Option Pricing, Hedging, and Risk Analysis Under Rough Volatility Models

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Problem Statement

- Recent research has shown that log-volatility is well modelled using a fractional Brownian motion process and has led to the development of so called rough volatility models.
- ► The purpose of this project is to develop a suite of tools that will enable the analysis of rough volatility models, in particular the rough Bergomi model.

The Rough Bergomi Model

Build a simulation framework in Python with the ability to generate sample paths of stock price and volatility for a given forward variance curve

$$dS_t = \sqrt{v_t} S_t dB_t$$
 $dB_t =
ho W_t^1 + \sqrt{1 -
ho^2} W_t^2$ $W_t^{lpha} = \sqrt{2lpha + 1} \int_0^t (t - u)^{lpha} dW_u^1$ $v_t = \xi_0(t) \exp\left(\eta W_t^{lpha} - rac{\eta^2}{2} t^{2lpha + 1}
ight)$ $\xi_0(t) = \mathbb{E}[v_t|\mathscr{F}_0]$

Exotic Payoffs

► Code payoffs for vanilla and exotic options including cliquet, barrier, asian, and autocallable

n-Period cliquet option payoff =
$$\max \left[\sum_{i=1}^n \min\left(\operatorname{cap}, \frac{S_{i/n}}{S_{(i-1)/n}} - 1\right), 0\right]$$

Up-and-out call payoff = $\begin{cases} \max(S_T - K, 0) & S_t < H \\ 0 & \text{otherwise} \end{cases}$

Asian call payoff = $\max\left(\frac{1}{n}\sum_{i=1}^n S_{t_i} - K, 0\right)$

Autocallable payoff: Observation Date 1: $S_{t_1} > S_0$ Observation Date 2: $S_{t_2} > S_0$ No Date 3: $S_{t_3} > S_0$ No Date 3: S_{t_3}

Model Calibration and Risk Analysis

Train a neural network to represent the pricing function that can be used for calibration

$$\hat{\boldsymbol{\theta}} = \operatorname*{arg\,min}_{\boldsymbol{\theta} \in \boldsymbol{\Theta}} \delta\left(\tilde{P}(\mathscr{M}(\boldsymbol{\theta}), \boldsymbol{\zeta}), \mathscr{P}^{\textit{MKT}}(\boldsymbol{\zeta})\right)$$

Project the risk of implied volatility dynamics on the vega risk profile of each product through a static hedge of vanilla instruments. Where E is a vector of exotics under different perturbations to the vol surface, H is the matrix of hedge instruments, and w is a vector of weights

$$E = Hw$$

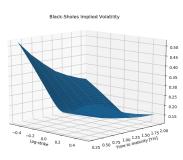
$$w = \arg\min_{w} \left\{ ||E - Hw||^2 + \lambda ||w||^2 \right\}$$



Monte Carlo Simulation

- rBergomi Python framework is able to generate sample paths of the stock and volatility process and execute Monte Carlo simulation to price vanilla and exotic options
- Efficient hybrid scheme of convolution and Riemann sums implemented to generated fBM

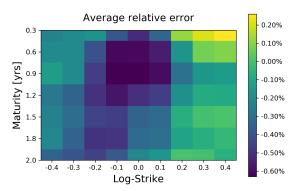




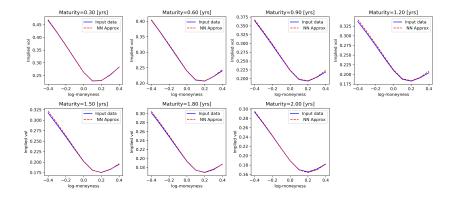


Calibration

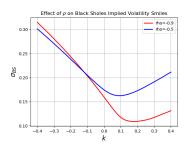
► A large set of randomly selected model parameters is then used to generate many volatility surfaces in order to produce the training data for the neural network

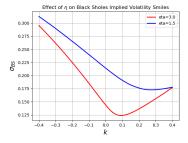


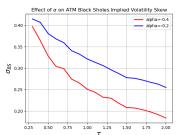


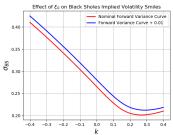


Sensitivity Analysis



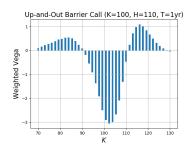


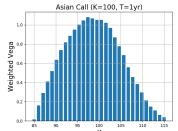


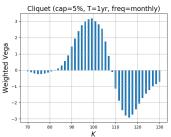


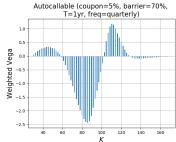


Projected Risk of Implied Volatility Dynamics on Vega Profile











Thank you & Questions