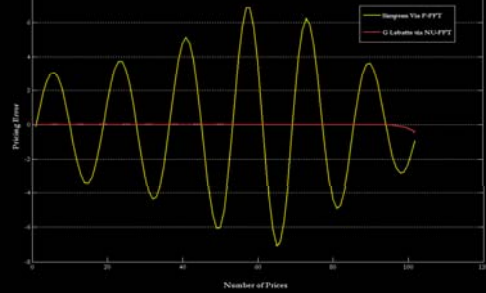


Further Developments in Semianalytical Derivatives Pricing

A Lewis Formula's implementation of Fractional and Non Uniform Discrete Transforms



Syllabus of the presentation

- Review of Derivative Pricing via DFT
 - The Lewis Standard Machine
 - DFT Convergence to FT
 - Convergence Theorems for Uniform Grids
 - Convergence Theorems for Non Uniform Gaussian Grids
- Fast Derivative Pricing
 - Fractional FFT
 - Non Uniform FFT
 - Gaussian Gridding: a matter of interpolation
 - Fractional vs Non Uniform FFT: Empirical Analysis
 - Conclusions

Syllabus of the presentation

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The Lewis Standard Machine

$$\tilde{w}(z) = \int_{-i}^{+i} e^{-izx} w(x) dx$$

is the PayOff functional's Transform



Derivative Price V_t

The Lewis Standard Machine

$$\tilde{w}(z) = \int_{-i}^{+i} e^{-izx} w(x) dx$$

is the PayOff functional's Transform

$$\phi_T(z) = E^Q[e^{iz \ln S_T}]$$

under risk-neutral measure



Derivative Price V_t

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A linear direct mapping from Fourier Spectral Space



LEWIS REPRESENTATION

The Lewis Standard Machine

$$\tilde{w}(z) = \int_{-i}^{+i} e^{-izx} w(x) dx$$

is the PayOff functional's Transform

$$\phi_T(z) = E^Q[e^{iz \ln S_T}]$$

under risk-neutral measure



A linear direct mapping from Fourier Spectral Space



$$V_t = \frac{e^{-r(T-t)}}{2\pi} \int_{i\alpha-i\epsilon}^{i\alpha+\epsilon} e^{-iz \ln K} \phi_T(-z) \int_{-i}^{+i} e^{-izx} w(x) dx dz$$

The Lewis Standard Machine

Knowing $\tilde{w}(z)$



The Lewis Standard Machine

Knowing $\tilde{w}(z)$



implies reducing the problem to the calculation of a single integral

$$z = \frac{\xi}{\tau} + i\alpha$$

$$z = \frac{\xi}{\tau} + i\alpha$$

Financial Claim	$w(x)$	$\tilde{w}(x)$
Call Option	$\max[S_T - K, 0]$	$\frac{K^{\alpha+1}}{z^2 - \bar{z}}, \alpha > 1$
Put Option	$\max[K - S_T, 0]$	$\frac{K^{\alpha+1}}{z^2 - \bar{z}}, \alpha < 0$
Covered Call	$\min[S_T, K]$	$\frac{K^{\alpha+1}}{z^2 - \bar{z}}, 0 < \alpha < 1$
Money Market	1	$2\pi\delta(k), \alpha \in \mathbb{R}$
Self Quanto Call	$\max[S_T - K, 0] \cdot S_T$	$\frac{K^{2\alpha+2}}{(z+1)^{2\alpha}(z+2)^{2\alpha}}, \alpha < -2$
Power Call	$\max[S_T - K, 0]^d$	$\frac{K^{d(\alpha+1)}\Gamma(\alpha)\Gamma(d+1)}{\Gamma(\alpha+d+1)}, \alpha < -d$

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DFT Convergence to FT

Given the General DFT

$$\omega(m) = \sum_{j=0}^{N-1} e^{-i\frac{2\pi}{X}x_j(m-1)} f(x_j) \quad \text{where } m = 1, 2, \dots, M$$

