## Volatility Derivatives and the Implied Volatility Smile

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Judge Business School , 7/10/2005

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• Assume the risk-neutral stock-process  $S_t$  is a continuous martingale and set  $x_t = \ln(S_t/S_0)$ . Recall that the fair value of a variance-swap

$$\mathbb{E}\left[\langle x \rangle_T\right]$$

is given by a strip of European Options

$$\int_{0}^{S_{0}} \frac{2dK}{K^{2}} P(K) + \int_{S_{0}}^{\infty} \frac{2dK}{K^{2}} C(K)$$
$$= \int_{0}^{\infty} dK \ w(K) \begin{cases} P(K) \ \text{if } K < S_{0} \\ C(K) \ \text{if } K > S_{0} \end{cases}$$

 Recent work by Carr & Lee (to be reviewed in a little) suggests that

$$\mathbb{E}\left[f\left(\langle x\rangle_T\right)\right] = \int_0^\infty dK w_f(K; S_0) \begin{cases} P(K) \text{ if } K < S_0\\ C(K) \text{ if } K > S_0 \end{cases}$$

• **Theorem** (Structure of the ATM weights): If above holds then

$$w_{ATM} \equiv w_f(S_0; S_0) = 2f'(0)/S_0^2$$

**Proof:** Assume  $S_t$  follows an arbitrary stochastic volatility model possibly with non-zero correlation  $\rho$ . Dynamics:

$$dS_t = S_t \sqrt{v_t} dW_t^1$$
  

$$dv_t = a(v_t) dt + b(v_t) \left[ \rho dW_t^1 + \sqrt{1 - \rho^2} dW_t^2 \right]$$
  

$$dz_t = v_t dt, \qquad z_0 = 0.$$

As 3-dimensional diffusion its generator reads

$$\mathcal{L} = \frac{1}{2}S^2 v \partial_{SS} + (a \partial_v + \frac{1}{2}b^2 \partial_{vv} + \rho S \sqrt{v} \partial_{vS}) + v \partial_z.$$

Denote  $g_K(S)$  the payoff of out-of-money puts resp. calls struck at K. Solving the usual PDE may be written as

 $P(K; T, S_0, v_0) = \left[e^{\mathcal{L} T} g_K\right](S_0, v_0)$  and similar for C. Similar to pricing of Asian options,

$$\mathbb{E}\left[f\left(\langle x\rangle_{T}\right)\right] = \left[e^{\mathcal{L} T}f\right](S_{0}, v_{0})$$
$$= \left[e^{\mathcal{L} T}f\right](v_{0}).$$

Thus

$$\left[e^{\mathcal{L}T}f\right](v_0) = \int_0^\infty dK w_f(K; S_0) \left[e^{\mathcal{L}T}g_K\right](S_0, v_0).$$

Take derivatives w.r.t. T and evaluate at T = 0,  $[\mathcal{L} f](v_0) = \int_0^\infty dK w_f(K; S_0) [\mathcal{L} g_K](S_0, v_0).$ Note that none of the payoffs under consideration  $(f, g_K)$  depends on instantaneous variance v. Thus

$$v_0 f'(z_0) = \int_0^\infty dK w_f(K; S_0) \frac{1}{2} S_0^2 v_0 \partial_{SS} g_K(S_0)$$
  

$$v_0 f'(0) = \int_0^\infty dK w_f(K; S_0) \frac{1}{2} S_0^2 v_0 v_0 \delta_K(S_0)$$
  

$$= w_f(S_0; S_0) \frac{1}{2} S_0^2 v_0.$$

QED

• Applications: Variance Swap  $\Rightarrow w_{ATM} = 2/S_0^2$ Volatility Swap  $\Rightarrow w_{ATM} = +\infty$ Variance Call  $\Rightarrow$  $w_{ATM} \equiv 0$  for all positive (total var.) strikes !!! • Theorem (Carr/Lee): Assume independence between W and v. With  $p(\lambda) = 1/2 \pm \sqrt{1/4 + 2\lambda}$  have

$$\mathbb{E}[e^{\lambda \langle x \rangle_T}] = \mathbb{E}[e^{p(\lambda)x_T}].$$

**Proof:** Elementary computation when  $\langle x \rangle_T \equiv \sigma_{BS}^2 T$ . Then average over different realizations of  $\langle x \rangle_T$ . QED

• Assume a Laplace representation for  $\boldsymbol{f}$ 

$$f(y) = \frac{1}{2\pi i} \int_{a-i\infty}^{a+i\infty} F(\lambda) e^{\lambda y} d\lambda.$$

This yields

$$\mathbb{E}\left[f(\langle x \rangle_T)\right] = \frac{1}{2\pi i} \int_{a-i\infty}^{a+i\infty} F(\lambda) \mathbb{E}\left[e^{\lambda \langle x \rangle_T}\right] d\lambda.$$

On the other hand, the power-options with value

$$\mathbb{E}\left[e^{\lambda\langle x
angle_T}
ight]$$

expand naturally in terms of put/call options.

