

# Robust Hedging Performance and Volatility Risk in Option Markets

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## Outline

- Why ROBUST hedging?
- Nonparametric Volatility Estimation
- Empirical Hedging Performance: SPX & TXO
- Price Limit Effect & Hedging Performance
- An Asymptotic Analysis

## Why ROBUST hedging?

Bakshi et al. (1997), Lam et al. (2002) and Yung et al. (2003) documented that **stochastic volatility models, variance gamma models, and EGARCH (GARCH) models**, respectively, are superior in volatility forecast and/or option pricing, but these models perform just comparably or even worse than the ad hoc Black-Scholes model (Dumas et al. (1998)) in option hedging.

**AIM: model dependence of option hedging strategies should be minimized.**

## Two Hedging Categories

- Model-Free: Stop-Loss, adjusted SL
- Volatility-Model-Free\*: Delta, adjusted Delta, Delta-Gamma

BUT most of them require VOLATILITY as an input.

\*Fouque, Papanicolaou, Sircar (2000)

## WHAT VOLATILITY?

- Historical VOL: estimated by Quadratic Variation.
- Instantaneous VOL: estimated by Fourier Transform Method.
- Implied VOL: depend on BS model.

AIM: NONPARAMETRIC ESTIMATION.

## Volatility Matrix Estimation Problem \*

Suppose that each  $u_i(t)$  satisfies

$$du_i(t) = \mu_i(t)dt + \sum_{j=1}^d \sigma_{ij}(t)dW_{jt}, i = 1, \dots, d.$$

Task: Given all return series  $\mathbf{u}(t)$ , estimate the volatility matrix  $\Sigma(t)$ .

\*A discrete time paradigm can be found in Engle's book: Anticipating Correlations. Princeton Univ. Press, 2009.

## Fourier Transform Method (Step 1)\*

Fourier coefficients of  $du_i$  are:

$$a_0(du_i) = \frac{1}{2\pi} \int_0^{2\pi} du_i(t),$$

$$a_k(du_i) = \frac{1}{\pi} \int_0^{2\pi} \cos(kt) du_i(t),$$

$$b_k(du_i) = \frac{1}{\pi} \int_0^{2\pi} \sin(kt) du_i(t).$$

$$u_i(t) = a_0(du_i) + \sum_{k=1}^{\infty} \left[ -\frac{b_k(du_i)}{k} \cos(kt) + \frac{a_k(du_i)}{k} \sin(kt) \right].$$

\*Malliavin and Mancino (2002, 2009)

## Fourier Transform Method (Step 2)

Fourier coefficients of  $\Sigma_{ij}$  are:

$$a_0(\Sigma_{ij}) = \lim_{N \rightarrow \infty} \frac{2\pi}{N+1-n_0} \sum_{s=n_0}^N [a_s^*(du_i)a_s^*(du_j) + b_s^*(du_i)b_s^*(du_j)]$$

$$a_k(\Sigma_{ij}) = \lim_{N \rightarrow \infty} \frac{2\pi}{N+1-n_0} \sum_{s=n_0}^N [a_s^*(du_i)a_{s+k}^*(du_j) + b_s^*(du_i)b_{s+k}^*(du_j)]$$

$$b_k(\Sigma_{ij}) = \lim_{N \rightarrow \infty} \frac{2\pi}{N+1-n_0} \sum_{s=n_0}^N [a_s^*(du_i)b_{s+k}^*(du_j) - b_s^*(du_i)a_{s+k}^*(du_j)],$$

where  $n_0$  is any positive integer.



## Fourier Transform Method (Step 3)

$$\begin{aligned}\Sigma_N(t) &:= \sum_{k=0}^N a_k(\Sigma_{ij}) \cos(kt) + b_k(\Sigma_{ij}) \sin(kt) \\ \Sigma(t) &= \lim_{N \rightarrow \infty} \Sigma_N(t) \text{ in prob.}\end{aligned}$$

- **Smoothing** procedure in practical implementation.
- Reno (2008) alerts **boundary effect**.

