



FX derivatives

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Volatility

- ▶ The FX market
- ▶ Smile models
- ▶ Calibration and backmapping

Volatility is quoted in delta. Which delta?

- ▶ Spot-delta vs Forward-delta
- ▶ In FX two currencies, could quote delta in either of the two currencies.
- ▶ In FX the premium can be payed in either currency, which will effect the delta.

ATM

- ▶ ATM = forward
- ▶ ATM = delta neutral straddle



Volatility is quoted in market instruments:

Risk reversal

- ▶ X% delta risk reversal
- ▶ Long X% delta call, short X% delta put.
- ▶ Quoted as the difference of the call and put volatility

Butterfly

- ▶ X% delta fly
- ▶ Long Y% delta call, long Y% delta put, short ATM
- ▶ Quoted as the difference of the average call and put volatility to the ATM vol



The FX market

Simple Smile strangle construction

From risk reversal and butterfly

- ▶ $\text{call}_X = \text{ATM} + \frac{1}{2}\text{RR}_X + \text{Fly}_X$
- ▶ $\text{put}_X = \text{ATM} - \frac{1}{2}\text{RR}_X + \text{Fly}_X$

Simple construction, but is not market practice!

Market strangle

The average in volatility of two strike using the given 'common' butterfly volatility is given by the market:



$$K_{\text{call}}^{\text{Fly}}(\sigma_{\text{fly}} + \sigma_{\text{ATM}}, \delta)$$



$$K_{\text{put}}^{\text{Fly}}(\sigma_{\text{fly}} + \sigma_{\text{ATM}}, \delta)$$



The FX market

Risk Reversal smile construction

Risk reversal



$$K_{\text{call}}^{\text{RR}}(\sigma_{\text{ATM}} + \frac{1}{2}\sigma_{\text{RR}}, \delta)$$



$$K_{\text{put}}^{\text{RR}}(\sigma_{\text{ATM}} - \frac{1}{2}\sigma_{\text{RR}}, \delta)$$

For small risk reversal and moderate maturities the simple construction is a good approximation.



The FX market

Market strangle smile construction

The problem to be solved is not an interpolation problem anymore. The smile to be constructed has a single point as an anchor: the ATM point. The other points are not explicitly given, but as constraints.

Risk reversal constraint:

$$P_{\text{call}}(K_{\text{call}}^{\text{RR}}, \sigma(K_{\text{call}}^{\text{RR}})) - P_{\text{put}}(K_{\text{put}}^{\text{RR}}, \sigma(K_{\text{put}}^{\text{RR}})) = P_{\text{RR}}$$

with

$$P_{\text{RR}} = P_{\text{call}}(K_{\text{call}}^{\text{RR}}, \sigma_{\text{ATM}} + \frac{1}{2}\sigma_{\text{RR}}) - P_{\text{put}}(K_{\text{put}}^{\text{RR}}, \sigma_{\text{ATM}} - \frac{1}{2}\sigma_{\text{RR}})$$



The FX market

Market strangle smile construction

Strangle constraint:

$$P_{\text{call}}(K_{\text{call}}^{\text{Fly}}, \sigma(K_{\text{call}}^{\text{Fly}})) + P_{\text{put}}(K_{\text{put}}^{\text{Fly}}, \sigma(K_{\text{put}}^{\text{Fly}})) = P_{\text{Fly}}$$

with

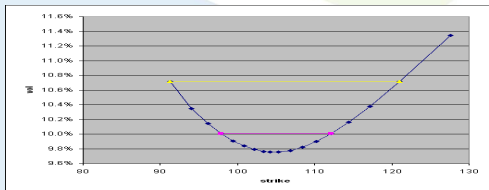
$$P_{\text{Fly}} = P_{\text{call}}(K_{\text{call}}^{\text{Fly}}, \sigma_{\text{ATM}} + \sigma_{\text{Fly}}) + P_{\text{put}}(K_{\text{put}}^{\text{Fly}}, \sigma_{\text{ATM}} + \sigma_{\text{Fly}})$$