 Using put-call symmetry and working with dimensionless quantities

$$k = \log(K/S_0)$$
  
 $c(k) = C(K)/K$ , etc.

find

$$\mathbb{E}\left[f(\langle x \rangle_T)\right] = \int_0^\infty dk \ c(k) \ w(k)$$

with (formal) weights w(k) equal to

$$4 e^{k/2} \left( \frac{1}{2\pi i} \int F(\lambda) \lambda \cosh[k\sqrt{1/4 + 2\lambda}] d\lambda \right).$$

- For comparison, the variance swap reads  $\mathbb{E}\left[\langle x\rangle_T\right] = \int_0^\infty dk \ c(k) \ 4e^{k/2} \cosh\left[k/2\right].$
- Apply this to the Volatility Swap

$$f(\langle x \rangle_T) = \sqrt{\langle x \rangle_T}.$$

Brute force computation (Mathematica)  $\Rightarrow$ 

$$\begin{split} w_f(k) &= \left(\sqrt{\frac{\pi}{2}}I_1(k/2) + \sqrt{2\pi}\delta_0(k)\right)e^{k/2} \\ &\approx \sqrt{2\pi}\delta_0(k), \qquad I_1 \dots \text{ mod. Bessel Fct.} \end{split}$$

Simple understanding of approximation via standard expansion of B.S. formula,

$$c(\mathbf{0})\sim rac{1}{\sqrt{2\pi}}\sqrt{\sigma^2 T}=rac{1}{\sqrt{2\pi}}\sqrt{\langle x
angle_T}.$$

**Proof (no brute force):** W.I.o.g.  $T \equiv 1$ . Ansatz:

$$\int_0^\infty dk \, \left(\sqrt{\frac{\pi}{2}}F'(k/2) + \sqrt{2\pi}\delta(k)\right) e^{k/2}c_{BS}(k;\sigma) = \sigma$$
  
for some  $F$  to be found with  $F(0) = 1$ . This last  
choice and the constant  $\sqrt{\frac{\pi}{2}}$  are motivated by the  
following integration by parts argument,

$$\int_{0}^{\infty} dk \, \left( \sqrt{\frac{\pi}{2}} F'(k/2) + \sqrt{2\pi} \delta(k) \right) e^{k/2} c_{BS}(k;\sigma) \\ = -\sqrt{2\pi} \left( \int_{0}^{\infty} dk F(k/2) \frac{\partial}{\partial k} \left[ e^{k/2} c_{BS}(k;\sigma) \right] \right).$$

Our statement is equivalent to saying that the above strip of European has Black–Scholes-vega equal to one. Using the well-known BS-vega for  $c_{BS}(k;\sigma) = e^{-k}C_{BS}(k;\sigma)$  with

$$d_1 = \frac{-k + \sigma^2/2}{\sigma} = \frac{-k + v/2}{\sqrt{v}}$$

find

$$-\sqrt{2\pi} \left( \int_0^\infty dk F(k/2) \frac{\partial}{\partial k} \left[ e^{k/2} \frac{\partial}{\partial \sigma} c_{BS}(k;\sigma) \right] \right)$$
  
=  $-\sqrt{2\pi} \left( \int_0^\infty dk F(k/2) \frac{\partial}{\partial k} \left[ e^{-k/2} \frac{1}{\sqrt{2\pi}} e^{-d_1^2/2} \right] \right)$   
=  $\frac{e^{-v/8}}{v} \int_0^\infty dk F(k/2) k e^{-k^2/(2v)} \equiv 1 \forall v$ 

A power-expansion shows that

$$F(k) = \sum_{m=0}^{\infty} \frac{(k^2/4)^m}{(m!)^2}.$$

We recognize F as Bessel function  $I_0(k)$  and finally recall

$$I_1(k) = \partial_k I_0(k).$$

QED

• Apply this to Variance Calls with payoff, say  $K = 0.04 = (20\%)^2 \times 1$  year.

$$f(\langle x \rangle_T) = (\langle x \rangle_T - K)^+.$$

Well-known Laplace-transform of f is

$$F(\lambda) = e^{-\lambda K} / \lambda^2.$$

Now the brute-force computation  $\dots$  but defining integral for w does not converge!

