

Local volatility models enhanced with jumps

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Joint work with Pierre Henry-Labordère ¹

¹http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2781102

Mathematical analysis/algorithm

- Two models:
 - LVM with jumps:

$$\frac{dS_t}{S_t} = \sigma(t, S_t) dW_t + (J - 1)(dN_t - \lambda_t dt)$$

- Regime-switching model:

$$\begin{aligned} \frac{dS_t}{S_t} &= \sigma_1(t, S_t) dW_t + (J - 1)(dN_t - \lambda_t dt), \quad \forall t \leq \tau \\ \frac{dS_t}{S_t} &= \sigma_2(t, S_t) dW_t, \quad \forall t > \tau, \quad \sigma_2 := J_S \sigma_1 \end{aligned}$$

- Find σ so that: $\mathbb{E}(S_T - K)_+ = C^{\text{mkt}}(T, K)$
- Leads to nonlinear McKean SDEs

Calibration condition-McKean SDE

- Dynamics of LVM with jumps:

$$\frac{dS_t}{S_t} = \sigma(t, S_t) dW_t + (J(S_t) - 1) (dN_t - \lambda_t dt)$$

- If $S_t \sim \mathbb{P}_t^{\text{mkt}}$ then

$$\sigma^2(t, K) = \sigma_{\text{Dupire}}^2(t, K) - 2 \frac{\Lambda(t, K)}{K^2 \partial_{KK} C^{\text{mkt}}(t, K)}.$$

where:

$$\Lambda(t, K) \equiv \mathbb{E} [\lambda_t (K - J(S_t) S_t) (1_{S_t > K} - 1_{J(S_t) S_t > K})]$$

- No existence/unicity result for this McKean SDE.

McKean SDE: Regularizing the SDE

- Regularize the function $\sigma \rightarrow \sigma^\epsilon$.

Proposition 1

Let us define

$$\frac{dS_t^\epsilon}{S_t^\epsilon} = \sigma^\epsilon(t, S_t^\epsilon) dW_t + (J(S_t^\epsilon) - 1)(dN_t - \lambda_t dt)$$

Then this non-linear SDE admits a unique solution S_t^ϵ .

- How close is $\mathbb{E}(S_T^\epsilon - K)_+$ from $C^{\text{mkt}}(T, K)$

Main theorem²

Theorem 2

For all $(t, K) \in [0, T] \times \mathbb{R}_+$:

$$\lim_{\epsilon \rightarrow 0} \mathbb{E}[(S_t^\epsilon - K)^+] = C^{\text{mkt}}(t, K).$$

Proof:

$u_\epsilon(t, K) = \mathbb{E}[(S_t^\epsilon - K)^+] - C^{\text{mkt}}(t, K)$. Find a PDE family (E_ϵ) s.t:

(i) u_ϵ solves (E_ϵ) .

(ii) (E_ϵ) admits only one solution that tends to 0 as $\epsilon \rightarrow 0$.

²http:

//papers.ssrn.com/sol3/papers.cfm?abstract_id=2781102

Numerical computations: particle method

N independent particles $(S^i, \lambda^i, N^i)_{i=1, \dots, N}$

Algorithm

$[0, T] = \bigcup_i [i\Delta, (i+1)\Delta]$.

- 1 Set $\sigma(t, S) = \sigma_{\text{Dupire}}(t, S), \forall t \in [0, \Delta]$
- 2 Compute $\Lambda(\Delta, K)$:

$$\Lambda(\Delta, K) = \frac{1}{N} \sum_{i=1}^N \lambda_{\Delta}^i (K - JS_{\Delta}^i) (1_{S_{\Delta}^i > K} - 1_{S_{\Delta}^i J(S_{\Delta}^i) > K})$$

set $\sigma(t, K) = \sigma(\Delta, K) \forall t \in [\Delta, 2\Delta]$.

- 3 Iterate up to T .

