moderately upon the market volatility. Thus, the breakeven points and maximum profit value are volatility

Figure 2. Profit Profile Evolution - ATM Option Time Spread

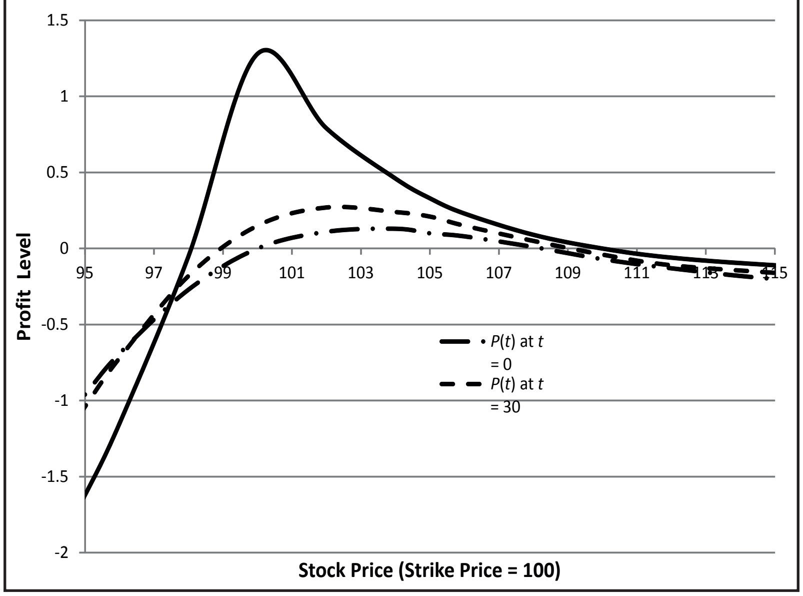
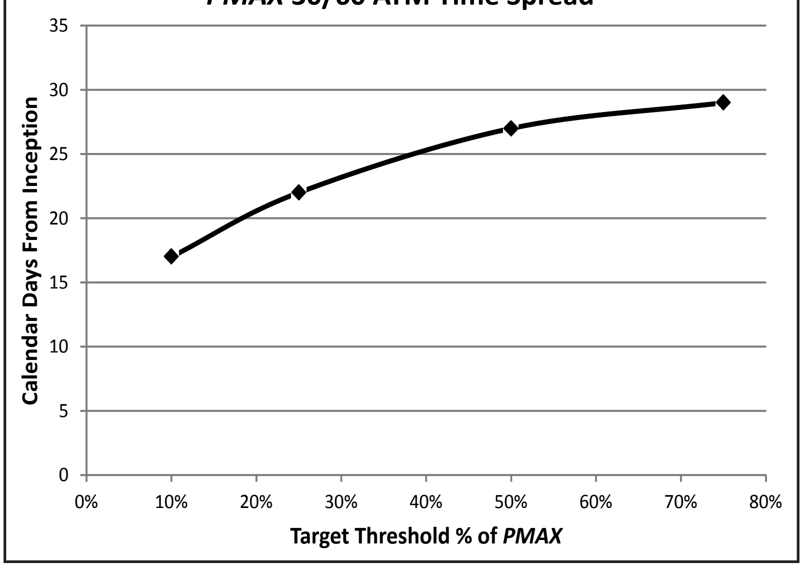


Figure 3. Calendar Days to Capture Threshold % of *PMAX* 30/60 ATM Time Spread



dependent. Once established, such an ATM time spread may quickly become profitable with a sudden rise in volatility, making this type of spread valuable for turbulent market environments.