The FX market

Market strangle smile construction

Symmetric smile

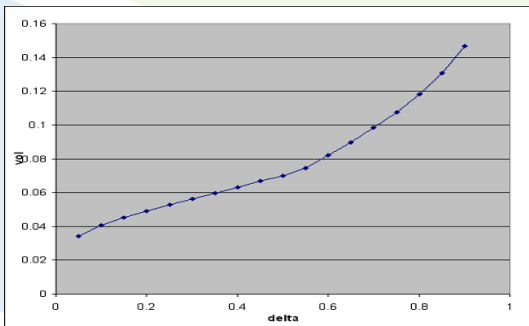




The FX market

Market strangle smile construction

Difficulties for skewed smile

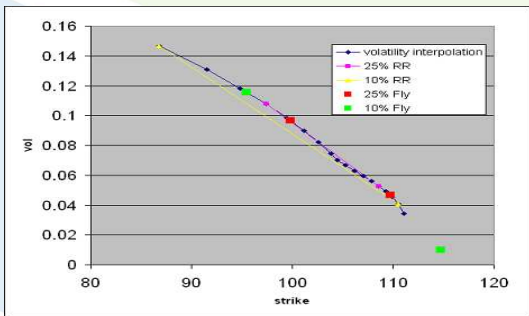




The FX market

Market strangle smile construction

Difficulties for skewed smile





The FX market

Temporal interpolation

- ▶ one day forward volatility is not the same for all days
- ▶ weekends and global holidays are non-volatile days
- ▶ local holidays are non-volatile days for local currencies
- ▶ economic indicator and number publications create additional variance



Smile models

Introduction

- ▶ smile-consistency
- ▶ control forward-smile dynamics
- ▶ reproduce market prices



Smile models

Vanna-volga model

- ▶ Vega-hedge motivated
- ▶

$$P = P_{\text{ATM}} + \Theta_{S\sigma} C_{\text{vanna}} \quad \partial_{S\sigma} P + \Theta_{\sigma\sigma} C_{\text{volga}} \quad \partial_{\sigma\sigma} P$$

The vanna cost C_{vanna} and volga cost C_{volga} is usually derived from 25 Δ risky and fly. The factors $\Theta_{S\sigma}$, $\Theta_{\sigma\sigma}$ are often chosen as the expected survival time in percent of the maturity. There is some justification for OT to do so.

- ▶ Dupire's local volatility
- ▶ Parametric local volatility

$$\frac{dS}{S} = (r^d(t) - r^f(t))dt + \sigma_i(S, t)dW$$
$$\sigma_i(S_t, t) = f(S_0, S_t, t)$$

Parametric local volatility

$$\begin{aligned}f_1(S_0, S_t, t) &= f(LR = \ln(S_t/S_0), t) = c(t) + b(t)LR + a(t)LR^2 \\f_2(S_0, S_t, t) &= c_{-2}(t)LR^{-2} + c_{-1}(t)LR^{-1} + c_0(t) \\&\quad + c_1(t)LR + c_2(t)LR^2\end{aligned}$$

other forms are available and are more adapted to other asset classes.

Most popular is the Heston model

$$\begin{aligned}\frac{dS}{S} &= (r^d(t) - r^f(t))dt + \sigma_i(t)dW \\ d\sigma^2 &= \kappa(\bar{\sigma}^2 - \sigma^2(t))dt + \xi\sigma_i dV\end{aligned}$$

with $\langle dW, dV \rangle = \rho dt$. A closed form solution exists.



Introduce mixing of stochastic volatility model and local volatility model.

$$\begin{aligned}\frac{dS}{S} &= (r^d(t) - r^f(t))dt + \sigma_i(t)f_\lambda(S_t, t)dW \\ d\sigma^2 &= \kappa(\bar{\sigma}^2 - \sigma^2(t))dt + \xi_\lambda\sigma_idV\end{aligned}$$

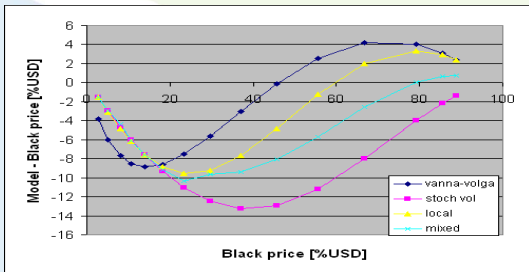
with $\langle dW, dV \rangle = \rho dt$ and the mixing factor λ . For $\lambda = 1$ full Heston model, and $f = 1$, for $\lambda = 0$ full local vol model with local vol function and $\xi_\lambda = 0$.