DFT Convergence to FT

Given the General DFT

$$\omega(m) = \sum_{j=0}^{N-1} e^{-i\frac{2\pi}{X}x_j(m-1)} f(x_j) \quad \text{where } m = 1, 2, \dots, M$$

$M \neq N$

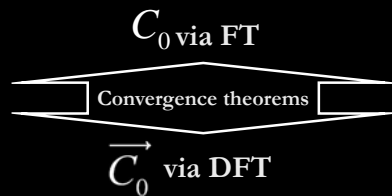
DFT Convergence to FT

The Convergence Theorem for General DFT's (C Th)

$$\mathcal{F}[f(x)](t_m) = \lim_{N \rightarrow \infty} \sum_{j=1}^N e^{-i\frac{2\pi}{X}x_j(m-1)} f(x_j, X)$$

$$t_m = \frac{2\pi}{X}(m-1)$$

DFT Convergence to FT



Syllabus of the presentation

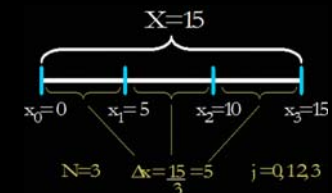
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Convergence Theorems for Uniform Grids

Condition 1

Uniform Discretization Grid



Condition 2

N=M



DFT specialized

$$\omega(n) = \sum_{j=0}^{N-1} e^{-i \frac{2\pi}{N} x_j (n-1)} f(x_j) \quad \text{where } n=1,2,\dots,N$$

Condition 1

Condition 2



DFT Simplified Formula

$$\omega(n) = \sum_{j=0}^{N-1} e^{-i2\pi k_j \gamma} f(x_j) \quad \text{where } n = 1 \dots N$$

Nyquist – Shannon Limit (N-S)

$$\mathcal{F}[f(x)](t_n) = \lim_{N \rightarrow \infty} \frac{X}{N} \omega(n)$$

$$\{t_n\}_{n=1 \dots \frac{N}{2}} \quad \text{for } N \text{ even}$$

$$\{t_n\}_{n=1 \dots \frac{N+1}{2}} \quad \text{for } N \text{ odd}$$

$$C_t = \frac{K e^{-r(T-t)}}{2\pi} \int_{i\alpha-\epsilon}^{i\alpha+\epsilon} e^{-iz \ln K} \frac{\phi_T(-z)}{z^2 - iz} dz$$



Uniform Discretization Grids for ϕ_T

$$1. \quad \phi_T(\xi_{j-1}) = e^{-i(j-1)\eta[\ln S_T - b]} \Psi_0[(j-1)\eta]$$

$$2. \quad \phi_T(\xi_{j-1}) = e^{-i(j-1)\eta[\ln S_T - b]} \Psi_0[(j-1)\eta] \cdot [3 + (-1)^{j+1} - \delta_j - \delta_{N-j}]$$

1.

$$C_t = \frac{K e^{-r(T-t)}}{2\pi} \int_{i\alpha-\epsilon}^{i\alpha+\epsilon} e^{-iz \ln K} \frac{\phi_T(-z)}{z^2 - iz} dz$$

$$\phi_T(\xi_{j-1}) = e^{-i(j-1)\eta[\ln S_T - b]} \Psi_0[(j-1)\eta]$$

+

N-S

$$C_0[\ln K]_u^- \approx \frac{e^{-\alpha[\ln S_T - b + \lambda(u-1)]}}{b} \cdot \Re(\omega(u))$$

2.

$$C_t = \frac{K e^{-r(T-t)}}{2\pi} \int_{i\alpha-\epsilon}^{i\alpha+\epsilon} e^{-iz \ln K} \frac{\phi_T(-z)}{z^2 - iz} dz$$

$$\phi_T(\xi_{j-1}) = e^{-i(j-1)\eta[\ln S_T - b]} \Psi_0[(j-1)\eta] \cdot [3 + (-1)^{j+1} - \delta_j - \delta_{N-j}]$$