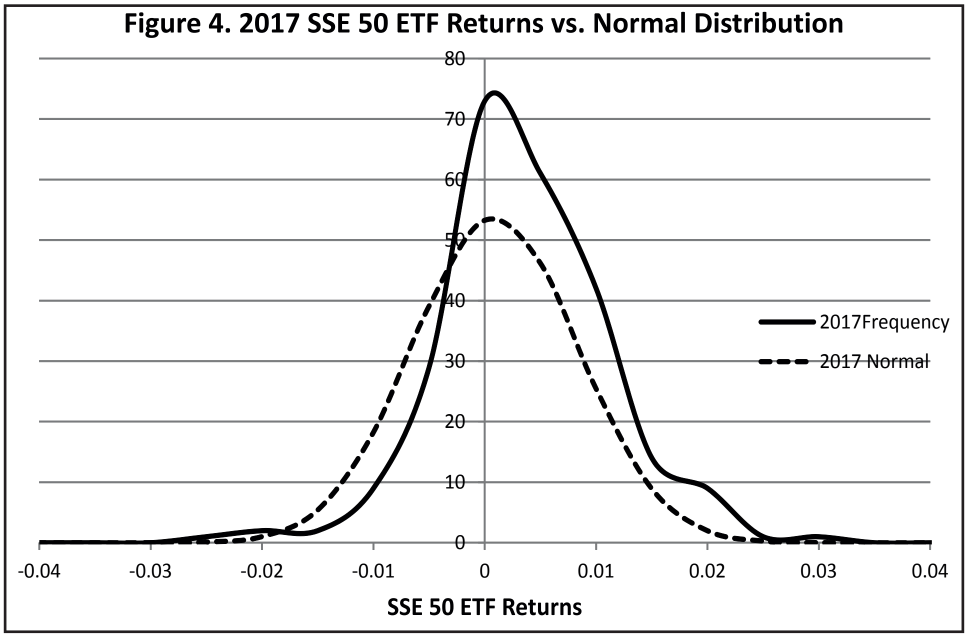
The nonlinear behavior of the theta differential leads directly to Figure 3, where the number of calendar days taken to capture a target threshold percent of the maximum potential profit *(PMAX)* is seen to rise with the targeted percentage capture. In Figure 3, the front/back month times to expiry are taken to be 30/60 days.

Data Analysis, Results, and Discussion

Results for the four important statistical tests conducted on the SSE 50 ETF daily returns appear in Table 4. That a

Table 4. Daily ETF Return Statistical Tests

Matlab Test	For	2017	2018
Jarque-Bera	Normality	Not Normal	Normal
ADF	Stationary	Stationary	Stationary
KPSS	Stationary	Stationary	Stationary
Engle ARCH	ARCH Effects	No ARCH Effects	No ARCH Effects



Jarque - Bera test of 2017 daily log returns confirmed a non - normal distribution was not surprising because China regulators limit daily returns to a maximum of plus or minus 10% (Figure 4). In Figure 4, the frequency distribution for 2017 data peaked above a normal distribution profile. This non-normality suggests a possible degree of market inefficiency.

Inspection of Figure 5 suggests that the 2018 return volatility is greater than for 2017, an observation confirmed in Table 5. Generally, greater volatility expresses itself in more opportunities for trading profitably ; however, analysis of 2018 data does not support this intuitive rule of traders.

For both 2017 and 2018 data, the slope and intercept of the linear regression of daily ETF returns vs. trade day, each prove to be zero as does the time series mean. This suggests that the return time series are very likely to be stationary and both the ADF and KPSS tests more rigorously confirm this stationarity. ARCH effects are not present in the time series of residuals for 2017 or 2018, and this eases the task in the future for constructing volatility and price forecasts.

(1) Parkinson Return Volatility : In general, the most common method to calculate return volatility is to compute the standard deviation of closing price differences. However, there are other advanced volatility measures, which give a statistically stronger estimate compared to the simple closing returns's standard deviation. In our research, we adopt the Parkinson volatility (Parkinson, 1980) to measure the variation of spread returns.