Numerical implementation

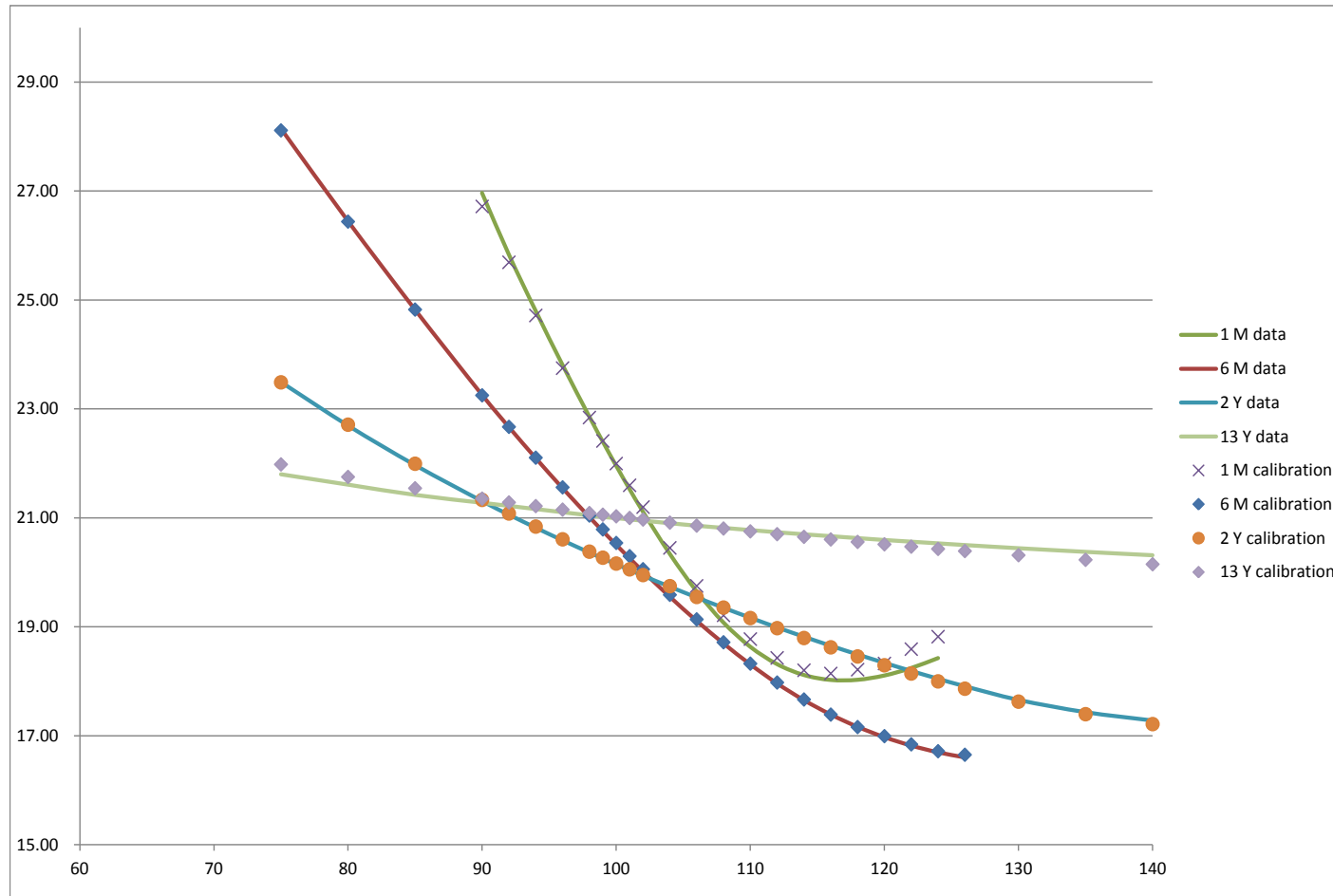


Figure: Calibrated implied volatilities compared to implied volatilities. $J = 0.9$, $\sigma_\lambda = 100\%$, $\rho_{S\lambda} = -40\%$, 10000 particles for the calibration.

Regime-switching model

SDE:

$$\frac{dS_t}{S_t} = \sigma_1(t, S_t) dW_t + (J - 1)(dN_t - \lambda_t dt), \quad \forall t \leq \tau$$
$$\frac{dS_t}{S_t} = \sigma_2(t, S_t) dW_t, \quad \forall t > \tau$$

where τ is the first time to default of a Poisson process $(N_t)_{t \geq 0}$.

Calibration condition

Setting $\sigma_2(t, K) = J_S(t, K)\sigma_1(t, K)$,

Proposition 3

$S_t \sim \mathbb{P}_t^{\text{mkt}}$ for all $t \leq T$ if and only if

$$\begin{aligned}\sigma_1(t, K)^2 &= \frac{\sigma_{\text{Dupire}}(t, K)^2}{1 + (J_S(t, K)^2 - 1)P_2(t, K)} \\ &+ 2 \frac{(J - 1)(\Lambda(t, K) - K\partial_K\Lambda(t, K))}{\partial_{KK}C^{\text{mkt}}(t, K)(1 + (J_S(t, K)^2 - 1)P_2(t, K))} \\ &- 2 \frac{J\Lambda(t, \frac{K}{J}) - \Lambda(t, K)}{\partial_{KK}C^{\text{mkt}}(t, K)(1 + (J_S(t, K)^2 - 1)P_2(t, K))}\end{aligned}$$

where: $P_2(t, K) := \mathbb{E}[\mathbf{1}_{\tau < t} | S_t = K]$ and
 $\Lambda(t, K) := \mathbb{E}[\lambda_t \mathbf{1}_{\tau > t} (S_t - K)_+]$.

