

Comparative Analysis of the Variance Risk Premium: Theoretical Foundations, Empirical Evidence, and Research Design for CNVIX

2025 October

1 What is the VIX?

The **VIX**, often referred to as the *Volatility Index*, represents the market's expectation of future volatility over the next 30 days. It is calculated by the Chicago Board Options Exchange (CBOE) based on option prices of the S&P 500 index.

Mathematically, it corresponds to the square root of the expected variance of log returns under the risk-neutral measure. In other words, VIX provides a model-free measure of the market's implied volatility, extracted from a wide range of option prices.

2 What is a Variance Swap?

A **variance swap** is a financial derivative that allows investors to trade future realized variance against current implied variance. The payoff of a variance swap at maturity T is given by:

$$\text{Payoff} = \text{Realized Variance} - K_{\text{var}},$$

where K_{var} is the *variance strike*, i.e., the market's expectation of realized variance at inception. Variance swaps are particularly useful because they allow direct exposure to volatility itself rather than to price direction.

3 An Example of Variance Swap

For a variance swap, the payoff structure at maturity is:

$$\text{Payoff} = N_{\text{var}} \times (\sigma_{\text{real}}^2 - K_{\text{var}}),$$

where:

- N_{var} : Notional amount. The unit is typically “per 1 variance point (0.01) how much money”.
- K_{var} : The pre-agreed variance strike (the “implied variance” when the contract is initiated).
- σ_{real}^2 : The realized annualized variance during the contract period.

In words: at maturity, if the realized variance is higher than the variance strike, the long side profits; otherwise, it loses.

To measure daily volatility, we use the daily log returns, then annualize them by averaging squared returns:

$$r_t = \ln \frac{S_t}{S_{t-1}}, \quad \sigma_{\text{real}}^2 = \frac{A}{n} \sum_{t=1}^n r_t^2,$$

where:

- S_t : Closing price on day t .
- n : Number of trading days within the observation period.
- A : Annualization factor, typically 252 (trading days) or 365 (calendar days), depending on contract convention.

Intuitively: the more frequently and sharply prices fluctuate day to day, the higher the realized variance will be.

3.1 Numerical Example

Assume:

- Notional amount $N_{\text{var}} = \$10,000$ per variance point.
- Variance strike $K_{\text{var}} = 0.0400$ (corresponding to 20% volatility).
- Observation period of 5 trading days.
- Annualization factor $A = 252$.

The 5-day daily log returns (approximate example):

$$r = [0.010, -0.020, 0.005, 0.000, 0.015].$$

Then:

$$r^2 = [0.000100, 0.000400, 0.000025, 0, 0.000225],$$

$$\sum_{t=1}^5 r_t^2 = 0.000750.$$

Annualized realized variance:

$$\sigma_{\text{real}}^2 = \frac{A}{n} \sum_{t=1}^n r_t^2 = \frac{252}{5} \times 0.000750 = 0.0378.$$

Hence, the realized volatility is:

$$\sigma_{\text{real}} = \sqrt{0.0378} \approx 19.44\%.$$

Final payoff:

$$\text{Payoff} = N_{\text{var}} \times (\sigma_{\text{real}}^2 - K_{\text{var}}) = 10,000 \times (0.0378 - 0.0400) = -\$2,200.$$

Thus, the long side loses \$2,200 because the realized variance is lower than the variance strike.

4 Why use Variance Swaps to measure the VIX?

The VIX index is essentially derived from the theoretical fair value of a variance swap on the S&P 500 index. In the risk-neutral world, the fair strike of the variance swap K_{var} equals the expected future realized variance. By constructing a portfolio of out-of-the-money call and put options, one can replicate this expected variance — leading to the model-free formula that defines VIX.

5 Variance Swap Pricing

Our aim is to price the variance strike so that we make sure this contract is fair to both side. The payoff of a variance swap equals the realized variance minus the market's expected variance.

$$\text{Payoff} = \text{Realized Variance} - K_{\text{var}}$$

Variance swap doesn't have a premium, thus its current value is 0.

$$0 = \mathbb{E}_{\mathbb{Q}} \left[e^{\int_0^T -r_s ds} \text{Payoff} \right]$$

$$\mathbb{E}_{\mathbb{Q}} \left[e^{\int_0^T -r_s ds} \text{Realized Variance} \right] = \mathbb{E}_{\mathbb{Q}} \left[e^{\int_0^T -r_s ds} K_{\text{var}} \right]$$