The Parkinson volatility method was created by Michael Parkinson in 1980 and is especially useful for estimating the volatility for trading where samples of data are small such as in our case. This method uses daily

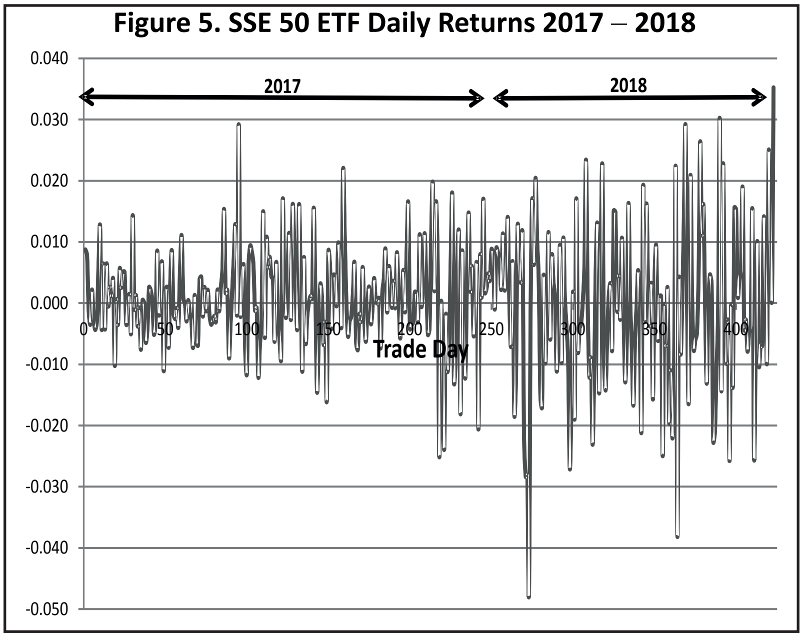


Table 5. Daily SSE 50 ETF Return Statistics

Statistic	2017	2018
Mean	0.0009	–0.0005
Standard Error	0.0005	0.0010
Median	0.0004	0.0000
Mode	0.0000	0.0000
Standard Deviation	0.0074	0.0132
Sample Variance	0.0001	0.0002
Kurtosis	1.5366	0.6135
Skewness	0.0660	–0.2465
Range	0.0543	0.0826
Minimum	–0.0251	–0.0474
Maximum	0.0292	0.0352
Sum	0.2229	–0.0824
Count	244	179

high and low prices instead of closing prices only.

Parkinson return volatility is calculated as :

$$Parkinson\ Volatility = Vp = \sqrt{\frac{1}{N}}\sqrt{\frac{1}{4Ln(2)}\sum_{i=1}^{N}\left[Ln\left(\frac{h_i}{l_i}\right)\right]^2}$$

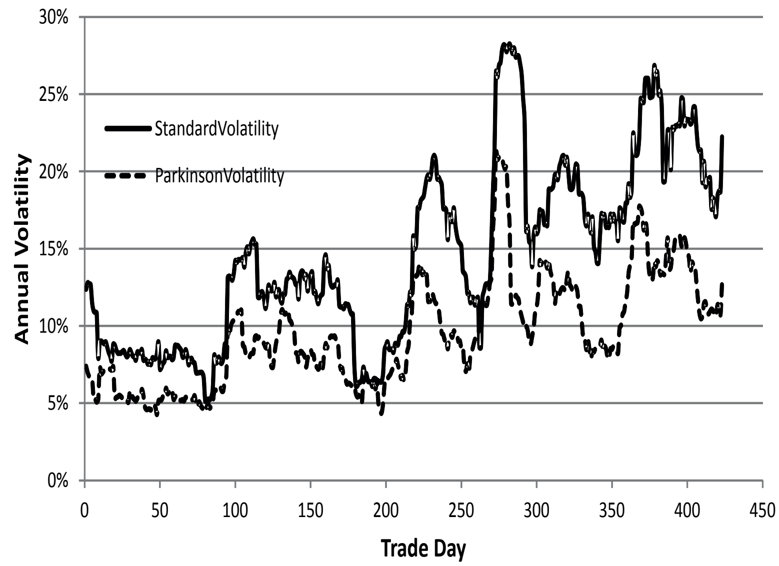
h_i = High price on trade day i,

l_i = Low price on trade day i,

N = sample size.

An alternative choice of volatility measure is that developed by Yang - Zhang (2000). This measure has a rather

Figure 6. SSE 50 Standard and Parkinson Volatility 2017 – 2018



low error of estimation compared with close-to-close and Parkinson volatility. This estimator computes the weighted average of overnight volatility (close-open volatility).

