Trading Value of Volatility Index: Empirical Evidence from Chinese Option Market

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Abstract

This paper uses a new method for constructing a generalized volatility index (GVIX) for the Chinese market, which is not based on the assumption of geometric Brownian motion underlying the traditional VIX index. The article examines the properties of GVIX in the Chinese market with reference to the existing literature. Finally, the study compares GVIX with other volatility indices by evaluating the performance of option trading strategies using each index as the implied volatility input. The results demonstrate that GVIX-based strategies achieve the highest annualized returns of 47.62% and a competitive Sharpe ratio of 1.94, suggesting that GVIX offers effective volatility information for option pricing.

Introduction

The 1987 stock market crash highlighted the need for volatility indices like the VIX, which measures market volatility and investor sentiment. While global markets have adopted such indices, China's underdeveloped derivatives market has struggled to establish a stable VIX index. This paper addresses the urgent need for a robust Chinese volatility index to improve market sentiment measurement and risk management, contributing to the internationalization of China's financial markets.

Contribution

▶ The VIX index relies on the assumption that the underlying asset prices follow a geometric Brownian motion, which is often difficult to realize in real financial markets. To address this issue, GVIX index is adopted, which does not rely on a specific diffusion process. The GVIX is calculated directly based on the definition of the logarithmic return variance, which has the potential to more accurately represent the expected volatility of the market. In this paper, we follow their methodology and construct the GVIX index for the Chinese market.

Contribution

▶ After constructing the GVIX index, this paper further investigates the statistical properties of the two VIX indices and the underlying asset prices. Specifically, this paper investigates the direction of bias of VIX, the correlation between VIX, GVIX and future underlying asset prices, and the asymmetry leverage effect of VIX and GVIX, which is different from the performance of the US market.

Contribution

▶ Since there is no official VIX index and VIX futures launched in the Chinese financial market, how to reflect the trading value of VIX has become a research difficulty. This paper proposes an option pricing strategy based on the GVIX index and demonstrates that compared with other volatility measures, the GVIX index encapsulates the information of the option market and has better asset pricing ability. The results demonstrate that GVIX-based strategies achieve the highest annualized returns of 47.62% and a competitive Sharpe ratio of 1.94, suggesting that GVIX offers effective volatility information for option pricing.

Chinese GVIX Index Compilation

We extend the compilation of the VIX index into GVIX based on three aspects: option price (Q_k) , the no-arbitrage forward price of the underlying asset $F_0 = S_0 \exp(rT)$, and the risk-free interest rate (r). The calculations are as follows:

$$\begin{split} \hat{\mu}_T &= \left[\ln \left(\frac{K_0}{S_0} \right) + \left(\frac{F_0}{K_0} - 1 \right) \right] - \exp(rT) \sum_i \frac{1}{K_i^2} Q(K_i) \Delta K_i, \\ \hat{V}_T &= \left[\ln^2 \left(\frac{K_0}{S_0} \right) + 2 \ln \left(\frac{K_0}{S_0} \right) \left(\frac{F_0}{K_0} - 1 \right) \right] \\ &+ 2 \exp(rT) \sum_i \frac{1}{K_i^2} \left[1 + \ln \left(\frac{S_0}{K_i} \right) \right] Q(K_i) \Delta K_i, \\ \sigma_1^2 &= \sqrt{\frac{\hat{V}_T - (\hat{\mu}_T)^2}{T}}. \end{split}$$

Chinese GVIX Index Compilation

To align with CBOE's VIX estimation, we adjust the GVIX index based on a 30-day basis:

$$GVIX_{a} = \sqrt{\left[\frac{N(T_2) - N(30)}{N(T_2) - N(T_1)}(T_1 \cdot \sigma_1^2) + \frac{N(30) - N(T_1)}{N(T_2) - N(T_1)}(T_2 \cdot \sigma_2^2)\right] \left(\frac{N(365)}{N(30)}\right)}.$$