Smile models

Model comparison

USD/JPY OT 1y upside

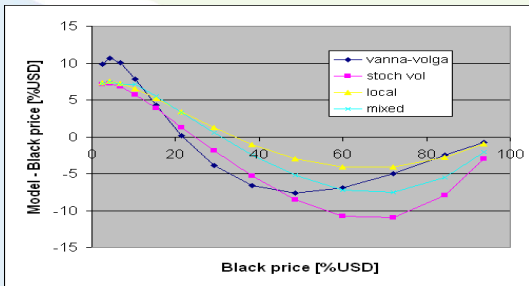




Smile models

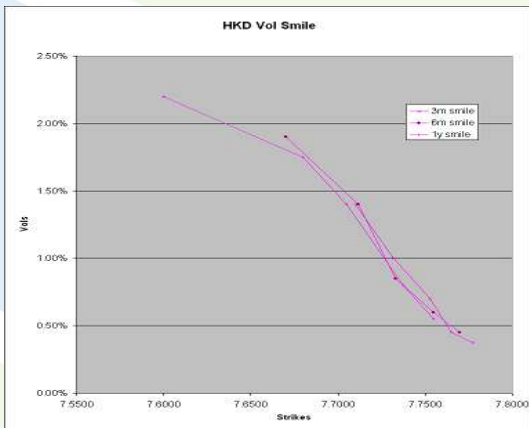
Model comparison

USD/JPY OT 1y downside





Pegged and managed currencies





Smile models

Other FX related models

- ▶ jump diffusion models
 - ▶ distribution of jump-size [Kou, Merton]
 - ▶ stochastic-volatility and jumps
- ▶ stochastic skew model



Smile models

Other FX related models

- ▶ jump diffusion models
 - ▶ distribution of jump-size [Kou, Merton]
 - ▶ stochastic-volatility and jumps
- ▶ stochastic skew model skew in some markets very volatile, RR changes sign



Smile models

Market models of vol

- ▶ Avoid Schoenbucher 'mean fleeing' dynamics close to maturity by a finite forward-vol model?
- ▶ Is it really necessary when we can use long time stepping for Heston model in Monte Carlo?



Calibration

FX specific

- ▶ Sparse input
- ▶ Least mean squares method in volatility, prices or weighted prices



Calibration

Calibration as a LMS problem

Assuming that calibration solves a least mean squares problem
The objective function for non linear least square optimisation
for instruments M_i with target price O_i

$$\sum_{i=1}^M (M_i(P) - O_i)^2. \quad (1)$$

The minimization of the objective function will lead to the local
normal equation to be fulfilled for all calibration parameters
 P_1, \dots, P_N .

$$\sum_{i=1}^M \partial_j M_i(P) (M_i(P) - O_i) = 0. \quad (2)$$

The sensitivity of the price of a product to the change in parameter β is given by

$$dV = \partial_{\beta} V d\beta + \sum_{k=1}^N \partial_{\alpha^k} V \partial_{\beta} \alpha^k d\beta, \quad (3)$$

One way to get that impact on the calibration is the finite difference on the parameter and a re-calibration.

The expansion of the price with respect to calibrated parameter α^k around the solution of the calibration procedure α_0^k yields the

$$M_i(\bar{\alpha}) = M_i(\alpha_0) + \sum_{j=1}^N \partial_{\alpha^j} M_i(\bar{\alpha}^j - \alpha_0^j) + O(2) \quad (4)$$

The LS eq. is rewritten (with $\alpha^j = \bar{\alpha}^j - \alpha_0^j$) as

$$\sum_{i=1}^M \left(M_i(\alpha_0) + \sum_{j=1}^N \partial_{\alpha^j} M_i \alpha^j - O_i \right) = 0. \quad (5)$$

Normal equations

$$\sum_{i=1}^M \sum_{j=1}^N \alpha^j \partial_{\alpha^j} M_i(\alpha_0) \partial_{\alpha^k} M_i(\alpha_0) = \sum_{i=1}^M (M_i(\alpha_0) - O_i) \partial_{\alpha^k} M_i(\alpha_0). \quad (6)$$

since $\alpha^j = 0$ is a solution by definition the constraint is

$$\sum_{i=1}^M M_i(\alpha_0) \partial_{\alpha^k} M_i(\alpha_0) = \sum_{i=1}^M O_i \partial_{\alpha^k} M_i(\alpha_0) \quad (7)$$

The required sensitivity is obtained by solving the system of equations

$$\sum_{i=1}^M \sum_{j=1}^N \partial_{\beta} \alpha^j \partial_{\alpha^j} M_i \partial_{\alpha^k} M_i = \sum_{i=1}^M (M_i - O_i) \partial_{\alpha^k \beta} M_i + \sum_{i=1}^M (\partial_{\beta} M_i - \partial_{\beta} O_i) \partial_{\alpha^k} M_i. \quad (8)$$