Figure 6 shows the Parkinson and standard return volatilities for the study period. The two volatilities have a correlation coefficient of 0.88. Time did not permit an extensive analysis of the unusual pattern of spread return volatilities, and so, this task is left for future research.

(2) Chauvenet's Criterion : Chauvenet's criterion (Chauvenet's Criterion, n.d.) is a measure that provides the basis for rejection of extreme data from a set of measurements. The criterion is especially helpful when sample sizes are relatively small (typically less than several thousand). Extreme data points, once removed, permit a new mean and standard deviation to be calculated.

PI = Precision Index : For a normal distribution *N*(0,1), a ratio of deviation to standard deviation adjusted for an empirical sample of size *N*.

For small *N*, *PI* is approximately 1.65. As *N* rises, so too does the *PI*.

Dmax = *PI* × *s* = maximum absolute deviation from sample mean. Deviations greater than *Dmax* are rejected by the Chauvenet criterion.

s = Sample standard deviation.

A partial listing of *PI* corresponding to the sample size *N* is found in Table 6.

For 2017 and 2018 time spreads in our study, *N* = 137 and 121, respectively and the interpolated *PI* from a standard table for normal distributions = 2.89 and 2.85. If *D0* is the initial debit with a standard deviation of .0045, and if *DFV* is the debit fair value, then the maximum allowed absolute deviation of *D0* – *DFV* from the 2017 sample mean is calculated to be 0.130. Any debit difference exceeding this absolute deviation from the sample mean should be rejected. There are only two such deviations exceeding this critical level and after rejection, the revised 2017 mean and standard deviation are calculated as – 0.0026 and 0.42%, respectively. In the 2018 sample, no data were rejected.

(3) Time Spread Trading Algorithm : A central question of interest in this study is whether a profitable strategy for

Table 6. Precision Index (*PI*) vs. Sample Size (*N*)

N	*PI*
1	1.65
10	1.96
20	2.24
40	2.49
80	2.74
100	2.81
200	3.02
500	3.29
1000	3.48

Source : Statistics How To (n.d.)

Table 7. SSE 50 Call Option Time Spread Algorithm

Entry Rule for each trade day *k* :	If at a day-end, *RSS* > Shibor 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*) > Initial Shibor and %*PMC*(*t*) > = *X*%, then unwind the *TS*. 10% < *X* < 100%.
	2. If on a subsequent trade day *t*, the *ETF* level is outside the breakeven range, then unwind the *TS*.
	3. There is a mandatory unwind 1 trade day prior to expiry. On unwind day, record trade day *t*' of the unwind, *RIU*(*t*'), *P*(*t*'), %*PMC*(*t*'), # Calendar Day's *TS* was held.

trading SSE 50 call option time spreads can be developed. The algorithm developed and tested in this study is governed by the simple entry and exit rules in Table 7. On each trading day-end, a nearest-the-money time spread is formed using the front month and nearest back month. If the standstill return is above the funding cost (taken to be Shibor) and the number of days to front month expiry is greater than 5 (to avoid price abnormalities near expiration), then the time spread is implemented.

Once initiated, a time spread could be unwound if one any of three exit rules are satisfied.

- **Rule 1 :** If on a subsequent trade day *t*, *RIU(t)* > Initial Shibor and % *PMC(t)* > = *X* %, then unwind the time spread. Vary *X* between a 10% and 100% threshold to determine an optimal profit outcome.
- **Rule 2 :** If on a subsequent trade day *t*, the ETF level is outside the breakeven range, then unwind the *TS*.
- **Rule 3 :** There is a mandatory unwind one trade day prior to expiry.

For 2017 and 2018, 137 and 121 time spreads, respectively were initiated using the algorithm entry rule.

Distributions of profit at unwind for 2017 and 2018 at the 75% threshold level appear in Figure 8 and are markedly different, with 2017 being skewed toward positive profits and 2018 being centered about zero. Threshold levels for 2017 vary between 10% and 100% (Figure 9) to help identify a most favorable value.

The total net profit from all valid time spreads peaked at the 75% threshold level (Figure 10) and is taken as the best performance parameter to apply to the 2018 out of sample data. When applied to 2018 data, the algorithm results are found to be disappointing (Figure 10).