GVIX Visualization

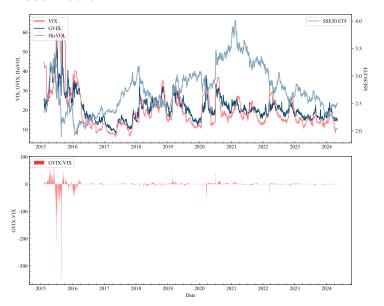


Figure: Time series plot of GVIX & ETF. The left Yaxis in the figure

GVIX Upward Bias

[?] identified a downward bias in the VIX for the U.S. market. In contrast, our study reveals an opposite bias in the Chinese market. To account for the COVID-19 pandemic's influence, we segmented the trading data into two periods: 2015-2019 and 2020-2024, for a detailed examination of the VIX bias. We presents a scatter plot of the VIX-GVIX difference versus VIX, with segmented regression lines derived from regression equation. The analysis suggests that the VIX does not show a significant downward bias. Instead, the bias hovers around zero at lower VIX levels and exhibits a discernible upward bias at higher levels.

$$(\widehat{VIX} - \widehat{GVIX}) = \alpha + \beta_1 * \widehat{VIX} * I(\widehat{VIX} < \tau) + \beta_2 * \widehat{VIX} * I(\widehat{VIX} \ge \tau) + \epsilon.$$

GVIX Upward Bias

Table: **VIX-bias regression.** This table reports the regression result of VIX bias. *,** and ***indicate significance at the 10%, 5% and 1% levels.

Before the pandemic	Coefficient	(Intercept)	β_1 (VIX \leq 30)	β_2 (VIX \geq 30)
	Estimate	-0.07403**	0.00235	0.00680***
After the pandemic	Coefficient	(Intercept)	β_1 (VIX \leq 25)	β_2 (VIX \geq 25)
	Estimate	0.00026	-0.00080	0.00005

VIX Upward Bias Before the Pandemic

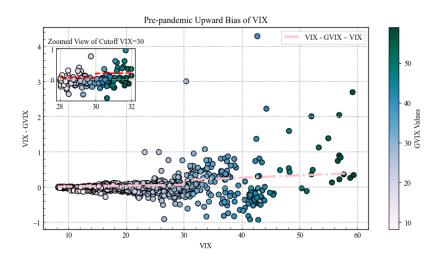


Figure: VIX upward bias before the pandemic

VIX Upward Bias After the Pandemic

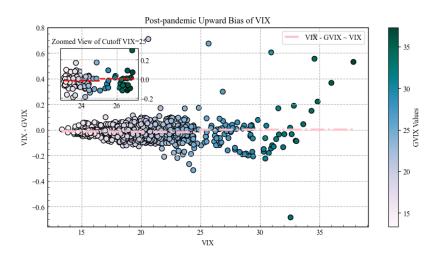


Figure: VIX upward bias after the pandemic

VIX Leverage Effect

Table: Leverage effect regression of VIX and GVIX. This Table reports the leverage effect regression for the index return from February 2015 to April 2024 and their standard error are reported in the parenthesis below. *, **, and *** indicate significance at the 10%, 5% and 1% levels.

VIX Type	Time Period	Intercept	$max(R_t, 0)$	$min(R_t, 0)$	Adj. R^2	Obs		
dVIX	2015	0.014	0.021	0.039	-0.008	218		
		(0.263)	(0.136)	(0.117)				
	2016-2017	-0.014	0.172*	0.215***	0.042	488		
		(0.056)	(0.074)	(0.063)				
	2018-2019	-0.411***	0.171**	-0.715***	0.213	487		
		(0.067)	(0.062)	(0.062)				
	2020-2024	-0.397***	0.233***	-0.670***	0.205	1048		
		(0.040)	(0.041)	(0.041)				
	Full Sample	-0.187***	0.110**	-0.282***	0.033	2241		
		(0.037)	(0.034)	(0.032)				
dGVIX	2015	0.007	0.140	0.153	0.009	218		
		(0.267)	(0.138)	(0.119)				
	2016-2017	-0.008	0.208**	0.275***	0.064	488		
		(0.057)	(0.075)	(0.064)				
	2018-2019	-0.416***	0.212***	-0.683***	0.198	487		
		(0.067)	(0.062)	(0.062)				
	2020-2024	-0.392***	0.253***	-0.642***	0.189	1048		
		(0.041)	(0.041)	(0.041)				
	Full Sample	-0.183***	0.165***	-0.217***	0.023	2241		
		(0.037)	(0.035)	(0.032)				
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VIX Correlation with ETF Return

