Computational Finance FIN-472 Transform methods for pricing I

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Outline

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Fourier Transform - Characteristic Function

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Definitions: Fourier Transform and Characteristic function

• Given $f \in L^1(\mathbb{R}^n)$, i.e. f is an integrable function, we denote by \widehat{f} the Fourier transform of f, defined by

$$\widehat{f}(\nu) \triangleq \int_{\mathbb{R}^n} \exp(i\langle \nu, x \rangle) f(x) \, dx \tag{1}$$

• For a real random variable $X \in \mathbb{R}^n$ with distribution μ , we denote by ϕ_X , the Characteristic Function of X, defined by

$$\phi_X(\nu) \triangleq \mathbb{E}[\exp(i\langle \nu, X \rangle)] = \int_{\mathbb{R}^n} \exp(i\langle \nu, x \rangle) \mu(dx)$$
 (2)

• Observation: If μ has density function f, i.e. $\mu(dx) = f(x)dx$, then $f \in L^1(\mathbb{R}^n)$ and

$$\phi_X = \hat{f}$$

Example - From space to frequency domain

Suppose that

$$f(x) = \cos(6\pi x) \exp(-\pi x^2)$$

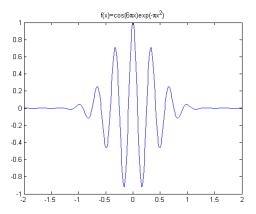


Figure: f oscillates 3 times per sec

Example - From space to frequency domain (cont.)

In this case the integrand in the Fourier transform takes the form

$$g(x,\nu) = \cos(6\pi x)\exp(-\pi x^2 + ix\nu)$$

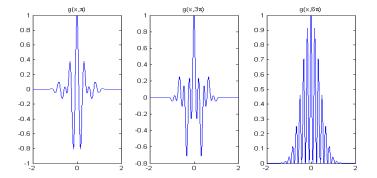


Figure: $Re(g(x, \nu))$ for different frequencies ν

Real part of Fourier Transform of f

Example - From space to frequency domain (cont.)

0.5

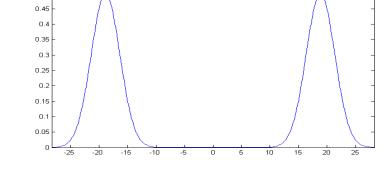


Figure: Graph of $Re(\widehat{f})$. Notice that the peaks occur at -6π and 6π . This is exactly when f(x) and $\exp(i\nu x)$ are "synced"

The Inversion Formula

Theorem 1

Suppose that f, \widehat{f} belong to $L^1(\mathbb{R}^n)$. Then the equality

$$f(x) = \frac{1}{(2\pi)^n} \int_{\mathbb{R}^n} \exp(-i\langle \nu, x \rangle) \widehat{f}(\nu) \, d\nu \tag{3}$$

holds for almost all $x \in \mathbb{R}^n$

Remark: If $f \in L^1(\mathbb{R})$ is piecewise smooth and $\widehat{f} \in L^1(\mathbb{R})$ then

$$\frac{1}{(2\pi)^n} \int_{\mathbb{R}^n} \exp(-i\langle \nu, x \rangle) \widehat{f}(\nu) \, d\nu = \frac{1}{2} (f(x-) + f(x+))$$

where f(x-) and f(x+) are the limits from the left and from the right, respectively

Plancherel - Parseval's Theorem

Theorem 2

If $f,g \in L^2(\mathbb{R}^n)$ then

$$\int_{\mathbb{R}^n} f(x)\overline{g(x)} \, dx = \frac{1}{(2\pi)^n} \int_{\mathbb{R}^n} \widehat{f}(\nu) \overline{\widehat{g}(\nu)} \, d\nu \tag{4}$$

where the Fourier transform for functions in $L^2(\mathbb{R}^n)$ is interpreted in an extended sense

Remark: Formally one can connect this to the inversion formula. Take $g(x) = \delta_{x_0}(x)$ (the delta function concentrated at x_0). Then $\widehat{g}(\nu) = \exp(i\langle x_0, \nu \rangle)$ and $\overline{\widehat{g}(\nu)} = \exp(-i\langle x_0, \nu \rangle)$. Hence,

$$f(x_0) = \int_{\mathbb{R}^n} f(x)\delta_{x_0}(x) dx = \frac{1}{(2\pi)^n} \int_{\mathbb{R}^n} \exp(-i\langle \nu, x_0 \rangle) \widehat{f}(\nu) d\nu$$