K_{var} is a constant, thus:

$$K_{\text{var}} = \mathbb{E}_{\mathbb{Q}}[\text{Realized Variance}]$$

In the real-world measure:

$$dS_t = \mu S_t dt + \sigma_t S_t dW_t$$

In the risk-neutral measure (under Girsanov's theorem):

$$dS_t = r S_t dt + \sigma_t S_t dW_t^{\mathbb{Q}}$$

Let $X_t = \ln S_t$. Then

$$dX_t = \left(r - \frac{1}{2} \sigma_t^2 \right) dt + \sigma_t dW_t^{\mathbb{Q}}$$

The realized variance is defined as the average quadratic variation of X_t :

$$\text{Realized Variance} = \frac{1}{T} \int_0^T \sigma_t^2 dt$$

Hence,

$$K_{\text{var}} = \mathbb{E}^{\mathbb{Q}}[\text{Realized Variance}] = \frac{1}{T} \mathbb{E}^{\mathbb{Q}} \left[\int_0^T \sigma_t^2 dt \right]$$

To calculate the expectation, we return to the risk-neutral measure.

Let's integrate the SDE of X_t :

$$dX_t = \left(r - \frac{1}{2} \sigma_t^2 \right) dt + \sigma_t dW_t^{\mathbb{Q}}$$

Integrate from 0 to T :

$$X_T - X_0 = \int_0^T \left(r - \frac{1}{2} \sigma_t^2 \right) dt + \int_0^T \sigma_t dW_t^{\mathbb{Q}}$$

Taking expectations on both sides ($\mathbb{E}^{\mathbb{Q}} \left[\int_0^T \sigma_t dW_t^{\mathbb{Q}} \right] = 0$):

$$\mathbb{E}^{\mathbb{Q}}[X_T - X_0] = rT - \frac{1}{2} \mathbb{E}^{\mathbb{Q}} \left[\int_0^T \sigma_t^2 dt \right]$$

Therefore,

$$\mathbb{E}^{\mathbb{Q}} \left[\int_0^T \sigma_t^2 dt \right] = 2 \left(rT - \mathbb{E}^{\mathbb{Q}}[X_T - X_0] \right)$$

Since $X_T - X_0 = \ln \frac{S_T}{S_0}$, we have

$$K_{\text{var}} = \frac{2}{T} \left(rT - \mathbb{E}^{\mathbb{Q}} \left[\ln \frac{S_T}{S_0} \right] \right)$$

5.1 Theorem (Carr–Madan Representation)

For any twice differentiable function f :

$$f(S_T) = f(K_0) + f'(K_0)(S_T - K_0) + \int_0^{K_0} f''(K)(K - S_T)^+ dK + \int_{K_0}^{\infty} f''(K)(S_T - K)^+ dK$$

In our problem, $f(S_T) = -\ln\left(\frac{S_T}{F_0}\right)$, choose $K_0 = F_0$. Here, F_0 denotes the **forward price** of the underlying asset under the risk-neutral measure.

$$f(S_T) = -\frac{1}{S_T}, \quad f'(S_T) = \frac{1}{S_T^2}$$

$$\Rightarrow -\ln\left(\frac{S_T}{F_0}\right) = -\ln 1 - \frac{1}{F_0}(S_T - F_0) + \int_0^{F_0} \frac{1}{K^2}(K - S_T)^+ dK + \int_{F_0}^{\infty} \frac{1}{K^2}(S_T - K)^+ dK$$

Take expectation ($\mathbb{E}_{\mathbb{Q}}[S_T] = F_0$):

$$\begin{aligned} \mathbb{E}_{\mathbb{Q}}\left[-\ln\left(\frac{S_T}{F_0}\right)\right] &= \mathbb{E}_{\mathbb{Q}}\left[\frac{S_T - F_0}{F_0}\right] + \int_0^{F_0} \frac{\mathbb{E}_{\mathbb{Q}}[(K - S_T)^+]}{K^2} dK + \int_{F_0}^{\infty} \frac{\mathbb{E}_{\mathbb{Q}}[(S_T - K)^+]}{K^2} dK \\ &= \left(\int_0^{F_0} \frac{P(K)}{K^2} dK + \int_{F_0}^{\infty} \frac{C(K)}{K^2} dK\right) e^{rT} \end{aligned}$$

where $P(K) = e^{-rT} \mathbb{E}_{\mathbb{Q}}[(K - S_T)^+]$, and $C(K) = e^{-rT} \mathbb{E}_{\mathbb{Q}}[(S_T - K)^+]$.