Table 3 displays the Pearson correlation coefficients between these indices and the ETF's average returns over a horizon of 3 to 60 trading days. The findings reveal a modest correlation with short-term returns but a robust negative correlation with returns over the subsequent one to two months. This underscores the efficacy of our VIX and GVIX indices in reflecting market sentiment and anticipating potential price downturns.

Table: Correlation of ETF Returns with VIX Indices

Days	3	5	7	10	15	20	25
VIX	-0.0322	-0.0457	-0.0636	-0.0854	-0.1235	-0.1364	-0.1354
GVIX	-0.0345	-0.0477	-0.0650	-0.0864	-0.1236	-0.1348	-0.1339
Days	30	35	40	45	50	55	60
VIX	-0.1526	-0.1778	-0.2038	-0.2128	-0.2256	-0.2344	-0.2344
GVIX	-0.1516	-0.1769	-0.2024	-0.2125	-0.2262	-0.2356	-0.2358

At each trading day t:

- 1. Calculate the fair value F_t of the option using the BSM formula
- 2. If $F_t > C_t$, take a long position for the option. If $F_t < C_t$, take the short position of the option.
- 3. Rebalance the portfolio at the close of the market, taking into account transaction costs and slippage.
- 4. Due to the high volatility in the options market, the strategy employs simple interest.
- 5. The backtest interval is from 2015-02-09 to 2024-04-30.

We present the outcomes of option pricing using GVIX. We assess the performance of our quantitative strategy using six key metrics: Total Return (TR), Annualized Return (AR), Annualized Volatility (Vol), Maximum Drawdown (MDD), Sharpe Ratio (SR), and Calmar Ratio (CR). The strategy's performance metrics are detailed below.

Table: Performance Metrics

TR AR Vol MDD SR CR 3097.57% 47.62% 24.52% 37.89% 1.94 1.26

Strategy - Monthly Returns (%)

2015	0.00	38.23	93.36	6.27	7.42	27.79	0.00	-18.48	5.98	14.94	10.17	6.19	
2016	-33.77	0.46	32.91	12.26	8.36	9.20	11.08	16.99	3.59	9.49	14.89	0.40	
2017	8.18	0.95	5.32	1.11	8.18	6.19	8.41	3.88	2.18	1.62	4.75	2.46	
2018	-3.46	6.82	-6.02	4.03	1.78	1.11	2.33	-0.98	2.41	-5.40	0.45	8.59	
2019	0.37	2.54	-0.24	-0.27	4.03	3.32	2.55	0.50	3.71	1.71	-0.63	-2.36	
2020	2.17	4.62	0.46	4.06	-0.62	4.71	5.23	1.93	0.58	1.75	2.75	-0.40	
2021	-0.89	0.99	-0.95	0.26	-2.54	2.11	-2.95	-0.54	1.64	1.35	-0.02	0.85	
2022	1.39	0.79	0.33	-1.87	0.87	1.73	0.42	0.50	0.46	-2.51	3.83	0.74	
2023	0.15	1.28	2.06	0.78	2.66	0.46	-1.36	2.49	0.37	-0.49	-0.32	2.29	
2024	1.33	2.88	1.51	0.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	

Figure: Strategy Monthly Return Heatmap

Subsequently, we analyze the impact of varying commission rates on the strategy's performance. This examination aims to determine if the strategy remains effective under higher commission fees, thereby validating the strategy's profitability even in costlier trading environments.