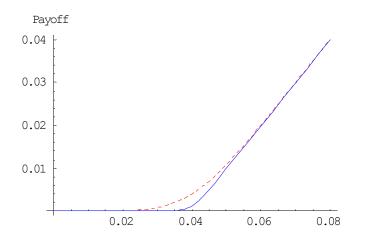


Figure 1:

• To see what is going on (and to guarantee converge) use convolution of payoff with Gauss-kernel of std.dev.  $\sqrt{h}$  for  $h = 10^{-4}$  (dashed line) and  $10^{-5}$  (solid) respectively. This introduces an exponential damping factor and the weights

$$w(k) = w_{call}(k, K; h)$$

are given by

$$\frac{4\,e^{k/2}}{2\pi i}\int_{a-i\infty}^{a+i\infty}\,e^{h\lambda^2/2}\frac{e^{-\lambda K}}{\lambda}\,\cosh\left[k\,\sqrt{1/4+2\lambda}\right]\,d\lambda.$$

• Still numerically hard since  $h \ll 1$  but scaling in  $\lambda$  does the trick and we can plot for any h > 0.

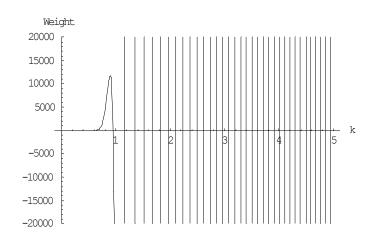


Figure 2: For  $h = 10^{-4}$ .

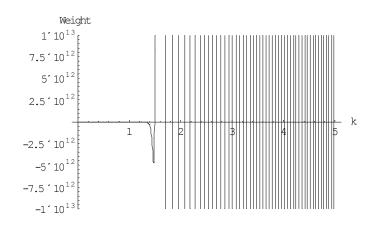


Figure 3: For  $h = 10^{-5}$ 

 Since w<sub>call</sub>(k, K; h) is now defined by absolutely convergent integrals have no problem differentiating under the integral. Fix h and set

$$\begin{split} &\tilde{w}(k,K) \\ &= \frac{2\pi i}{4e^{k/2}} w_{call} \\ &= \int_{a-i\infty}^{a+i\infty} e^{h\lambda^2/2} \frac{e^{-\lambda K}}{\lambda} \cosh\left[k\sqrt{1/4+2\lambda}\right] d\lambda. \end{split}$$

Then  $\tilde{w}$  satisfies a heat equation (with killing) on the domain  $[0,\infty) \times [0,\infty)$ 

$$\frac{\partial^2}{\partial k^2} \tilde{w} = \dots$$
$$= \frac{1}{4} \tilde{w} - 2 \frac{\partial}{\partial K} \tilde{w}.$$

but the "time-derivative"  $\frac{\partial}{\partial K}$  has the wrong sign. (Try to solve heat equations against the natural time direction ...)

Mathematically, such equations have exponential blowup of all Fourier-modes and the oscillations seen before become understandable.

## **Dealing with Ill-posedness:**

- Recall our standing assumptions (in particular ρ = 0) and that normalized BS-prices only depend only log-strike k and total variance y = σ<sup>2</sup>T.
- Let g denote the law of total variance. As observed by Hull/White

(\*) 
$$c(k) = \int_0^\infty c_{BS}(k, y) \, dg(y) =: [\mathfrak{L}g(.)](k).$$

( $\sim$  convolution using a BS-integral kernel).

• Suffices to invert this relation such as to find the law g.Then simply price

$$\mathbb{E}\left[f(\langle x \rangle_T)\right] = \int_0^\infty f(y) dg(y).$$

• How to invert (\*)? Similar to getting sharp pictures from Hubble ... (again, an ill-posed problem).

After a discretization can write

$$c_i = \sum_{j=1}^{\#var} A_{ij} g_j, \quad i = 1, ..., \#c.$$

Naiv guess #var = #c# and invert matrix (badly conditioned). Ad hoc, stability can be obtained by  $\#var \gg \#c$  and use Moore-Penrose's pseudo-inverse to find the least-square solution

$$\mathbf{g} = \mathbf{A}^{\mathrm{T}} (\mathbf{A} \, \mathbf{A}^{\mathrm{T}})^{-1} \, \mathbf{c} =: \mathbf{M} \, \mathbf{c}$$

NB: Matrix-inversion takes place in the "smaller" dimension. This punishes (unwanted oscillations) in the probability vector g.

• Example (Heston with BCC parameters): From CIR bond pricing formula obtain explicit c.f. of total variance. Now can price variance calls using the Carr/Madan techniques in quasi-closed form.