Of course, this is only a heuristic argument

The moments

Moments via the characteristic function:

- Assume that n=1.
- The existence of moments is related to differentiability at 0 of the characteristic function

$$\mathbb{E}[X^n] = i^{-n} \phi_X^{(n)}(0) \tag{5}$$

In particular

$$\mathbb{E}[X] = -i\phi_X'(0)$$

• Also, if $Y = X - \mathbb{E}[X]$

$$\phi_Y(\nu) = \exp(-\nu \phi_X'(0))\phi_X(\nu)$$

Analyticity of the characteristic function

Suppose that

$$\mathbb{E}[\exp(-\alpha X)] < \infty$$

for
$$\alpha = a, b$$
 with $a < b$

• In this case it can be shown that the characteristic function ϕ_X is analytic on the open strip

$$\{\nu = \lambda + i\mu : \mu \in (a, b), \lambda \in \mathbb{R}\} \subset \mathbb{C}$$

and well-defined and continuous on the closure of the strip

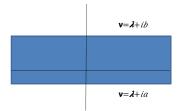


Figure: Region of analyticity of ϕ_X

Real valued functions

Proposition 1

Suppose that n=1 and f is a real-valued function. Then $Re(\widehat{f}(\nu))$ for $\nu \in \mathbb{R}$ is an even function and $Im(\widehat{f}(\nu))$ for $\nu \in \mathbb{R}$ is an odd function. In particular, if $\widehat{f} \in L^1(\mathbb{R})$, the following inversion formula holds

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \widehat{f}(\nu) \exp(-i\nu x) d\nu$$

$$= \frac{1}{\pi} \int_{0}^{\infty} Re\left(\widehat{f}(\nu) \exp(-i\nu x)\right) d\nu$$
(6)

Real valued functions (cont.)

Sketch of the proof: If $\nu = \lambda + i\mu$ with $\lambda, \mu \in \mathbb{R}$

$$\widehat{f}(\nu) = \int_{\mathbb{R}} f(x) \exp(-\mu x + ix\lambda) dx$$

$$= \int_{\mathbb{R}} f(x) \exp(-\mu x) \cos \lambda x dx + i \int_{\mathbb{R}} f(x) \exp(-\mu x) \sin \lambda x dx$$

Therefore

$$Re(\widehat{f}(\nu)) = \int_{\mathbb{R}} f(x) \exp(-\mu x) \cos \lambda x \, dx$$
$$Im(\widehat{f}(\nu)) = \int_{\mathbb{R}} f(x) \exp(-\mu x) \sin \lambda x \, dx$$

If $\mu=0$ ($\nu=\lambda$), we see that the real part is even and the imaginary part is odd in λ . Equation (6) follows

Convolution

ullet Given $f,g\in L^1(\mathbb{R}^n)$ one defines their convolution by the formula

$$(f * g)(y) = \int_{\mathbb{R}^n} f(x)g(y - x) dx \tag{7}$$

• From convolution to multiplication: We have that

$$\widehat{f * g}(\nu) = \widehat{f}(\nu)\widehat{g}(\nu) \tag{8}$$

Some complex analysis

Theorem 3 (Cauchy's integral theorem)

Suppose that f is a complex-function that is analytic on a domain D. Let γ be a closed-contour in D (start and end points of γ are the same). Then

$$\oint_{\gamma} f(z) \, dz = 0 \tag{9}$$

Remark: Suppose that f,g are analytic complex functions on a domain D such that

$$q' = f$$

Let γ be a path in D with start point ω_1 and end point ω_2 . Then

$$\int_{\gamma} f(z) dz = g(\omega_2) - g(\omega_1) \tag{10}$$

The exponential distribution: In this case the Probability Density Function (PDF) is of the form

$$f(x) = \lambda \exp(-\lambda x); \quad x \ge 0 \tag{11}$$

Then

$$\widehat{f}(\nu) = \lambda \int_0^\infty \exp((-\lambda + i\nu)x) \, dx$$

$$= \frac{\lambda}{\lambda - i\nu}$$
(12)

The one-dimensional standard normal distribution: In this case the PDF is of the form

$$f(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \tag{13}$$

Hence,

$$\widehat{f}(\nu) = \frac{\exp(-\nu^2/2)}{\sqrt{2\pi}} \int_{\mathbb{R}} \exp\left(-\frac{(x-i\nu)^2}{2}\right) dx$$

$$= \exp\left(-\frac{\nu^2}{2}\right)$$
(14)

