



# ADI Finite Difference Schemes for the Calibration of Stochastic Local Volatility Models: An Adjoint Method

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## Introduction: Why?

- ▶ European call option gives holder the right to buy a given asset at a prescribed date  $T$  for a prescribed price  $K$
- ▶  $S_\tau$  foreign exchange rate at  $\tau \geq 0$
- ▶ European call option: payoff  $u_0(S_T) = \max(S_T - K, 0)$
- ▶ Non-path-dependent European option:  
Fair value at  $\tau = 0$  is  $e^{-r_d T} \mathbb{E}[u_0(S_T)] = e^{-r_d T} \mathbb{E}[u_0(S_0 e^{X_T})]$
- ▶  $r_d, r_f$  risk-free interest rates



## Introduction: Why?

Modelling:  $X_\tau = \log(S_\tau/S_0)$

Local volatility (LV) model

$$dX_\tau = (r_d - r_f - \frac{1}{2}\sigma_{LV}^2(X_\tau, \tau))d\tau + \sigma_{LV}(X_\tau, \tau)dW_\tau$$

Stochastic local volatility (SLV) model

$$\begin{aligned}dX_\tau &= (r_d - r_f - \frac{1}{2}\sigma_{SLV}^2(X_\tau, \tau)V_\tau)d\tau + \sigma_{SLV}(X_\tau, \tau)\sqrt{V_\tau}dW_\tau^{(1)} \\dV_\tau &= \kappa(\eta - V_\tau)d\tau + \xi\sqrt{V_\tau}dW_\tau^{(2)}\end{aligned}$$

**Goal: Determine  $\sigma_{SLV}$  that reproduces market data**



## Difficulties

- ▶ For general  $\sigma_{SLV}$  European call values not known exactly
- ▶ Calibrate SLV model to underlying LV model

### Gyöngy '86

LV and SLV model define same European call values if

$$\sigma_{LV}^2(x, \tau) = \sigma_{SLV}^2(x, \tau) \mathbb{E}[V_\tau | X_\tau = x] = \sigma_{SLV}^2(x, \tau) \frac{\int_0^\infty v p(x, v, \tau) dv}{\int_0^\infty p(x, v, \tau) dv}$$

- ▶  $\mathbb{E}[V_\tau | X_\tau = x]$  dependent on  $\sigma_{SLV}$  in a non-trivial way
- ▶ For general  $\sigma_{LV}$  European call values not known exactly



# Valuation of European options

Common: numerically solving the backward PDE ( $t = T - \tau$ )

- ▶ LV model

$$u_t = \frac{1}{2}\sigma_{LV}^2 u_{xx} + (r_d - r_f - \frac{1}{2}\sigma_{LV}^2)u_x$$

Maturity  $T \rightarrow \mathbb{E}[u_0(S_0 e^{X_T})] = u(X_0, T)$

- ▶ SLV model

$$u_t = \frac{1}{2}\sigma_{SLV}^2 v u_{xx} + \rho\sigma_{SLV} v u_{xv} + \frac{1}{2}\xi^2 v u_{vv} + (r_d - r_f - \frac{1}{2}\sigma_{SLV}^2)u_x + \kappa(\eta - v)u_v$$

Maturity  $T \rightarrow \mathbb{E}[u_0(S_0 e^{X_T})] = u(X_0, V_0, T)$



## Theoretical alternative: forward PDE

► LV model

$$p_\tau = \frac{\partial^2}{\partial x^2} \left( \frac{1}{2} \sigma_{LV}^2 p \right) - \frac{\partial}{\partial x} \left( (r_d - r_f - \frac{1}{2} \sigma_{LV}^2) p \right)$$

$$\mathbb{E}[u_0(S_0 e^{X_T})] = \int_{-\infty}^{\infty} u_0(S_0 e^x) p(x, T) dx$$