+

N-S

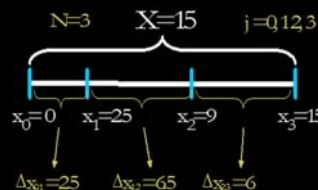
$$C_0[\ln K]_u^- \approx \frac{e^{-\alpha[\ln S_T - b + \lambda(u-1)]}}{3b} \cdot \Re(\omega(u))$$

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 - **Convergence Theorems for Non Uniform Gaussian Grids**

Condition 1

Non Uniform Discretization Grid



Condition 1

Gaussian Grids

Optimal choice of discretization points



Gauss Laguerre

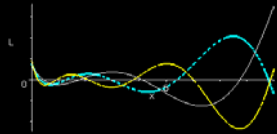
Gander Gautschi

Condition 1

Gaussian Grids

Optimal choice of discretization points

Gauss Laguerre



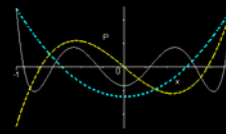
Zeros of Laguerre Pynomials

Condition 1

Gaussian Grids

Optimal choice of discretization points

Gauss Lobatto



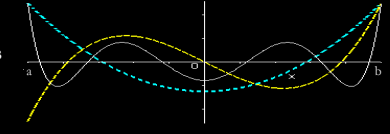
Zeros of Legendre Pynomials

Condition 1

Gaussian Grids

Optimal choice of discretization points

Gander Gautschi



Zeros of rescaled Legendre Pynomials

Condition 2

N ≠ M



General DFT

$$\omega(m) = \sum_{j=0}^{N-1} e^{-i \frac{2\pi}{X} x_j (m-1)} f(x_j) \text{ where } m=1,2,\dots,2M$$

The Convergence Theorem for General DFT's (C Th)



$$\mathcal{F}[f(x)](t_m) = \lim_{N \rightarrow \infty} \sum_{j=1}^N e^{-i \frac{2\pi}{X} x_j (m-1)} f(x_j, X)$$

$$t_m = \frac{2\pi}{X} (m-1)$$

$$C_t = \frac{K e^{-\nu(T-t)}}{2\pi} \int_{i\alpha-\epsilon}^{i\alpha+\epsilon} e^{-iz \ln K} \frac{\phi_T(-z)}{z^2 - iz} dz$$

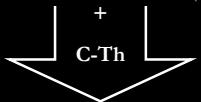
Gaussian Grids for ϕ_T

- $\phi_T(\xi_{j-1}) = e^{\left[1+i\left(\frac{M\pi}{a} \ln S_j\right)\right] \xi_{j-1}} \Psi_0[\xi_{j-1}] \cdot \frac{1}{L_{N+1}(\xi_{j-1}) L'_N(\xi_{j-1})}$
- $\phi_T\left(\frac{1}{2}a(1+\xi_{j-1})\right) = e^{\left[-i\left(\frac{1}{2}a(1+\xi_{j-1})\right) \left(\ln S_j - \frac{M\pi}{a}\right)\right] \xi_{j-1}} \Psi_0\left[\frac{1}{2}a(1+\xi_{j-1})\right] \cdot \frac{1}{[P_{N-1}(\xi_{j-1})]^2}$

1.

$$C_t = \frac{K e^{-\nu(T-t)}}{2\pi} \int_{i\alpha-\epsilon}^{i\alpha+\epsilon} e^{-iz \ln K} \frac{\phi_T(-z)}{z^2 - iz} dz$$

$$\phi_T(\xi_{j-1}) = e^{\left[1+i\left(\frac{M\pi}{a} \ln S_j\right)\right] \xi_{j-1}} \Psi_0[\xi_{j-1}] \cdot \frac{1}{L_{N+1}(\xi_{j-1}) L'_N(\xi_{j-1})}$$

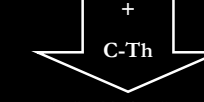


$$C_0([\ln K]_u^*) \approx -\Re \left[\frac{e^{-a(\ln S_j - \frac{M\pi}{a} - \frac{2\pi}{a}(-1))}}{\pi} \cdot \frac{1}{N-1} \cdot \omega^*(u) \right]$$