Remark: In the last integral we used Cauchy's integral theorem and the fact that

$$\int_{\mathbb{R}} \exp\left(-\frac{z^2}{2}\right) \, dz = \sqrt{2\pi}$$

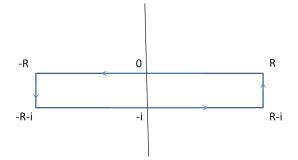


Figure: Contour used with $R \to \infty$

The normal distribution: If $X \sim N(\mu, \sigma)$, then

$$X \stackrel{d}{=} \mu + \sigma Z$$

with $Z \sim N(0,1)$. Hence,

$$\phi_X(\nu) = \exp(i\nu\mu)\mathbb{E}[\exp(i\sigma\nu Z)]$$

$$= \exp\left(i\mu\nu - \frac{\sigma^2\nu^2}{2}\right)$$
(15)

Let

$$F_{\alpha}(x) = \exp(-\alpha x)F(x), \quad x \in \mathbb{R}$$

with $F(x) = Pr(X \le x)$ the Cumulative Distribution Function (CDF) of a one-dimensional r.v. X

Proposition 2

Suppose that $\alpha > 0$ and $\mathbb{E}[\exp(-\alpha X)] < \infty$. Then $F_{\alpha} \in L^{1}(\mathbb{R})$, $\widehat{F_{\alpha}}(\nu)$ is well-defined for all $\nu \in \mathbb{R}$ and

$$\widehat{F_{\alpha}}(\nu) = \frac{\phi_X(\nu + i\alpha)}{\alpha - i\nu} \tag{16}$$

If in addition $\widehat{F_{\alpha}} \in L^1(\mathbb{R})$ then

$$F(x) = \frac{\exp(\alpha x)}{\pi} \int_0^\infty Re\left(\frac{\phi_X(\nu + i\alpha)}{\alpha - i\nu} \exp(-i\nu x)\right) d\nu \qquad (17)$$

- ullet This is the first example when we see the need to introduce a damping factor lpha
- \bullet Notice that without the damping factor $F\not\in L^1(\mathbb{R})$ and \widehat{F} would not necessarily be well-defined
- As we will see, this is related to a change of integration contour and the saddle point method
- The advantage of the calculation made in (18) is that it allows to express F in (17) using only one integration

Sketch of the proof: Let μ be the distribution of X. We have that

$$\widehat{F_{\alpha}}(\nu) = \int_{\mathbb{R}} \exp((i\nu - \alpha)x)F(x) dx$$

$$= \int_{\mathbb{R}} \int_{-\infty}^{x} \exp((i\nu - \alpha)x)\mu(dy) dx$$

$$= \int_{\mathbb{R}} \left(\int_{y}^{\infty} \exp((i\nu - \alpha)x) dx \right) \mu(dy)$$

$$= \frac{1}{\alpha - i\nu} \int_{\mathbb{R}} \exp(i(\nu + i\alpha)y)\mu(dy)$$

$$= \frac{\phi_{X}(\nu + i\alpha)}{\alpha - i\nu}$$
(18)

Formula (17) thus follows from (6) and (18)

An alternative heuristic derivation: Suppose that there is a Probability Density Function (PDF) f. We can write

$$F(x) = \int_{-\infty}^{x} f(y) \, dy$$
$$= \frac{1}{2\pi} \int_{-\infty}^{x} \int_{\mathbb{R}} \exp(-i\nu y) \widehat{f}(\nu) \, d\nu \, dy$$
$$= \frac{1}{2\pi} \int_{-\infty}^{x} G(y) \, dy$$

with

$$G(y) \triangleq \int_{\mathbb{R}} \exp(-i\nu y) \widehat{f}(\nu) d\nu$$

An alternative heuristic derivation (cont.): A change in integration contour allows to replace G(y) by

$$\int_{\mathbb{R}} \exp(-i(\nu + i\alpha)y) \widehat{f}(\nu + i\alpha) d\nu = \int_{\mathbb{R}} \exp((\alpha - i\nu)y) \widehat{f}(\nu + i\alpha) d\nu$$

Hence,

$$F(x) = \frac{1}{2\pi} \int_{-\infty}^{x} \int_{\mathbb{R}} \exp((\alpha - i\nu)y) \widehat{f}(\nu + i\alpha) \, d\nu \, dy$$
$$= \frac{1}{2\pi} \int_{\mathbb{R}} \frac{\exp((\alpha - i\nu)x) \widehat{f}(\nu + i\alpha)}{\alpha - i\nu} \, d\nu$$

which corresponds to (17)

Fourier Transform Pricing with the Ch. funct.