► SLV model

$$p_\tau = \frac{\partial^2}{\partial x^2} \left( \frac{1}{2} \sigma_{SLV}^2 v p \right) + \frac{\partial^2}{\partial x \partial v} (\rho \sigma_{SLV} v p) + \frac{\partial^2}{\partial v^2} \left( \frac{1}{2} \xi^2 v p \right) \\ - \frac{\partial}{\partial x} \left( (r_d - r_f - \frac{1}{2} \sigma_{SLV}^2) p \right) - \frac{\partial}{\partial v} (\kappa(\eta - v) p)$$

$$\mathbb{E}[u_0(S_0 e^{X_T})] = \int_0^\infty \int_{-\infty}^{\infty} u_0(S_0 e^x) p(x, v, T) dx dv$$



## Theoretical alternative: forward PDE

► LV model

$$p_\tau = \frac{\partial^2}{\partial x^2} \left( \frac{1}{2} \sigma_{LV}^2 p \right) - \frac{\partial}{\partial x} \left( (r_d - r_f - \frac{1}{2} \sigma_{LV}^2) p \right)$$

$$\mathbb{E}[u_0(S_0 e^{X_\tau})] = \int_{-\infty}^{\infty} u(x, T - \tau) p(x, \tau) dx$$

► SLV model

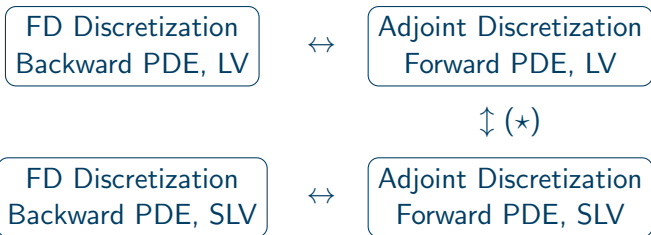
$$\begin{aligned} p_\tau = & \frac{\partial^2}{\partial x^2} \left( \frac{1}{2} \sigma_{SLV}^2 v p \right) + \frac{\partial^2}{\partial x \partial v} \left( \rho \xi \sigma_{SLV} v p \right) + \frac{\partial^2}{\partial v^2} \left( \frac{1}{2} \xi^2 v p \right) \\ & - \frac{\partial}{\partial x} \left( (r_d - r_f - \frac{1}{2} \sigma_{SLV}^2 v) p \right) - \frac{\partial}{\partial v} \left( \kappa (\eta - v) p \right) \end{aligned}$$

$$\mathbb{E}[u_0(S_0 e^{X_\tau})] = \int_0^\infty \int_{-\infty}^\infty u(x, v, T - \tau) p(x, v, \tau) dx dv$$





## Adjoint calibration technique



(\*) holds when similar discretizations for the backward PDEs



## Adjoint discretization (LV model)

- ▶ FD discretization backward equation ( $t = T - \tau$ ):

$$U'_{LV}(t) = A_{LV}(t)U_{LV}(t), \quad U_{LV,i}(t) \approx u(x_i, t)$$

- ▶ Approximations  $P_{LV,i}(\tau) \approx \int_{x_i-0.5}^{x_i+0.5} p(x, \tau) dx$

$$U_{LV,i_0}(T) = P_{LV}^T(\tau)U_{LV}(T-\tau) = P_{LV}^T(T)U_0 = \sum_i P_{LV,i}(T)U_{0,i}$$

- ▶ Adjoint discretization forward equation:

$$P'_{LV}(\tau) = A_{LV}^T(T - \tau)P_{LV}(\tau)$$



## Adjoint discretization (SLV model)

- ▶ FD discretization backward equation:  $\mathbf{U}_{SLV,i,j}(t) \approx u(x_i, v_j, t)$
- ▶ Approximations  $\mathbf{P}_{SLV,i,j}(\tau) \approx \int_{v_j-0.5}^{v_j+0.5} \int_{x_i-0.5}^{x_i+0.5} p(x, v, \tau) dx dv$
- ▶ Adjoint discretization forward equation:

$$\begin{aligned} \mathbf{U}_{SLV,i_0,j_0}(T) &= \sum_{i,j} \mathbf{P}_{SLV,i,j}(T) \mathbf{U}_{SLV,i,j}(T - \tau) \\ &= \sum_i \left( \sum_j \mathbf{P}_{SLV,i,j}(T) \right) U_{0,i} \end{aligned}$$