## Price Correction Scheme\*: Bias Reduction

$$\begin{aligned} du_t &\approx \sigma_t dW_{1t} \\ &= \exp(h_t/2) dW_{1t} \\ &\approx \exp\left(a + b\hat{h}_t/2\right) dW_{1t} \end{aligned}$$

After discretization,

$$\ln \frac{(u_{t+1} - u_t)^2}{dt} = a + b\hat{h}_t(t) + \ln \varepsilon_t^2$$

where  $\varepsilon_t$  is a standard normal random variable.

\*H. Liu, and Chen ('10)

## Simulation Study (I) - LV Model

$dS_t = \alpha (m - S_t) dt + \sigma_t dW_t$  and  $\sigma_t = \beta S_t^\gamma$ .  
 $S_0 = 0.08$ ,  $\alpha = 0.093$ ,  $m = 0.079$ ,  $\beta = 0.794$   
and  $\gamma = 1.474$ .

	Fourier	Corrected Fourier
MSE	7.5203E-04	7.6117E-06
MAE	0.0435	0.0135

## Simulation Study (II) - SV Model

$\sigma_t = \exp(Y_t/2)$  and  $dY_t = \alpha'(m' - Y_t) dt + \beta' dW_t'$ ,  
with  $Y_0 = -2$ ,  $m' = -2$ ,  $\alpha' = 5$  and  $\beta' = 1$ .

	Fourier	Corrected Fourier
MSE	0.0234	0.0016
MAE	0.2902	0.1392

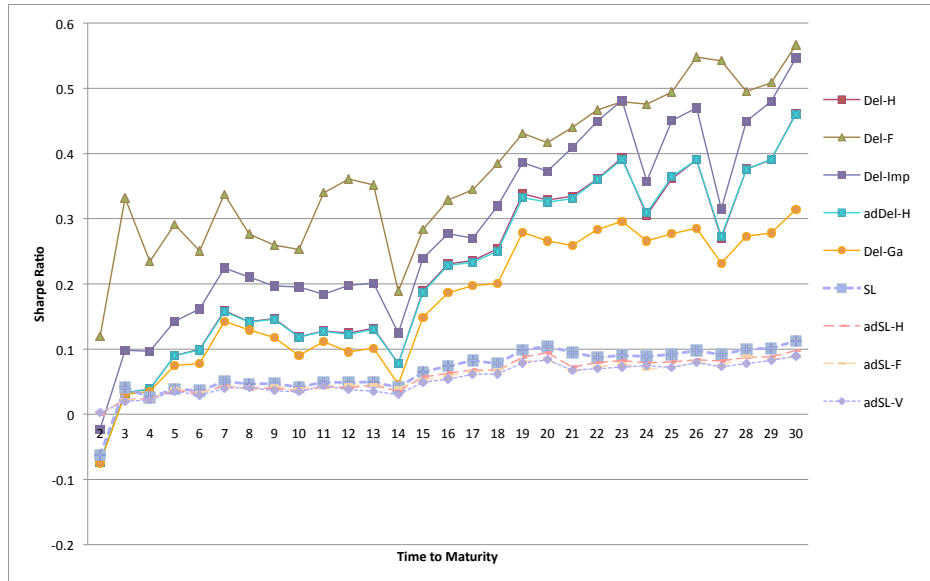
## Other Applications of Volatility

- VaR/CVaR Estimation under Stochastic Volatility\*.
- Monte Carlo calibration of implied volatility surface †
- ⋮