$$\mathbb{E}_{\mathbb{Q}}\left[\int_0^T \sigma_t^2 dt\right] = 2e^{rT} \left(\int_0^{F_0} \frac{P(K)}{K^2} dK + \int_{F_0}^{\infty} \frac{C(K)}{K^2} dK\right)$$

Hence, we get a continuous version of VIX:

$$VIX^2 = \frac{1}{T} \mathbb{E}_{\mathbb{Q}}\left[\int_0^T \sigma_t^2 dt\right] = \frac{2e^{rT}}{T} \left(\int_0^{F_0} \frac{P(K)}{K^2} dK + \int_{F_0}^{\infty} \frac{C(K)}{K^2} dK\right)$$

Note that by the **call–put parity**, we have

$$C(K, T) - P(K, T) = e^{-rT}(F_0 - K)$$

which implies

$$F_0 = K + e^{rT}[C(K, T) - P(K, T)].$$

Hence, F_0 can be inferred directly from market option prices with the same strike K and maturity T .

6 Variance Risk Premium in VIX: Overprediction and Measurement

The variance risk premium (VRP) associated with the VIX is the systematic wedge between the **risk-neutral** expectation of next-30-day return variance (proxied by a model-free variance swap rate or VIX_t^2 in annualized units) and the **physical** expectation of the subsequent realized variance; a large body of evidence documents that this wedge is positive on average, i.e., the options-implied 30-day variance tends to **overpredict** the ex-post 30-day realized variance [1, 2, 3, 4, 5, 6]. Formally, for a 30-calendar-day horizon ($T \approx 30/365$),

$$\text{VRP}_t := \underbrace{\mathbb{E}_t^{\mathbb{Q}}[\text{RV}_{t,t+30}]}_{\text{implied (variance swap rate)}} - \underbrace{\mathbb{E}_t^{\mathbb{P}}[\text{RV}_{t,t+30}]}_{\text{physical expectation}} \approx VIX_t^2 - \mathbb{E}_t^{\mathbb{P}}[\text{RV}_{t,t+30}],$$

so that a positive average VRP_t implies risk compensation for bearing variance risk [1].

6.1 Existence tests

(i) **Direct mean-difference test.** Construct the series $\Delta_t := \text{VIX}_t^2 - \text{RV}_{t,t+30}$ (both annualized) and test $\mathbb{E}[\Delta_t] > 0$ using HAC/Newey–West standard errors to handle overlapping 30-day windows. A significantly positive mean confirms that the VIX overpredicts 30-day realized variance on average, i.e., a positive VRP [1, 3, 7].

(ii) **Mincer–Zarnowitz (MZ) forecast-unbiasedness regression.** Run the regression

$$\text{RV}_{t,t+30} = \alpha + \beta \text{VIX}_t^2 + u_{t+30}.$$

Under unbiasedness (no premium), $H_0 : \alpha = 0, \beta = 1$. Empirically, one often finds $\alpha > 0$ and/or $\beta < 1$, consistent with implied variance *exceeding* realized variance on average (positive VRP). Use HAC corrections for the 30-day overlap [8, 6, 5].

(iii) **Forecast encompassing / information-content tests.** Estimate

$$\text{RV}_{t,t+30} = \alpha + \beta_1 \text{VIX}_t^2 + \beta_2 \widehat{\text{RV}}_{t,t+30}^{(\text{model})} + e_{t+30},$$

where $\widehat{\text{RV}}^{(\text{model})}$ is a physical-expectation forecast from a time-series model. If $\beta_1 > 0$ and β_2 insignificant, implied variance subsumes model-based information; if both are significant, each contains incremental information. Out-of-sample, compare loss (e.g., MSE) between forecasts via Diebold–Mariano and Giacomini–White tests [4, 5, 9, 10].

6.2 Measuring the size of the VRP

(iv) **GARCH-family physical expectation.** Fit a GARCH/EGARCH model to returns and form a 30-day-ahead *physical* variance forecast $\mathbb{E}_t^{\mathbb{P}}[\widehat{\text{RV}}_{t,t+30}]$. Define

$$\widehat{\text{VRP}}_t^{\text{GARCH}} = \text{VIX}_t^2 - \mathbb{E}_t^{\mathbb{P}}[\widehat{\text{RV}}_{t,t+30}],$$

and test whether its sample mean is > 0 (HAC t -test). This implements the definition of VRP as a risk-neutral minus physical expectation at the VIX horizon [1, 6].