An illustrating example - CDF from Fourier Transform (cont.)

Another derivation: As in Rogers and Zane (1999) we can write

$$F(x) = \lim_{\epsilon \to 0} \int_{-\infty}^{\infty} \exp(\epsilon(y - x)) 1_{\{y \le x\}} f(y) \, dy \tag{19}$$

Then

- Use Plancherel's Theorem and
- change the contour of integration to deduce (17)

The choice of α

- The identity (17) holds for all $\alpha>0$ that satisfy the hypotheses of Proposition 2
- However, the behaviour of the integrand

$$Re\left(\frac{\phi_X(\nu+i\alpha)}{\alpha-i\nu}\exp(-i\nu x)\right)$$
 (20)

is different for different values of α

• If the integral in (17) is computed numerically the results depend on the choice of α

Example: Probabilities of a standard normal

In this case $\phi_X(\nu) = \exp(-\nu^2/2)$

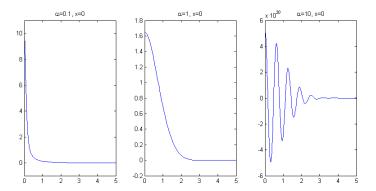


Figure: Plots of the integrand (20)

Example: Probabilities for a standard normal (cont.)

	x=0		
α	L=1	L=2	L=3
0.1	0.4808	0.4979	0.4999
1	0.4006	0.4956	0.5002
10	-3.6724e+18	1.4872e+18	-1.5466e+17
	x=1		
α	L=1	L=2	L=3
0.1	0.7503	0.8371	0.8415
1	0.9187	0.8674	0.8407
10	-1.9849e+23	1.6048e+22	2.9270e+21

Table: Approximated probabilities using formula (17). L denotes the truncation bound in the numerical integration. Exact values for x=0 and x=1 are 0.5 and 0.8413, respectively

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Carr-Madan formula

Notation and assumptions:

- Suppose that $S_t = \exp(X_t)$ and that $\mathbb{E}[S_T^{\alpha+1}] < \infty$ with $\alpha > 0$
- Let $\phi := \phi_{X_T}$ be the characteristic function of X_T (under the risk neutral measure)
- Let $k = \log K$
- Define C(k) as the price at time 0 of a call option with expiration T and strike $K=\mathrm{e}^k$, and let

$$C_{\alpha}(k) := \exp(\alpha k)C(k)$$

A common simplification

• The call option's price C(k) can be written as

$$C(k) = e^{-rT} \mathbb{E}[(S_T - K)_+]$$

$$= e^{-rT} S_0 \mathbb{E}[(S_T / S_0 - K / S_0)_+]$$

$$= S_0 e^{-rT} \mathbb{E}[(e^{X_T - X_0} - e^{k - X_0})_+]$$

$$= S_0 \widetilde{C}(k - X_0)$$

where $\widetilde{C}(k-X_0)$ is the price of a call option with log strike $k-X_0$ and maturity T in a model with log returns $\widetilde{X}=(X_t-X_0)_{0\leq t\leq T}$

ullet \widetilde{X} has the same dynamics as X and

$$\phi_{\widetilde{X}_T}(\nu) = e^{-i\nu X_0} \phi_X(\nu)$$

- The fact that $\widetilde{X}_0=0$ simplifies a lot of the formulas that will be discussed later. This explains why often for the implementations one calculates $\widetilde{C}(k-X_0)$
- ullet In our presentation, to simplify notation, we keep working with the original log returns X

Carr-Madan formula (cont.)

Theorem 4

The characteristic function of C_{α} is well-defined on the real line and has the form

$$\widehat{C}_{\alpha}(\nu) = e^{-rT} \frac{\phi(\nu - i(\alpha + 1))}{\alpha^2 + \alpha - \nu^2 + i\nu(2\alpha + 1)}$$
(21)

Moreover, we have the following representation of the call price

$$C(k) = \frac{e^{-rT - \alpha k}}{\pi} \int_0^\infty Re\left(\frac{\phi(\nu - i(\alpha + 1))}{\alpha^2 + \alpha - \nu^2 + i\nu(2\alpha + 1)}e^{-i\nu k}\right) d\nu \quad (22)$$

Carr-Madan formula (cont.)