The most likely factor possibly explaining this outcome is the presence in 2017 of a positive return pickup arising from the debit deviation from fair value as confirmed by statistical tests of data in Figure 7 and its absence in 2018. At a 95% confidence level, the initial debit difference from fair value ($D0 - DFV$) is found to be zero for 2018 but non-zero and negative (– 0.0028) for 2017, suggesting time spreads initiated in 2017 offered an opportunity to result in a positive return from the day of initiation. Alternatively, the 2018 debit difference is statistically zero, suggesting that any positive returns would have to come from efficient algorithm exit rules. With no 2018 debit deviations from fair value at day-end, any positive performance would have to originate from intraday trading opportunities.

Figure 7. Time Spread Debit Difference from Debit Fair Value 2017, 2018

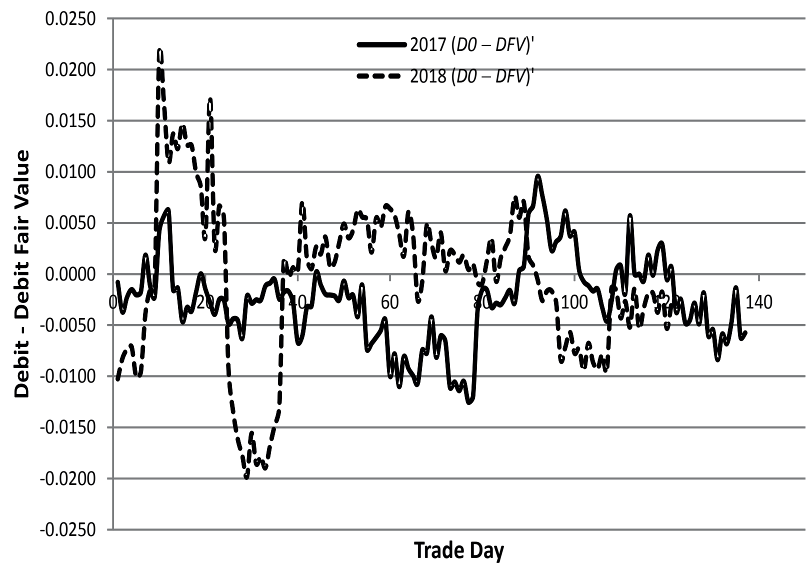


Figure 8. 2017, 2018 Profit Distributions

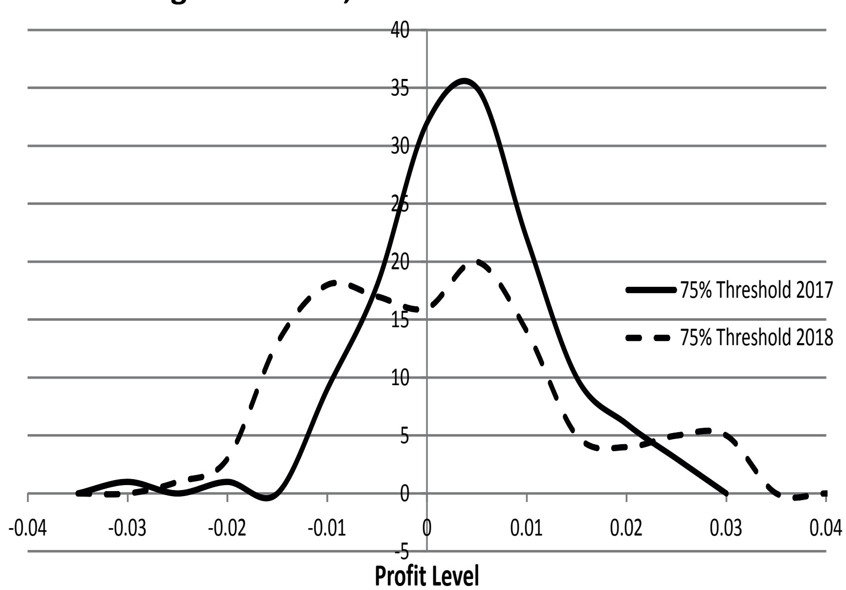


Figure 9. 2017 Frequency Distributions for Profit at Unwind for Varying Threshold Levels