2.

$$C_t = \frac{K e^{-\nu(T-t)}}{2\pi} \int_{i\alpha-\epsilon}^{i\alpha+\epsilon} e^{-iz \ln K} \frac{\phi_T(-z)}{z^2 - iz} dz$$

$$\phi_T\left(\frac{1}{2}a(1+\xi_{j-1})\right) = e^{\left[-i\left(\frac{1}{2}a(1+\xi_{j-1})\right) \left(\ln S_j - \frac{M\pi}{a}\right)\right] \xi_{j-1}} \Psi_0\left[\frac{1}{2}a(1+\xi_{j-1})\right] \cdot \frac{1}{[P_{N-1}(\xi_{j-1})]^2}$$



$$C_0([\ln K]_u^*) \approx \Re \left[\frac{e^{-a(\ln S_j - \frac{M\pi}{a} - \frac{2\pi}{a}(-1))}}{\pi} \cdot \frac{1}{N(N-1)} \cdot \omega^*\left(\frac{1}{2}a(1+v_{j-1})\right) \right]$$

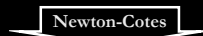
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\vec{C}_i via DFT



Fast Fourier Transform Algorithms

\vec{C}_i via DFT



Fractional FFT

\vec{C}_i via DFT



NonUniform FFT

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Fractional FFT

The Fractional DFT



Fractional FFT

The Fractional DFT



$$\omega(n) = \sum_{j=0}^{N-1} e^{-i2\pi kj\gamma} f(x_j) \text{ where } n = 1 \dots N$$

Fractional FFT

The Fractional DFT



$$\omega(n) = \sum_{j=0}^{N-1} e^{-i2\pi kj\gamma} f(x_j) \text{ where } n = 1 \dots N$$

with γ that can be any complex number

Fractional FFT

If $\gamma = \frac{1}{N}$



$$\omega(n) = \sum_{j=0}^{N-1} e^{-i\frac{2\pi}{N}j(n-1)} f(x_j) \text{ where } n = 1, 2, \dots, N$$

The standard DFT definition

Fractional FFT

Choosing two independent uniform grids



Choosing two independent uniform grids



$$x_j = jg\left(\frac{\alpha}{N}\right) \text{ for } j = 1 \dots N$$

Spectral Grid

$$[\ln K]'_u = \ln S_u - b + \lambda_u \text{ for } u = 1, \dots, N$$

Log-Strike Grid

Choosing two independent uniform grids

Choosing two independent uniform grids



Implies choosing a specific value of γ

Choosing two independent uniform grids



Implies choosing a specific value of γ

$$\gamma = \frac{\lambda g\left(\frac{\alpha}{N}\right)}{2\pi}$$

Fast Fractional Reconstruction



Step 1

Bailey-Swarztrauber F-DFT Characterization



$$\hat{\omega}(n) = e^{-i\pi(n-1)^2\gamma} \sum_{j=0}^{N-1} y_j z_{n-j-1} \text{ where } n = 1, 2, \dots, N$$

$y_j = f(x_j)e^{-i\pi j^2\gamma}$

$z_j = e^{i\pi j^2\gamma}$

Fast Fractional Reconstruction



Step 2

2p-extension of DFT's coefficients



$$y = \left\{ \left((j-1)g\left(\frac{\alpha}{N}\right) \right) e^{-i\pi j^2\gamma} \right\}_{j=0}^{N-1}, (0)_{j=0}^{N-1}$$

$$z = \left\{ \left(e^{i\pi j^2\gamma} \right)_{j=0}^{N-1}, \left(e^{i\pi(N-j)^2\gamma} \right)_{j=0}^{N-1} \right\}$$