(v) **Realized-variance (HAR-RV) physical expectation.** Build a HAR-RV forecast using high-frequency realized variance and its daily/weekly/monthly lags to obtain $\mathbb{E}_t^{\mathbb{P}}[\widehat{\text{RV}}_{t,t+30}]$, then compute $\widehat{\text{VRP}}_t^{\text{HAR}} = \text{VIX}_t^2 - \mathbb{E}_t^{\mathbb{P}}[\widehat{\text{RV}}_{t,t+30}]$ and evaluate its mean and dynamics; again, the mean is typically positive [1, 11].

(vi) **Model-free variance swap replication (measurement of $\mathbb{E}^{\mathbb{Q}}$).** Use the CBOE model-free options integral (weighted OTM puts/calls with $1/K^2$ weights) to compute the *variance swap rate* as the risk-neutral expectation of 30-day variance (closely related to VIX_t^2). Corridor/weighting nuances (e.g., CIV) matter for implementation but do not overturn the qualitative finding that implied variance tends to exceed subsequent realized variance [2, 12, 4].

6.3 Practical implementation notes

- **Annualization and horizon matching:** Compare VIX_t^2 to an identically annualized 30-day realized variance (or a 30-day-ahead physical forecast) to avoid scaling biases.
- **Overlapping windows:** 30-day overlapping targets induce serial correlation in regression residuals; use HAC/Newey–West standard errors [7].
- **Out-of-sample evaluation:** When comparing implied vs. model-based forecasts for $\text{RV}_{t,t+30}$, use Diebold–Mariano and Giacomini–White tests to assess forecast dominance and conditional predictive ability [9, 10].

Across these approaches—mean-difference tests, MZ regressions, and model-based physical-expectation constructions (GARCH/HAR)—the consensus is that VIX^2 *systematically overpredicts* 30-day realized variance on average, yielding a time-varying and economically meaningful VRP [1, 3, 4, 5].

7 Comparison between VIX and CNVIX

In the existing literature, an important observation is that both the **VIX** [13] (Volatility Index by CBOE) and the **CNVIX(iVX)** [14] (China Volatility Index) share a broadly similar methodological foundation. They are both designed to extract a model-free, forward-looking measure of implied variance from option prices using weighted integrations over out-of-the-money (OTM) options.

Although both VIX and CNVIX (iVX) adopt the same mathematical framework for computing implied volatility, significant structural differences exist between the two markets. According to Wu [15], the iVX index employs the same formula as the CBOE VIX model, but the underlying assets and market mechanisms differ substantially. Specifically, iVX is based on the trading prices of **SSE 50 ETF options**, while VIX uses **S&P 500 index options**. Despite both being European-style index options reflecting overall market volatility, their contract specifications and trading systems diverge.

For instance, a single S&P 500 option contract represents 100 shares of the index, whereas an SSE 50 ETF option represents 10,000 shares of the underlying ETF. The expiration cycles also differ: SSE 50 ETF options follow a four-month sequential cycle—the current month, the following month, and the last months of the next two quarters—and expire on the fourth Wednesday of the expiration month. Furthermore, option trading in China is limited to three specific daily time intervals, which restricts liquidity and may hinder iVX from fully capturing real-time implied volatility.

Wu [15] also highlights that China imposes a **10% price boundary** on both stock and option trading. Once the upper or lower limit is reached, trading is suspended for that security for the day. This mechanism, while stabilizing prices, prevents the market from immediately incorporating investors’ expectations into option prices, thereby reducing the responsiveness of iVX to short-term volatility shocks.

Overall, while CNVIX mathematically mirrors the CBOE VIX model, **market microstructure constraints**—including contract size, trading windows, and price limits—may lead to systematic lags or under-reactions in the iVX index’s reflection of market volatility.

Therefore, although CNVIX may not exhibit all the empirical characteristics of VIX, the **methodological framework used to study VIX**—including its statistical relationships with the underlying index, its volatility transmission patterns, and its role in risk management—provides a valuable foundation for analyzing and interpreting CNVIX within the context of the Chinese financial market.