This is a very useful equation, that can be used in many cases. It simplifies for specific cases as well.

$$\sum_{i=1}^M \sum_{j=1}^N \partial_{\beta} \alpha^j \partial_{\alpha^j} M_i \partial_{\alpha^k} M_i = -\partial_{\alpha^k} M_i. \quad (9)$$

- ▶ sensitivity to input prices O_i

$$\sum_{i=1}^M \sum_{j=1}^N \partial_{\beta} \alpha^j \partial_{\alpha^j} M_i \partial_{\alpha^k} M_i = -\partial_{\beta} O_i \partial_{\alpha^k} M_i. \quad (9)$$

- ▶ sensitivity to input prices O_i or vols

$$\sum_{i=1}^M \sum_{j=1}^N \partial_{\beta} \alpha^j \partial_{\alpha^j} M_i \partial_{\alpha^k} M_i = -\partial_{\beta} O_i \partial_{\alpha^k} M_i. \quad (9)$$

$$\sum_{i=1}^M \sum_{j=1}^N \partial_{\beta} \alpha^j \partial_{\alpha^j} M_i \partial_{\alpha^k} M_i = -\sum_{i=1}^M \partial_{\beta} \sigma \partial_{\sigma} O_i \partial_{\alpha^k} M_i. \quad (10)$$

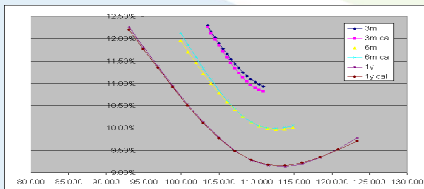
- ▶ sensitivity to input prices O_i or vols
- ▶ sensitivity to ATM, RR and Fly as a strategy



Calibration

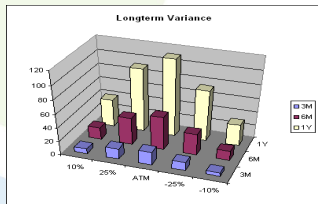
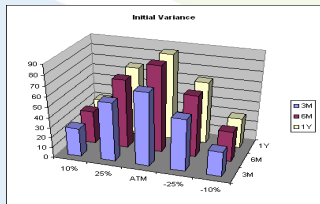
Sensitivity/Example

- ▶ USDJPY market data 1y [modified]
- ▶ Calibration set maturities 3m, 6m, 1y
- ▶ equivalent strikes to 10%, 25%, ATM, -25%, -10%



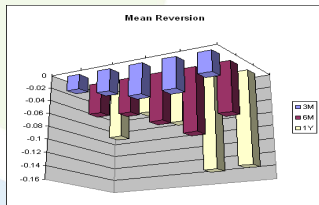
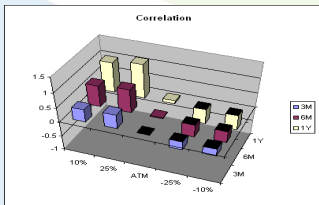


Initial variance and long term variance





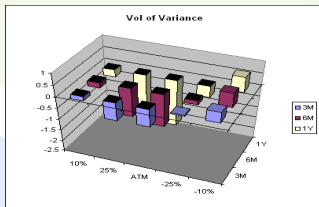
Correlation variance and Mean reversion





Calibration

Sensitivity/Example



Risk for vol of variance

Estimated calibration change and actual change [scaled by 10000] for parallel move of the vol surface

	estimated	actual
initial var	5.19	3.84
longterm var	3.77	3.41
correlation	44.1	49.5
meanreversion	30.0	-625.07
vol of var	-29.95	-42.26

Estimated calibration change and actual change [scaled by 10000] for risk reversal

	estimated	actual
initial var	-0.3	0.6
longterm var	-1.7	-0.5
correlation	491	793
meanreversion	56	58
vol of var	-9.61	6.16



Calibration

Sensitivity/Example

Estimated calibration change and actual change [scaled by 10000] for butterfly

	estimated	actual
initial var	0.69	1.2
longterm var	0.96	0.65
correlation	79	141
meanreversion	-314	-598
vol of var	91	123

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- ▶ Back-mapping of sensitivities improves speed and stability of the greeks when calibration is involved.

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- ▶ Selection criteria for a smile model are different for different markets, in particular for non G7 markets
- ▶ Back-mapping of sensitivities improves speed and stability of the greeks when calibration is involved.
- ▶ Back-mapping of sensitivities improves the understanding of the model