Fast Fractional Reconstruction



Step 3

Bailey's Lemma



$$\hat{\omega}(n) = e^{-i\pi(n-1)^2\gamma} \cdot \bar{A}_n$$

$$\bar{A}_n = \sum_{j=0}^{2p-1} \bar{y}_j [\bar{z}_{n-j-1}]_{2p}$$

$0 \leq n \leq N-1$

Fast Fractional Reconstruction



Step 4

2p points DFT's computation



$$\bar{Z}(m) = \sum_{j=0}^{2p-1} e^{-i\frac{2\pi}{p}j(m-1)} \bar{z}(x_j) \text{ where } m = 0, 1, \dots, 2p-1$$

$$\bar{Y}(m) = \sum_{j=0}^{2p-1} e^{-i\frac{2\pi}{p}j(m-1)} \bar{y}(x_j) \text{ where } m = 0, 1, \dots, 2p-1$$

Fast Fractional Reconstruction



Step 5

Circular Convolution Theorem



$$\bar{\Delta}(m) = \bar{Y}(m) \cdot \bar{Z}(m)$$

FFT

Fast Fractional Reconstruction

Step 6

F-DFT derivation as a function of DFT

$$\hat{\omega}(n) = e^{-i\pi(n-1)^2\gamma} \cdot \bar{X}_n$$

$$\bar{\Delta}(m) = \bar{Y}(m) \cdot \bar{Z}(m)$$

Fast Fractional Reconstruction

Step 6

F-DFT derivation as a function of DFT

$$\hat{\omega}(n) = e^{-i\pi(n-1)^2\gamma} \cdot \bar{X}_n$$

$$\bar{\Delta}(m) = \bar{Y}(m) \cdot \bar{Z}(m)$$

$$\hat{\omega}(n) = \frac{e^{-i\pi(n-1)^2\gamma}}{2^p} \cdot \sum_{m=0}^{2^p-1} e^{i\frac{\pi}{2^p}m(n-1)} \bar{\Delta}(m+1)$$

for $n=1,2,\dots,N$

Fast Fractional Reconstruction

Step 7

F-FFT computation

Fast Fractional Reconstruction

Step 7

F-FFT computation

$$\hat{\omega}(n) = \frac{e^{-i\pi(n-1)^2\gamma}}{2^p} \sum_{m=0}^{2^p-1} e^{i\frac{\pi}{2^p}m(n-1)} \bar{\Delta}(m+1)$$

FFT

Fast Fractional Reconstruction

Step 7

F-FFT computation

$$\hat{\omega}(n) = \frac{e^{-i\pi(n-1)^2\gamma}}{2^p} \sum_{m=0}^{2^p-1} e^{i\frac{\pi}{2^p}m(n-1)} \bar{\Delta}(m+1)$$

F-FFT

FFT

Fast Fractional Reconstruction

The total computational cost drops

from

$$O(N^2)$$

to

$$O(6N \log_2 2N)$$

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Non Uniform FFT

The Non Uniform DFT

$$\omega(m) = \sum_{j=0}^{N-1} e^{-i\frac{2\pi}{M}x_j(m-1)} f(x_j) \quad \text{where } m = 1, 2, \dots, M$$

$M \neq N$

Non Uniform FFT

Choosing two perfectly independent grids

x_j arbitrary for $j = 1, \dots, N$

Spectral Grid

$[\ln K]_u = \ln S_t - b + \lambda_u$ for $j = 1, \dots, M$

Log-Strike Grid

Choosing two perfectly independent grids



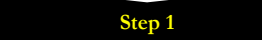
It's a natural property of the Non Uniform Approach

Gaussian Gridding Reconstruction



Step 1

Gaussian Gridding Reconstruction



Step 1

Gaussian Gridding Reconstruction



Step 1

Gaussian Convolution of the non uniformly sampled characteristic function

Gaussian Gridding Reconstruction



Step 1

Gaussian Convolution of the non uniformly sampled characteristic function

$$f_{\tau}(x) = \sum_{j=0}^{N-1} f(x_j) \sum_{k=-\infty}^{\infty} e^{-\frac{(x_j-x-2k\tau)^2}{4\tau}}$$