# Adjoint calibration

## If

- ▶ Same discretization in  $x$ -direction of the backward equations
- ▶ Adjoint spatial discretization of the forward equations
- ▶ 
$$\sigma_{LV}^2(x_i, \tau) = \sigma_{SLV}^2(x_i, \tau) \frac{\sum_j v_j \mathbf{P}_{SLV,i,j}(\tau)}{\sum_j \mathbf{P}_{SLV,i,j}(\tau)}$$

## Then

- ▶ 
$$P_{LV,i}(\tau) = \sum_j \mathbf{P}_{SLV,i,j}(\tau)$$
- ▶ 
$$U_{LV,i_0}(T) = \mathbf{U}_{SLV,i_0,j_0}(T)$$



# Adjoint calibration

## If

- ▶ Same discretization in  $x$ -direction of the backward equations
- ▶ Adjoint spatial discretization of the forward equations
- ▶  $\sigma_{LV}^2(x_i, \tau) = \sigma_{SLV}^2(x_i, \tau) \frac{\sum_j v_j \mathbf{P}_{SLV,i,j}(\tau)}{\sum_j \mathbf{P}_{SLV,i,j}(\tau)} \approx \sigma_{SLV}^2(x_i, \tau) \frac{\int_0^\infty vp(x_i, v, \tau) dv}{\int_0^\infty p(x_i, v, \tau) dv}$

## Then

- ▶  $P_{LV,i}(\tau) = \sum_j \mathbf{P}_{SLV,i,j}(\tau)$
- ▶  $U_{LV,i_0}(T) = \mathbf{U}_{SLV,i_0,j_0}(T)$



## Non-linear system of ODEs

- ▶ Adjoint discretization yields system of ODEs for  $\mathbf{P}_{SLV}$
- ▶ Corresponding discretization matrix depends on

$$\sigma_{SLV}^2(x_i, \tau) = \sigma_{LV}^2(x_i, \tau) \frac{\sum_j \mathbf{P}_{SLV,i,j}(\tau)}{\sum_j v_j \mathbf{P}_{SLV,i,j}(\tau)} \quad (1)$$

- ▶ Non-linear system of ODEs
- ▶ Modified Craig–Sneyd implicit time stepping with inner iteration



## Inner iteration

$P_{SLV,n} = P_{SLV,n-1}$  initial approximation to  $P_{SLV}(\tau_n)$ ;

for  $q$  is 1 to  $Q$  do

(a) approximate  $\sigma_{SLV}^2(x_i, \tau_n)$  by (1);

(b) update  $P_{SLV,n}$  by performing a MCS time step;

end

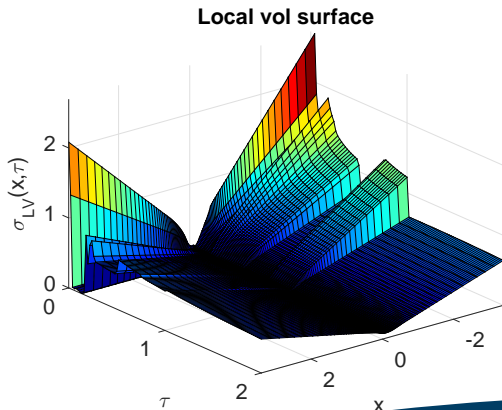
- ▶  $Q = 2$  performs excellent



## Numerical experiments, EUR/USD rate

$$S_0 = 1.0764, r_d = 0.03, r_f = 0.01$$

Local volatility surface up to  $\tau = 2$  years







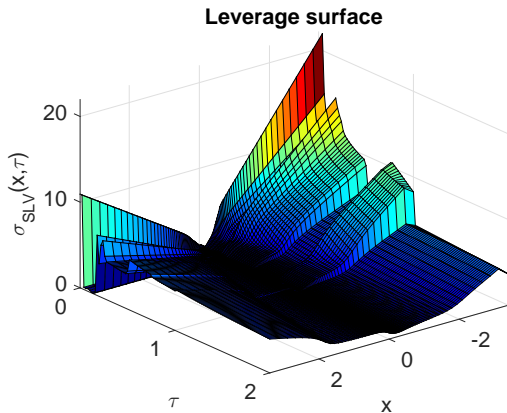
## Stochastic parameters

	Case 1	Case 2
$\kappa$	0.75	0.30
$\eta$	0.015	0.04
$\xi$	0.15	0.90
$\rho$	-0.14	-0.5
$T$	2Y	2Y
$S_0$	1.0764	1.0764
$V_0$	0.015	0.04