Table: Performance Metrics with Different Commission Settings

Commission	TR	AR	Vol	MDD	SR	CR
0.0005	3433.72%	49.29%	23.49%	34.78%	2.10	1.42
0.0010	3321.67%	48.75%	23.81%	35.77%	2.05	1.36
0.0015	3209.62%	48.19%	24.15%	36.80%	2.00	1.31
0.0020	3097.57%	47.62%	24.52%	37.89%	1.94	1.26
0.0025	2985.52%	47.03%	24.90%	39.02%	1.89	1.21
0.0030	2873.47%	46.42%	25.31%	40.33%	1.83	1.15

Table: Methods for Volatility Estimation

Category	Method	Description
GARCH	GARCH	Generalized Autoregressive Conditional Heteroskedasticity model
	TGARCH	Threshold GARCH model incorporating regime-switching behavior
	EGARCH	Exponential GARCH model capturing asymmetric volatility
	IGARCH	Integrated GARCH model for volatility persistence
Machine Learning	SVM	Support Vector Machine
	RF	Random Forest
	GBDT	Gradient Boosting Decision Trees
	XGB	eXtreme Gradient Boosting for nonlinear volatility patterns
Neural Networks	NN	Neural Networks for learning complex volatility patterns
Economic Indicator	GVIX	Generalized Volatility Index
	VIX	Volatility Index
	HIS	History 30-day Volatility
Realized Volatility	HARRV	High-Frequency AutoRegressive Realized Volatility model

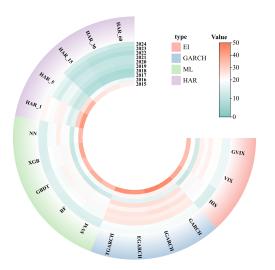


Figure: The mean values of different volatilities across various years.

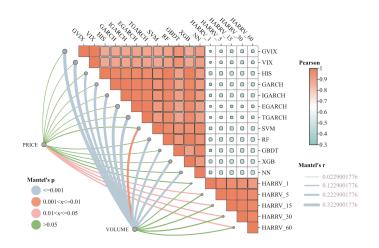


Figure: Correlation of different volatilities

Table: Performance Metrics Comparison

Method	TR	AR	Vol	MDD	SR	CR
GVIX	3097.57%	47.62%	24.52%	37.89%	1.94	1.26
VIX	2394.16%	43.55%	21.34%	37.92%	2.04	1.15
HIS	1896.75%	40.01%	41.95%	71.46%	0.95	0.56
GARCH	2586.11%	44.75%	29.07%	47.55%	1.54	0.94
IGARCH	2555.56%	44.57%	29.57%	49.03%	1.51	0.91
EGARCH	2567.87%	44.64%	29.06%	42.77%	1.54	1.04
TGARCH	2522.98%	44.37%	32.85%	53.90%	1.35	0.82
SVM	2325.12%	43.10%	29.42%	47.06%	1.47	0.92
RF	1981.73%	40.67%	44.48%	73.65%	0.91	0.55
GBDT	2345.45%	43.24%	23.26%	27.83%	1.86	1.55
XGB	1647.22%	37.92%	39.43%	72.89%	0.96	0.52
NN	2220.86%	42.40%	31.58%	41.67%	1.34	1.02
HARRV_1	1135.66%	32.66%	59.70%	92.00%	0.55	0.35
HARRV_5	1108.47%	32.33%	34.91%	70.15%	0.93	0.46
HARRV_15	1088.38%	32.08%	36.18%	71.07%	0.89	0.45
HARRV_30	1052.63%	31.62%	38.42%	73.74%	0.82	0.43
HARRV_60	1111.42%	32.36%	34.43%	71.07%	0.94	0.46

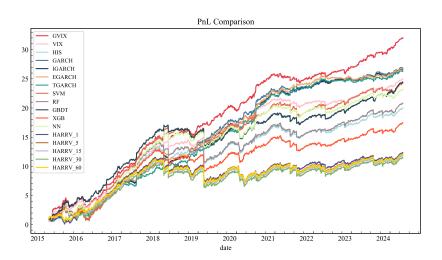


Figure: Strategy Return Comparison

Conclusion

This study develops the VIX and GVIX indices for China's SSE 50 ETF, revealing a less pronounced and inverse VIX bias compared to the US market. It demonstrates GVIX's superior predictive power for asset price volatility over other indices, with the GVIX-based strategy achieving the highest returns and Sharpe ratio, underscoring its effectiveness in option trading and risk management.