Gaussian Gridding Reconstruction

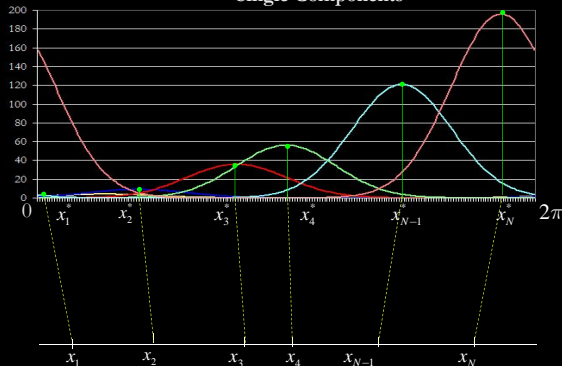


Step 1

Gaussian Convolution of the non uniformly sampled characteristic function

$$f_{\tau}(x) = \sum_{j=0}^{N-1} f(x_j) \sum_{k=-\infty}^{\infty} e^{-\frac{(x_j-x-2k\tau)^2}{4\tau}}$$

Single Components



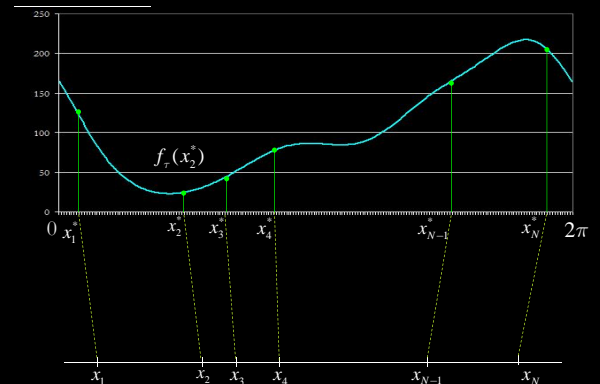
Gaussian Gridding Reconstruction



Step 1

Gaussian Convolution of the non uniformly sampled characteristic function

$$f_{\tau}(x) = \sum_{j=0}^{N-1} f(x_j) \sum_{k=-\infty}^{\infty} e^{-\frac{(x_j-x-2k\tau)^2}{4\tau}}$$



Gaussian Gridding Reconstruction

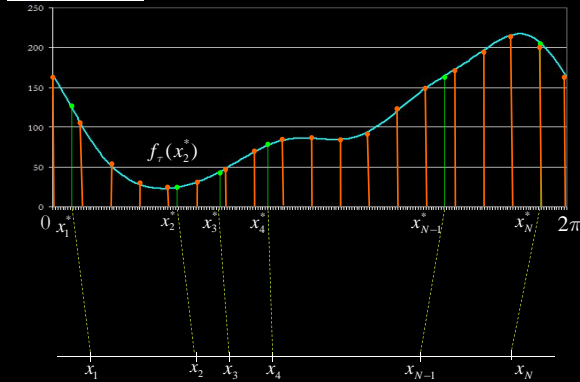
Step 2

Discretization on an uniform oversampled grid of $f_\tau(x)$

$$\tilde{f}_\tau(y_m) = \sum_{j=0}^{N-1} f(x_j) \tilde{K}(y_m, x_j, \sqrt{2\tau}; 2\pi)$$

where

$$\tilde{K}(y_m, x_j, \sqrt{2\tau}; 2\pi) = \begin{cases} \sum_{k=-\infty}^{\infty} e^{i(\sqrt{2\tau}x_j - y_m - 2\pi k)^2} & \text{opposite} \\ \sum_{k=-\infty}^{\infty} e^{i(\sqrt{2\tau}x_j - y_m)^2} & \text{same} \end{cases}$$



Gaussian Gridding Reconstruction

Step 3

Computation of the Fourier Coefficient of $f_\tau(x)$ discretised

$$F_\tau(n) = \lim_{M_\tau \rightarrow \infty} \frac{1}{M_\tau} \sum_{m=0}^{M_\tau-1} \tilde{f}_\tau\left(m \frac{2\pi}{M_\tau}\right) e^{-im \frac{2\pi}{M_\tau} (n-1)}$$