8 Empirical Evidence on CNVIX and the Variance Risk Premium

Empirical research on the existence and behavior of the variance risk premium in the Chinese market remains limited compared to the extensive literature on the U.S. VIX. To date, the most systematic study is provided by Yue, Zhang, and Pan [16], who examine whether the China Volatility Index (CNVIX, or iVX) exhibits a positive VRP similar to that observed in the U.S. market. Using data from the SSE 50 ETF options market, they construct a model-free implied variance following the same methodology as the CBOE VIX, and compare it to the subsequent 30-day realized variance of the underlying index.

Their results reveal that CNVIX also tends to **overpredict** future realized variance, indicating the presence of a positive variance risk premium in China. However, the magnitude of the CNVIX-VRP is smaller and less persistent than its U.S. counterpart, which the authors attribute to China’s relatively lower option market liquidity, tighter price limits, and more constrained arbitrage opportunities. Furthermore, while the VIX-VRP in the U.S. is well known to predict future equity returns, Yue *et al.* find weaker predictive power for CNVIX-VRP in forecasting SSE 50 returns, suggesting that **variance risk may not be fully priced** in the Chinese market yet.

Methodologically, their estimation of the VRP parallels that in U.S. studies: they calculate CNVIX-implied variance from option prices under the risk-neutral measure \mathbb{Q} , and realized variance from daily returns over the following 30 calendar days under the physical measure \mathbb{P} . They also perform Mincer–Zarnowitz regressions and Newey–West adjusted mean-difference tests, both confirming that CNVIX² significantly exceeds realized variance on average. These results collectively support the existence of a **positive but weaker VRP** in China’s volatility market.

This line of evidence suggests that although CNVIX and VIX share an identical theoretical structure, differences in market microstructure—including option liquidity, trading restrictions, and investor composition—lead to a less efficient incorporation of risk-neutral expectations into market prices. Consequently, while CNVIX does exhibit a positive VRP, its **economic significance and return predictability** remain limited compared to the mature VIX market.

9 Research Gap and Methodology Design

While Yue, Zhang, and Pan [16] provide the first comprehensive evidence of a positive CNVIX variance risk premium, several important questions remain unresolved. Their sample period is relatively short and limited to the SSE 50 ETF options market, and their analysis primarily relies on static mean-difference and regression tests without exploring the time-varying dynamics or predictive content of the CNVIX-VRP. Moreover, the physical expectation of variance is approximated directly by ex-post realized variance, leaving room for improvement through econometric modeling.

Building on this foundation, our study aims to extend the literature in three directions:

1. **Dynamic characterization.** We will construct a longer time series (2016–2025) of CNVIX-VRP to investigate its temporal evolution and its response to market stress or policy shocks.
2. **Methodological refinement.** Instead of using realized variance as a direct proxy for the physical expectation, we will estimate $\mathbb{E}_t^{\mathbb{P}}[\text{RV}_{t,t+30}]$ using both GARCH(1,1) and HAR-RV models, following the approach used in U.S. VRP studies [1, 6]. This allows a more accurate decomposition of implied versus expected variance.
3. **Comparative analysis.** We will conduct a cross-market comparison between the CNVIX-VRP and VIX-VRP using synchronized daily data from the Shanghai Stock Exchange and the CBOE, analyzing both correlation structures and predictive relationships for index returns.

Data. CNVIX and SSE 50 ETF option data will be obtained from the Shanghai Stock Exchange, while VIX and S&P 500 data will be sourced from CBOE. Realized volatility measures will be computed from high-frequency index returns.

Expected results. We anticipate that CNVIX-VRP will remain **positive on average** but less persistent and more sensitive to market policy interventions. We further expect weaker return predictability relative to the U.S. VIX-VRP, reflecting structural and institutional constraints in China’s option market. Nevertheless, the methodological consistency between the two indices enables a unified comparative framework for analyzing volatility risk pricing across markets.

References

- [1] Tim Bollerslev, George Tauchen, and Hao Zhou. “Expected Stock Returns and Variance Risk Premia”. In: *Review of Financial Studies* 22.11 (2009). Accessed: 2025-10-10, pp. 4463–4492. URL: https://public.econ.duke.edu/~boller/Published_Papers/rfs_09.pdf.
- [2] Peter Carr and Liuren Wu. “Variance Risk Premia”. In: *Review of Financial Studies* 22.3 (2009). Accessed: 2025-10-10, pp. 1311–1341. URL: <https://engineering.nyu.edu/sites/default/files/2019-01/CarrReviewofFinStudiesMarch2009-a.pdf>.