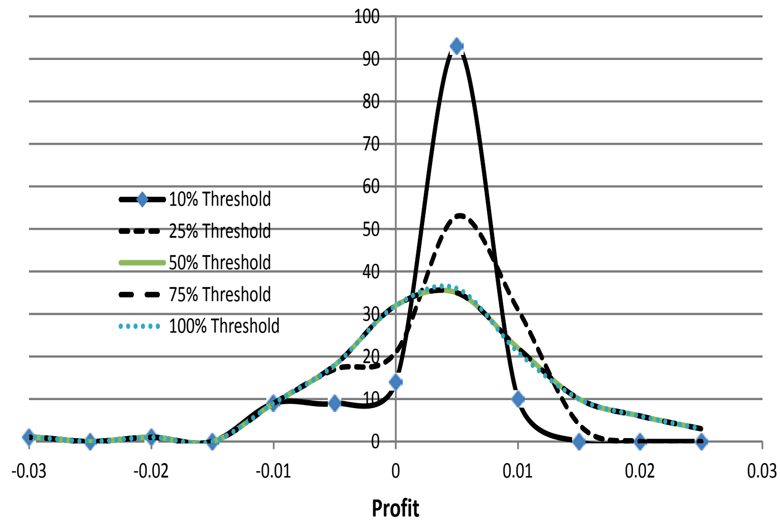
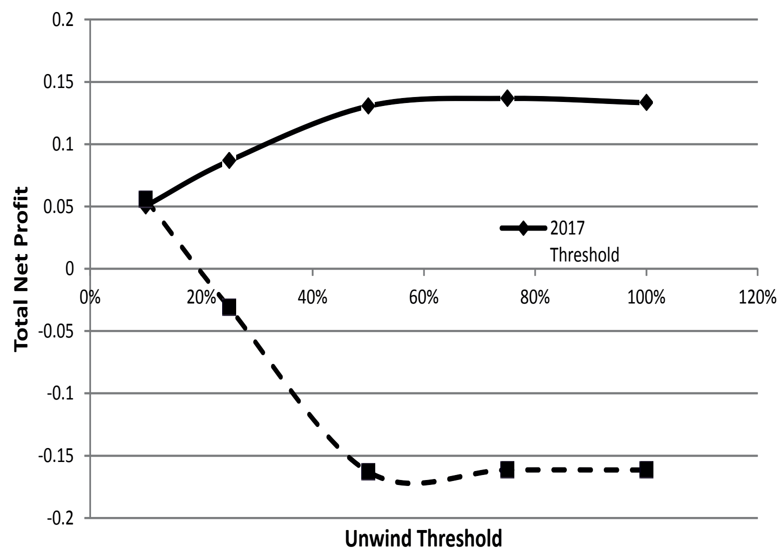


Figure 10. Time Spread Total Net Profit vs. Unwind Threshold



Summary and Conclusions

All steps outlined in the data and methodology section were completed for both in-sample and out-of-sample data. Progress in completing the list of steps included the following :

➪ Daily SSE 50 ETF log returns were tested for normality using the Jarque - Bera test. Non-normality was confirmed for 2017 but not for 2018 data. Some of the origin of non-normality originates with China's regulatory limit of daily % price moves to plus or minus 10%.

↳ Log return residuals were found to be stationary using Augmented Dickey - Fuller (ADF) and KPSS tests, a necessary condition for ARCH testing. Since the residual time series is stationary, daily returns are mean reverting and were tested for ARCH effects using the Engle ARCH test.

↳ A high degree of correlation between standard and Parkinson historical daily return volatilities was confirmed and Parkinson volatility was used in all further parts of this study. Parkinson volatility is preferred for its accuracy when sample sizes are small.

↳ Chauvenet's criterion was employed as a basis for rejection of extreme time series values. This criterion is especially helpful when sample sizes are small as was the case for our study. For in- and out-of-sample periods, a nearest-the-money call option time spread was written on each SSE trading day, satisfying an algorithm entry rule. All quantities in Table 3 were calculated for each time spread and summarized.