Gaussian Gridding Reconstruction

Step 4

NU-DFT representation of the Fourier Coefficient $F_\tau(n)$

$$\tilde{\omega}(n) = \sqrt{\frac{\pi}{\tau}} e^{n^2 \tau} F_\tau(n)$$

Gaussian Gridding Reconstruction

Step 5

DFT representation of the Fourier Coefficient $F_\tau(n)$

$$F_\tau(n) = \lim_{M_\tau \rightarrow \infty} \frac{1}{M_\tau} \omega(n)$$

for $n = 1, 2, \dots, \frac{M}{2}$

Gaussian Gridding Reconstruction

Step 6

NU-DFT derivation as a function of DFT

Gaussian Gridding Reconstruction

Step 6

NU-DFT derivation as a function of DFT

$$F_\tau(n) = \lim_{M_\tau \rightarrow \infty} \frac{1}{M_\tau} \omega(n)$$

$$\tilde{\omega}(n) = \sqrt{\frac{\pi}{\tau}} e^{n^2 \tau} F_\tau(n)$$

$$\tilde{\omega}(n) = \lim_{M_\tau \rightarrow \infty} \sqrt{\frac{\pi}{\tau^*}} e^{n^2 \tau^*} \frac{1}{M_\tau} \omega(n)$$

for $n = 1, 2, \dots, \frac{M}{2}$

Gaussian Gridding Reconstruction

Step 7

NU-FFT computation

Gaussian Gridding Reconstruction

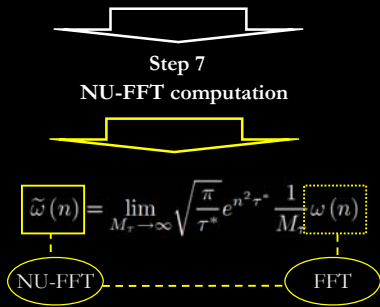
Step 7

NU-FFT computation

$$\tilde{\omega}(n) = \lim_{M_\tau \rightarrow \infty} \sqrt{\frac{\pi}{\tau^*}} e^{n^2 \tau^*} \frac{1}{M_\tau^*} \omega(n)$$

FFT

Gaussian Gridding Reconstruction



Computational Cost

The major computational cost of the Procedure is the FFT on the oversampled grid

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The major computational cost of the Procedure is the FFT on the oversampled grid

Choosing the oversampling ratio
 $M_\tau = 2M$

Computational Cost

The major computational cost of the Procedure is the FFT on the oversampled grid

Choosing the oversampling ratio
 $M_\tau = 2M$

The total cost of the procedure is $\approx 2M \log_2 2M$

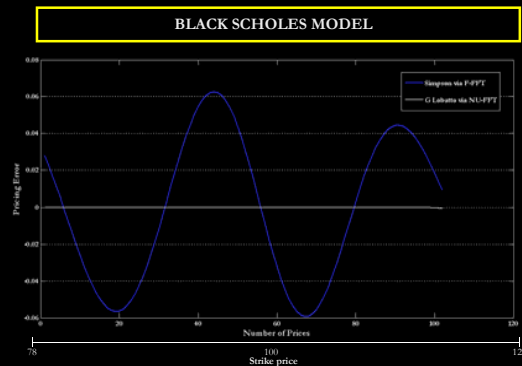
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ACCURACY