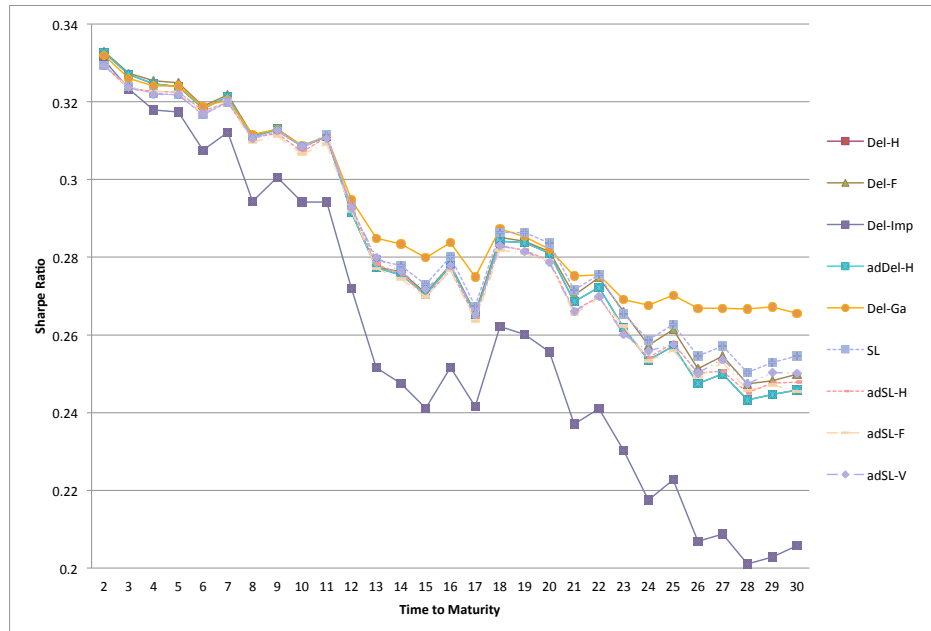
\*H. Liu and Chen, 2010, submitted.

†working in progress.

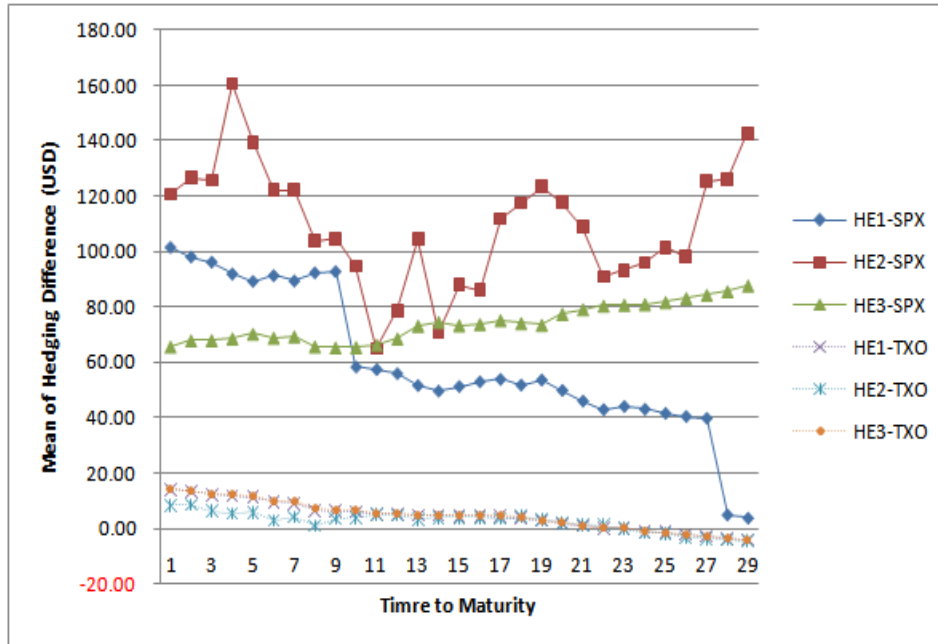
# Evolution of Sharpe Ratios of Hedging Strategies on SPX



