The deep structure of numerical instability inherent to Fourier transform methods in option pricing:



Syllabus of the presentation

- Review of FFT approach in Option Pricing
- Gauss-Lobatto FFT approach
 - Gauss Lobatto theory
 - Gauss Lobatto option pricing
- Pricing Performance and Calibration





Review of FFT approach in option pricing

the single integration formula Carr - Madan (1999)

$$C_{0}\left(\ln K\right)=\frac{e^{-\alpha\ln K}}{\pi}\int_{0}^{\infty}\Re\left[e^{-i\upsilon\ln K}\psi_{0}\left(\upsilon\right)\right]d\upsilon$$

where:

$$\begin{split} \psi_0\left(\upsilon\right) &= \frac{e^{-rT} \phi_T \left(\upsilon - \left(\alpha + 1\right) i\right)}{\alpha^2 + \alpha - \upsilon^2 + i \left(2\alpha + 1\right) \upsilon} \\ \phi_T[q\left(\ln S_T\right)]\left(\xi\right) &= \int_{-\infty}^{\infty} e^{i\xi \ln S_T} q\left(\ln S_T\right) d\ln S_T \end{split}$$



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Main Features

Only one integral to be computed (doubles speed in FT-Q methods) Problems of Accuracy reduced of an order of 1/2

Arbitrary choice of a dampening parameter







Fast Fourier Transform Method - Implementation

FFT Implementation









FFT Implementation



Quadrature Algorithm







Quadrature Algorithms- theory

Newton – Cotes Schemes

Proposition The integral of a generic function $f : \mathbb{R} \to \mathbb{R}$ can be approximated in the form:

$$\int_{\alpha}^{\beta} f(x) dx \approx \frac{n}{c} h \sum_{j=0}^{n} a_{j}^{(i)} \cdot f(x_{j})$$

where: \circ d is the grade of the approximating polynomial; $\circ n = i \cdot d - is$ the number of subintervals of $i = 1, 2, 3, ..., N - [\alpha, \beta]$; $\circ c = \sum_{i=1}^{n} a_i^{(i)}$ • $h = \frac{(\beta - \alpha)}{n}$ is the dimension if each subinterval; $\circ x_i = \alpha + jh \quad per \ i = 0, 1, ..., d;$









They use a fixed, equally spaced, discretization grid for the characteristic formula Quadrature Algorithms- theory



They use a fixed, equally spaced, discretization grid for the characteristic formula



This implies that, if the characteristic formula is smooth











Quadrature Algorithms- theory











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Gauss Schemes

They use an optimal choice for the discretization grid



















ENHANCE The Gauss Lobatto formula

They develop a GL recursive adaptive algorithm for a generic interval







Quadrature Algorithms- theory





Accurate







The Gautschi - Gander extension (2000)





Quadrature Algorithms- theory

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The Fundamental Theorem of Gaussian Quadrature states that the optimal <u>abscissas</u> of the N-point Gaussian quadrature <u>formulas</u> are precisely the roots of the orthogonal <u>polynomial</u> for the same interval and <u>weighting function</u>.









The Roots of Legendre Polynomials are optimal discretization points



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Quadrature Algorithms- theory

Legendre Polynomials are oscillating functions



Increasing the order of N is useful to fit the oscillatory decay of the characteristic functions

Quadrature Algorithms- theory



Legendre Polynomials are oscillating functions



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Quadrature Algorithms- theory

Legendre Polynomials are oscillating functions



Even if great, N remains finite, so the GL schemes cannot EXPLODE when the characteristic function goes to infinity











 Quadrature Algorithms- theory

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Fast Fourier Transform Method – The Pricing via Quadrature Algorithms

The Pricing via Gauss-Lobatto Algorithm



Fast Fourier Transform Method - The Pricing via Quadrature Algorithms

The Pricing via Gauss-Lobatto Algorithm



It requires a proper readjustment of Cooley-Tukey Algorithm to take care of the variable grid size











Fast Fourier Transform Method – The Pricing via Quadrature Algorithms

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Pricing performance and calibration



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The deep structure of numerical instability inherent to Fourier transform methods in option pricing:

A Gauss-Lobatto FFT approach





Marcello Minenna - Paolo Verzella Trieste - XXX Congresso AMASES