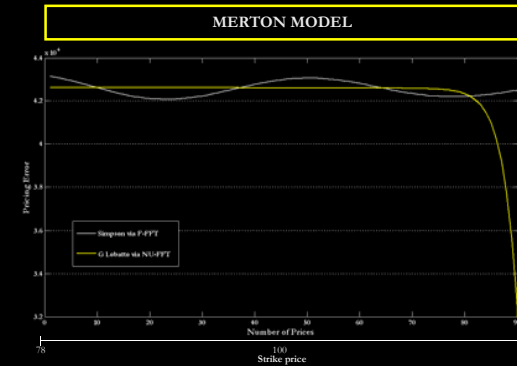
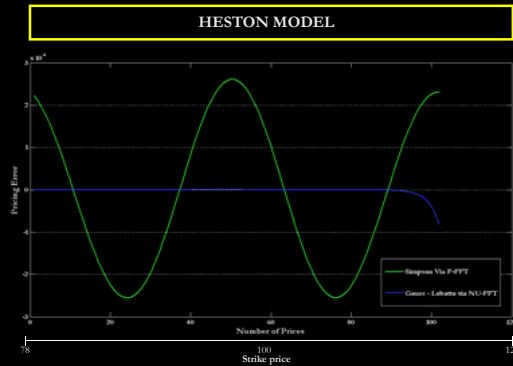
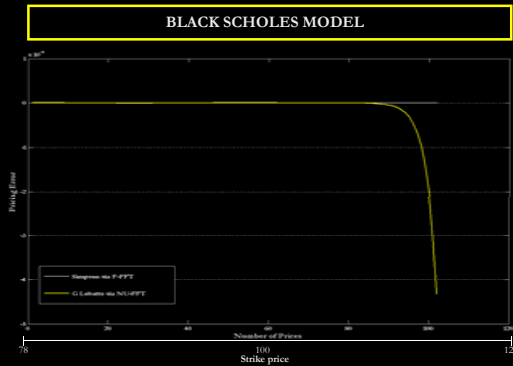
$\sigma = 0.3$



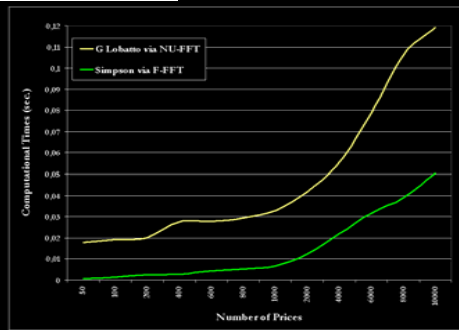
$\sigma = 0.1$



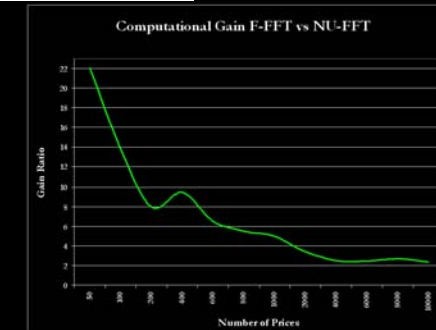
STABILITY



SPEED



Centrino 1600Mhz – 1gb RAM
Mean Value over 1000 runs



Centrino 1600Mhz – 1gb RAM
Mean Value over 1000 runs

At very low time scales, the differences are negligible

- Review of Derivative Pricing via DFT
 - The Lewis Standard Machine
 - DFT Convergence to FT
 - Convergence Theorems for Uniform Grids
 - Convergence Theorems for Non Uniform Gaussian Grids
- Fast Derivative Pricing
 - Fractional FFT
 - Non Uniform FFT
 - Gaussian Gridding: a matter of interpolation
 - Fractional vs Non Uniform FFT: Empirical Analysis
 - Conclusions

Use of Gaussian Grids

F-FFT	NO
NU – FFT	YES

Indifference to Nyquist-Shannon Limit

F-FFT	YES
NU – FFT	YES

Indipendent Price Grids

F-FFT	YES
NU – FFT	YES

FFT's like - Accuracy

F-FFT	YES
NU – FFT	YES

Stability of Pricing

F-FFT	NO
NU – FFT	YES

Speed of Pricing

F-FFT	YES
NU – FFT	YES

	F-FFT	NU – FFT
Gaussian Grids		■
NS Limit	■	■
Indipendent Grids	■	■
Accuracy	■	■
Stability		■
Speed	■	■