- [3] Geert Bekaert, Marie Hoerova, and Marco Lo Duca. “Risk, Uncertainty and Monetary Policy”. In: *Journal of Monetary Economics* 60.7 (2013). ECB Working Paper version; Accessed: 2025-10-10, pp. 771–788. URL: <https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1565.pdf>.
- [4] George J. Jiang and Yisong S. Tian. “The Model-Free Implied Volatility and Its Information Content”. In: *Review of Financial Studies* 18.4 (2005). Accessed: 2025-10-10, pp. 1305–1342. URL: <https://ideas.repec.org/a/oup/rfinst/v18y2005i4p1305-1342.html>.
- [5] Bevan J. Blair, Ser-Huang Poon, and Stephen J. Taylor. “Forecasting S&P 100 Volatility: The Incremental Information Content of Implied Volatilities and High-Frequency Index Returns”. In: *Journal of Econometrics* 105.1 (2001). Accessed: 2025-10-10, pp. 5–26. URL: <https://econpapers.repec.org/RePEc:eee:econom:v:105:y:2001:i:1:p:5-26>.
- [6] Ralf Becker, Adam E. Clements, and Scott I. White. “Does Implied Volatility Provide Any Information Beyond That Captured in Model-Based Volatility Forecasts?” In: *Journal of Banking & Finance* 31.8 (2007). Accessed: 2025-10-10, pp. 2535–2549. URL: <https://ideas.repec.org/a/eee/jbfina/v31y2007i8p2535-2549.html>.
- [7] Whitney K. Newey and Kenneth D. West. “A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix”. In: *Econometrica* 55.3 (1987). Accessed: 2025-10-10, pp. 703–708. URL: <https://www.ssc.wisc.edu/~kwest/publications/1980/A%20Simple%20PSD%20HAC%20Covariance%20Matrix.pdf>.
- [8] Jacob A. Mincer and Victor Zarnowitz. “The Evaluation of Economic Forecasts”. In: *Economic Forecasts and Expectations*. Accessed: 2025-10-10. NBER, 1969, pp. 3–46. URL: <https://www.nber.org/system/files/chapters/c1214/c1214.pdf>.
- [9] Francis X. Diebold and Roberto S. Mariano. “Comparing Predictive Accuracy”. In: *Journal of Business & Economic Statistics* 13.3 (1995). Accessed: 2025-10-10, pp. 253–263. URL: <https://www.ssc.wisc.edu/~bhansen/718/DieboldMariano1995.pdf>.
- [10] Raffaella Giacomini and Halbert White. “Tests of Conditional Predictive Ability”. In: *Econometrica* 74.6 (2006). Accessed: 2025-10-10, pp. 1545–1578. URL: <https://fmwww.bc.edu/EC-P/wp572.pdf>.
- [11] Torben G. Andersen and Luca Benzoni. *Realized Volatility*. Tech. rep. WP 2008-14. Accessed: 2025-10-10. Federal Reserve Bank of Chicago, 2008. URL: <https://www.chicagofed.org/~media/publications/working-papers/2008/wp2008-14-pdf.pdf>.
- [12] Torben G. Andersen and Oleg Bondarenko. “Construction and Interpretation of Model-Free Implied Volatility”. In: *Volatility as an Asset Class*. Ed. by Israel Nelken. NBER Working Paper No. 13449; Accessed: 2025-10-10. Risk Books, 2007, pp. 141–181. URL: <http://www.nber.org/papers/w13449.pdf>.
- [13] Chicago Board Options Exchange (CBOE). *The Cboe Volatility Index (VIX) White Paper*. https://cdn.cboe.com/api/global/us_indices/governance/Volatility_Index_Methodology_Cboe_Volatility_Index.pdf. 2019.
- [14] Shanghai Stock Exchange (SSE). *China Volatility Index (CNVIX) Methodology*. https://www.sse.com.cn/market/sseindex/disclosure/c/c_20161104_4198915.shtml. 2016.
- [15] Yaofei Wu. “Performance Analysis of Shanghai Stock Exchange iVX Index and Its Potential for Risk Management”. Accessed: 2025-10-10. Honors Thesis. New York University Shanghai, 2017. URL: https://cdn.shanghai.nyu.edu/sites/default/files/media/yaofei_wu_thesis_nyush_honors_2017.pdf.
- [16] Ting Yue, Jin Zhang, and Zheyao Pan. “The Volatility Index and Variance Risk Premium in China”. In: *Pacific-Basin Finance Journal* 79 (2023), p. 102077. URL: <https://doi.org/10.1016/j.pacfin.2023.102077>.