Sketch of the proof: Let μ be the distribution of X_T . Then

$$C_{\alpha}(k) = e^{\alpha k} C(k)$$

$$= e^{-rT + \alpha k} \mathbb{E}[(S_T - K)_+]$$

$$= e^{-rT + \alpha k} \mathbb{E}[(e^{X_T} - e^k)_+]$$

$$= e^{-rT} \int_k^{\infty} (e^{x + \alpha k} - e^{(\alpha + 1)k}) \mu(dx)$$

Carr-Madan formula (cont.)

Sketch of the proof (cont.): We have then

$$\widehat{C_{\alpha}}(\nu) = \int_{\mathbb{R}} C_{\alpha}(k) e^{ik\nu} dk$$

$$= e^{-rT} \int_{\mathbb{R}} \int_{k}^{\infty} (e^{x+\alpha k} - e^{(\alpha+1)k}) e^{ik\nu} \mu(dx) dk$$

$$= e^{-rT} \int_{\mathbb{R}} \mu(dx) \int_{-\infty}^{x} (e^{x+\alpha k} - e^{(\alpha+1)k}) e^{ik\nu} dk$$

$$= e^{-rT} \int_{\mathbb{R}} \left(\frac{e^{ix(\nu - i(\alpha+1))}}{\alpha + i\nu} - \frac{e^{ix(\nu - i(\alpha+1))}}{(\alpha+1) + i\nu} \right) \mu(dx)$$

$$= e^{-rT} \phi(\nu - i(\alpha+1)) \left(\frac{1}{\alpha + i\nu} - \frac{1}{(\alpha+1) + i\nu} \right)$$

$$= e^{-rT} \frac{\phi(\nu - i(\alpha+1))}{\alpha^2 + \alpha - \nu^2 + i\nu(2\alpha+1)}$$

Carr-Madan (cont.)

Remarks:

- Once again this computation has the advantage that it involves only one integration
- It is possible to write the call price in terms of tails probabilities. Formula (22) can be derived in a similar manner as (17)
- Alternatively, one can use Plancherel's theorem to derive this formula

Example: The choice of α

- As before the behavior of the integrand in (22) depends on the choice of α
- For the Heston model with parameters $(\kappa, \theta, \sigma, \rho)$, we have that

$$\phi(u) = \mathbb{E}[\exp(iu\ln(S_t))]$$

$$= \frac{\exp\left(iu\ln S_0 + iurt + \frac{\kappa\theta t(\kappa - i\rho\sigma u)}{\sigma^2}\right)}{\left(\cosh\frac{\gamma t}{2} + \frac{\kappa - i\rho\sigma u}{\gamma}\sinh\frac{\gamma t}{2}\right)^{\frac{2\kappa\theta}{\sigma^2}}} \exp\left(\frac{-(u^2 + iu)V_0}{\gamma\coth\frac{\gamma t}{2} + \kappa - i\rho\sigma u}\right)$$
(23)

where $\gamma = \sqrt{\sigma^2(u^2 + iu) + (\kappa - i\rho\sigma u)^2}$, r is the risk free rate and, S_0 and V_0 are the initial values of the price process and the volatility process

Example: The choice of α - The Integrand

Let

$$\psi(\nu) = \frac{e^{-rT - \alpha k}}{\pi} Re \left(\frac{\phi(\nu - i(\alpha + 1))}{\alpha^2 + \alpha - \nu^2 + i\nu(2\alpha + 1)} e^{-i\nu k} \right)$$

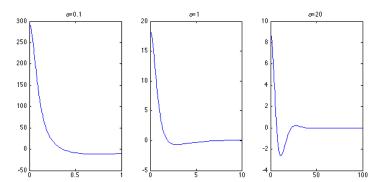


Figure: Plots of the integrand ψ for different values of α . Here $\kappa=2$, $\theta=V_0=0.04$, $\sigma=0.5$, $\rho=-0.7$, r=0.03, $S_0=100$, K=90, T=0.5

Example: The choice of α - Prices

We truncate the integral in (22) at a level L

$$C(k) \approx \frac{\mathrm{e}^{-rT - \alpha k}}{\pi} \int_0^L Re\left(\frac{\phi(\nu - i(\alpha + 1))}{\alpha^2 + \alpha - \nu^2 + i\nu(2\alpha + 1)} \mathrm{e}^{-i\nu k}\right) d\nu$$

α	L=5	L=10	L=50
0.1	0.0328	0.0282	1.4322e-05
1	0.0341	0.0404	2.1461e-05
20	1.4324	1.1903	0.0010

Table: Relative error of call option prices for different values of α and L. The parameters are the same as in the previous figure. True price ≈ 13.2023