For varying threshold levels of %*PMC*, the total average algorithm profit across all 2017 time spreads was calculated, revealing the 75% threshold to be optimal. However, this choice was not optimal for 2018, where 10% appeared to be the best choice. The 2018 outcome was likely attributed to the statistical absence of any debit difference from debit fair value. Four areas of research were identified for future study.

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

By constraining daily SSE 50 ETF returns to plus or minus 10%, it may be thought that China regulators thereby introduce market abnormalities that created the 2017 profitable time spread trading opportunities observed in this study. However, the absence of 2018 profitable transactions is more likely attributable to the marketplace's debit pricing consistently at fair value despite a rise in volatility. Traders seeking to identify excess time spread returns will probably have to search for opportunities intraday.

The following areas of research are identified to be of interest for future studies.

↳ **Extending the Database :** In this study, only call option data from 2017 and most of 2018 were analyzed. Data from prior years and from October 2018 to present should also become part of the extended database and analysis. If the debit deviation from fair value continues to remain zero, then intraday data should be used to further test the trading algorithm.

↳ **Extending Time Spread Formation :** Assuming a reasonable level of liquidity for the 2017 and 2018 period, time spreads could have been formed using front month and second (vs. first) back month to compare with the current results. It may be that these secondary time spreads perform better than the front-back month spreads studied here. Also assuming a reasonable level of liquidity for the 2017 and 2018 period, time spreads could have been formed using front month and back month puts to compare with the current call results.

↳ **Inclusion of Transaction Costs :** Reasonable assessments of commissions, fees, borrow rates, and related transaction costs should be made and included in return calculations for the next step in analysis.

↳ **Understanding Volatility :** Understanding profit profile behavior in varying volatility environments might lead to improved algorithm performance.

References

Cretien, P. D. (2012, January 1). Eurodollar options : Interest rate forecasts and calendar spreads. *Futures Magazine*, pp. 28, 29, 33.

Cretien, P. D. (2013, April 1). Seize the day with forex calendar spreads. *Futures Magazine,* pp. 20, 21, 27.

Hilliard, J. E., & Xhang, H. (2017). *Regulator's soft interventions and limits on arbitrage in the Chinese option market.* Auburn Alabama : Auburn University.

Koshiyama, A. S., Firoozye, N., & Treleaven, P. (2019). A derivatives trading recommendation system: The mid-curve calendar spread case. *Intelligent Systems in Accounting, Finance & Management, 26* (2), 83 – 103.

Parkinson, M. (1980). The extreme value method for estimating of the rate of return. *The Journal of Business, 53* (1), 61 – 65.

Schneider, L., & Tavin, B. (2018). From the Samuelson volatility effect to a Samuelson correlation effect : An analysis of crude oil calendar spread options. *Journal of Banking and Finance, 95,* 185 –202.

Seok, J. B., Brorsen, B. W., & Niyibizi, B. (2018). Modeling calendar spread options. *Agricultural Finance Review, 78* (5), 551 – 570.

Statistics How To. (n.d.). *Statistics definitions - Chauvenet's Criterion.* Retrieved from https://www.statisticshowto.datasciencecentral.com/chauvenets-criterion/

Tongtong, X., Susheng, W., Ke, P., Dandan, Y., & Mingzhu, H. (2017). *Intraday trading patterns in the SSE50 ETF option.* 3rd International Conference on Economics, Social Science, Arts, Education and Management Engineering (pp. 1793 – 1797). Huhhot, China : Atlantis Press.

Chauvenet's Criterion. (n.d.). In*, Wikipedia*. Retrieved December 20, 2019 from https://en.wikipedia.org/wiki/Chauvenet%27s_criterion

Pan, H., & Song, J. (2017). Volatility cones and volatility arbitrage strategies - Empirical study based on SSE ETF option. *China Finance Review International, 7*(2), 203 – 227.

Yang, D., & Zhang, Q. (2000). Drift - independent volatility estimation based on high, low, open and close prices. *Journal of Business, 73* (3), 477 – 491.

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