Alternatively, we compute call-price (also in quasiclosed form) with BCC parameters but zero correlation and use the machinery above.

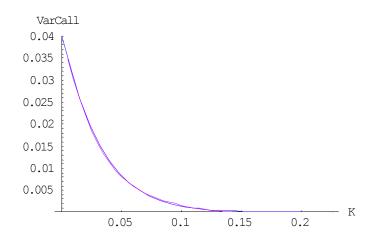


Figure 4: Blue line from quasi-closed form based on CIR formula. Red line from Moore-Penrose approach.

Heston/CIR dynamics for instantaneous variance

$$dv_t = -\lambda (v_t - \bar{v}) dt + \eta \sqrt{v_t} dB_t$$

and consider variance calls with payoffs

$$\mathbb{E}\left[\left(\langle x\rangle_T - K\right)^+\right] = \mathbb{E}\left[\left(\int_0^T v_t dt - K\right)^+\right]$$

with BCC-fit:  $v_0 = \bar{v} = 0.04, \ \lambda = 1.15, \ \eta = 0.39$ 

- The quality of the Moore-Penrose inversion deteriorates for high vvol  $\eta \sim 1$  and high variances-strikes K which arise naturally in the pricing of Capped Variance Swaps.
- To get stable result in such regimes follow the standard procedure in the theory of ill-posed problems. Minimize

$$g \mapsto O(g) = \sum_{j=1}^{n_{Strikes}} \left| \left( \sum_{i=1}^{n_{Var}} g_i c_{BS}(k_j, y_i) \right) - c(k_j) \right|^2$$
$$+\epsilon_1 \times \sum_{i=1}^{n} g_i^2$$
$$+\epsilon_2 \times d(p, g)$$

The Moore-Penrose inversion is a special case of the above with  $\epsilon_2 = 0, \epsilon_1 \rightarrow 0$ . The very last term with  $\epsilon_2$  weight serves as a distance between g and some apriori probability vector p. An example for a distance d between two probability vectors is given by

$$\sum p_i \ln \left[ p_i / q_i \right]$$
 .

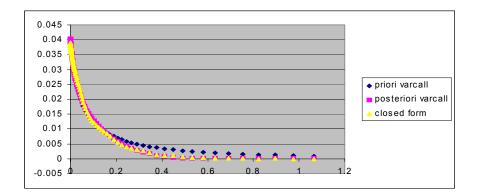


Figure 5: Heston with modified BCC parameter;  $\eta=1$  instead of 0.39

How to choose a good a priori law p? Take a 2 parameter family of laws (e.g. log-normal) and match variance and volatiliy swap.

• Recap: for var-swaps and zero-correlation vol-swaps

$$\mathbb{E} \langle x \rangle_T = \int_0^\infty dk \ c(k) \ 4e^{k/2} \cosh\left[k/2\right]$$
$$\mathbb{E} \sqrt{\langle x \rangle_T} = \int_0^\infty dk \ c(k) \ \left(\sqrt{\frac{\pi}{2}} I_1(\frac{k}{2}) + \sqrt{2\pi}\delta_0(k)\right) e^{\frac{k}{2}}$$

• Matytsin showed: if  $z \equiv d_2(k) = \frac{-k - \sigma^2(k)T/2}{\sigma(k)\sqrt{T}}$  then

$$\mathbb{E}\left[\langle x \rangle_T\right] = \int_{-\infty}^{\infty} dz N'(z) \,\sigma_{implied}^2\left(k\left(z\right)\right)$$

Var-swap price directly from the smile!

• Similar for vol-swap?

- Observe how d<sub>2</sub> comes into play although our setup is far more general than Black-Scholes.
- To understand  $d_2(k)$  need to understand  $\sigma_{implied}(k)$ .
- Fundamental result by Roger Lee

$$\begin{array}{ll} \beta &\equiv \lim\sup_{k\to\infty} \frac{\sigma_{implied}^2\left(k\right)}{k} \in [0,2] \\ p &\equiv \sup\left\{q: ES_T^{1+q} < \infty\right\} \\ \\ \text{then } \beta = 2 - 4\left(\sqrt{p^2 + p} - p\right) \text{ resp. 0 if } p = \infty. \\ \text{(Similar formula for } k \to -\infty) \end{array}$$

- Interpretation: implied (variance) smile is asymptotically linear with slope  $\beta$
- Too naiv: in Merton's jump model we have  $p = \infty$  but smile is certainly not flat!

- [F Benaim] Implied variance in Merton is linear with logarithmic correction. Proof based on saddle point approximation.
- Other results: Hagan's SABR formula is wrong in the wings ...