# Evolution of Sharpe Ratios of Hedging Strategies on TXO

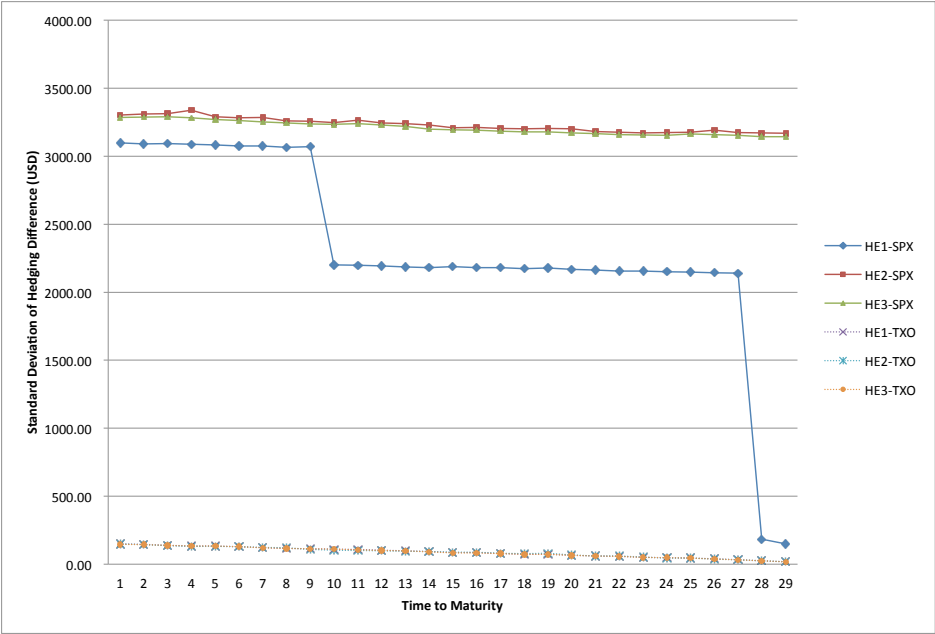


# Hedging Differences: SL VS Delta (mean)





# Hedging Differences: SL VS Delta (sd)



## Why Such Asymmetric Phenomenon

Empirical Observation on hedging performance of SL and Delta:

SPX: well separated.

TXO: same numeric order.

## A Time-Scale Change & Price Limit

### A Qualitative Approach

$$\begin{aligned}\frac{dS_t}{S_t} &= \mu d\delta t + \sigma dW_{\delta t} \\ &= \mu \delta dt + \sigma \sqrt{\delta} dW_t,\end{aligned}$$

$$\begin{aligned}\mathcal{L}^\delta P^\delta(t, x) &= 0 \\ \mathcal{L}^\delta &= \frac{\partial}{\partial t} + \frac{\sigma^2 \delta x^2}{2} \frac{\partial^2}{\partial x^2} + r x \frac{\partial}{\partial x} - r.\end{aligned}$$

## Differences of Hedging Portfolios

$$\begin{aligned} & HE_T^{(1)} - HE_T^{(2)} \\ = & \int_0^T \left( \alpha_t^{(1)} - \alpha_t^{(2)} \right) dS_t - \int_0^T \left( \alpha_t^{(1)} - \alpha_t^{(2)} \right) r S_t dt \\ = & \int_0^T \left( \alpha_t^{(1)} - \alpha_t^{(2)} \right) (\mu \delta - r) S_t dt \\ & + \sigma \sqrt{\delta} \int_0^T \left( \alpha_t^{(1)} - \alpha_t^{(2)} \right) S_t dW_t. \end{aligned}$$

$\alpha_t$  denotes some hedging strategy.

## Asymptotic Moment Estimates

**Theorem 1.**  $E \left\{ \left( HE_T^{(1)} - HE_T^{(2)} \right)^n \right\} \leq \frac{C}{\sqrt{\delta}} e^{-1/\delta}$   
for some constant  $C$  independent of  $\delta$ .

$HE_T^{(1)}$  : cumulative SL hedging portfolio value.  
 $HE_T^{(2)}$  : cumulative Delta hedging portfolio value.

## Conclusions

- This paper extends previous empirical studies on option hedging performance. **Robust hedging strategies** and **nonparametric volatility estimations** are comprehensively studied.
- explain a documented phenomenon by a **time-scale change method**.
- An asymptotic **analysis confirms** estimated moments of hedging portfolio differences with our **empirical finding**.

Thank You