Numerical implementation

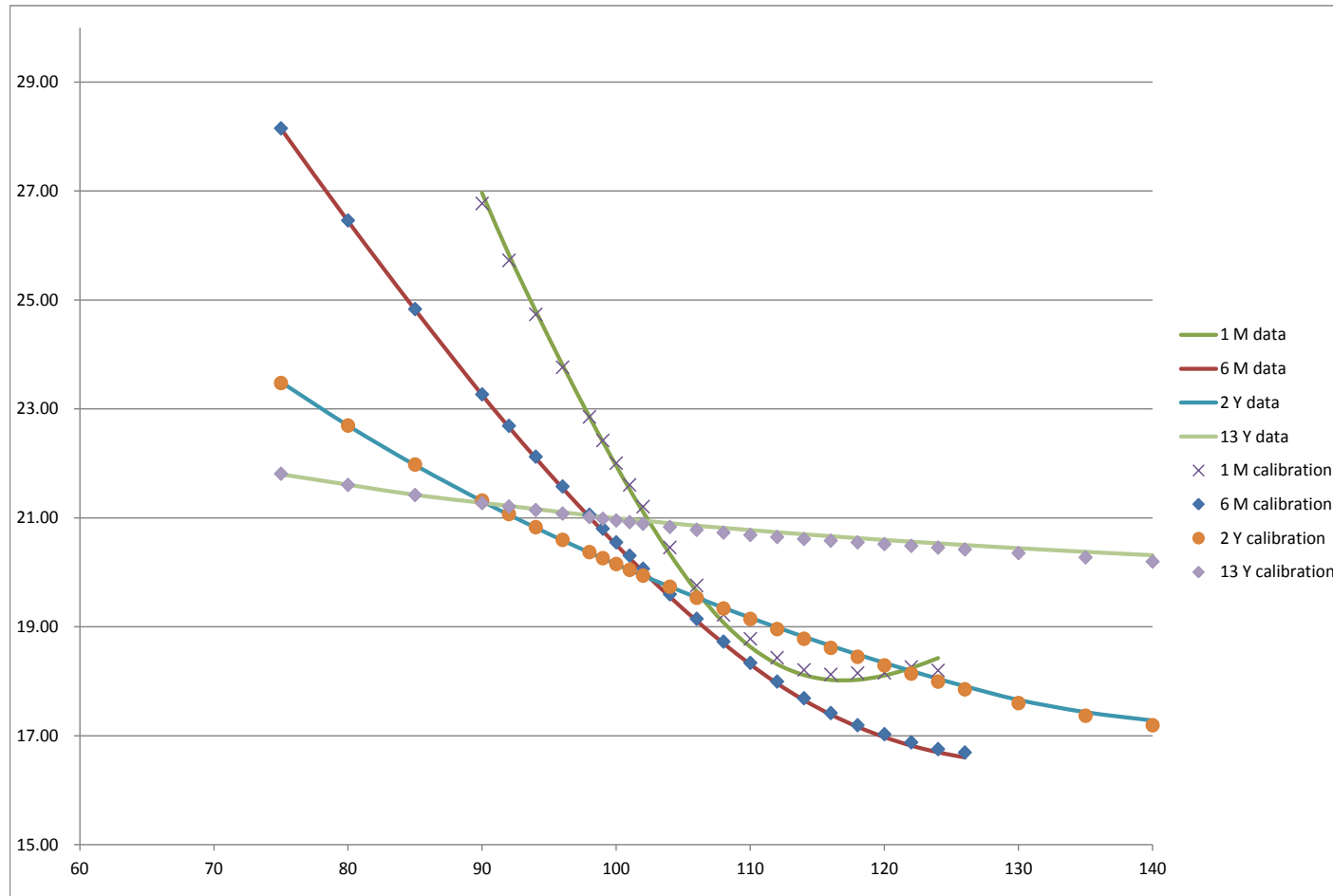


Figure: Calibrated implied volatilities compared to implied volatilities, $J = 0.9$, $J_S = 1.2$, $\sigma_\lambda = 100\%$, $\rho_{S\lambda} = -40\%$, 10000 particles for calibration.

Conclusion

- Robust numerical method
- The approach to prove: $\lim_{\epsilon \rightarrow 0} \mathbb{E}[(S_t^\epsilon - K)^+] = C^{\text{mkt}}(t, K)$
could be used for other calibration problems!