- ▶ Case 1: Actual EUR/USD parameters from Clarke (2011)
- ▶ Case 2: Challenging parameters from Andersen (2008)



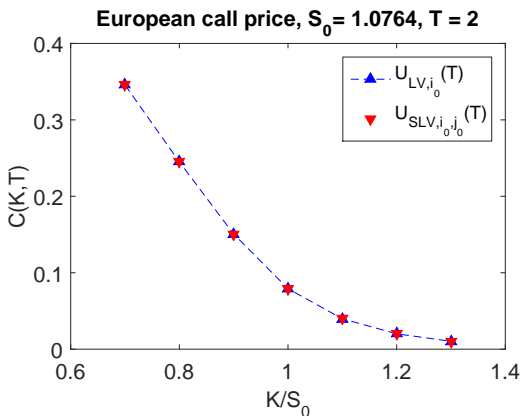
# Leverage surface, Case 1





# European call prices, Case 1

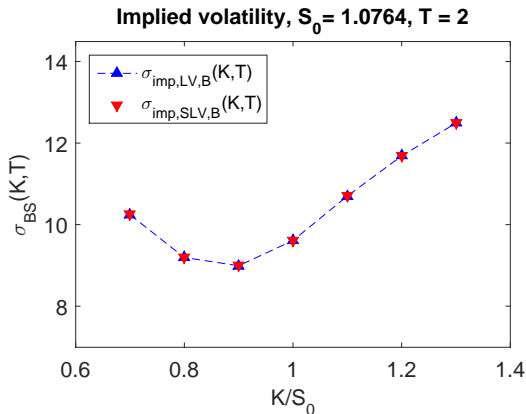
Strike  $K$ , maturity  $T \rightarrow U_{0,i} = \max(S_0 e^{x_i} - K, 0)$





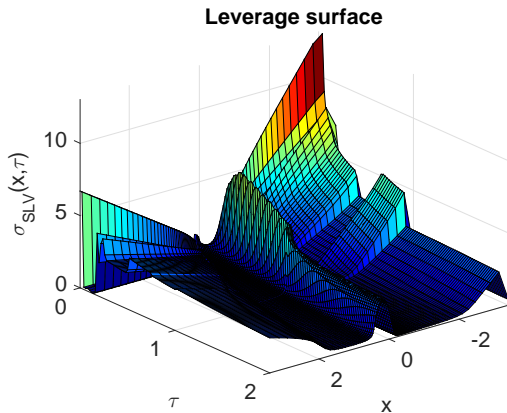
# Implied vols (in %), Case 1

$$U_{LV,i_0}(T) \rightarrow \sigma_{imp,LV,B}(K, T), \quad U_{SLV,i_0,j_0}(T) \rightarrow \sigma_{imp,SLV,B}(K, T)$$



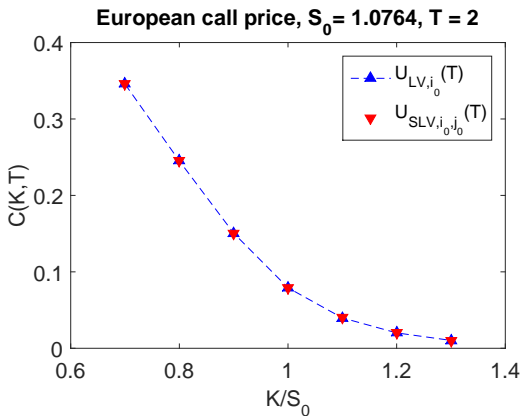


## Leverage surface, Case 2



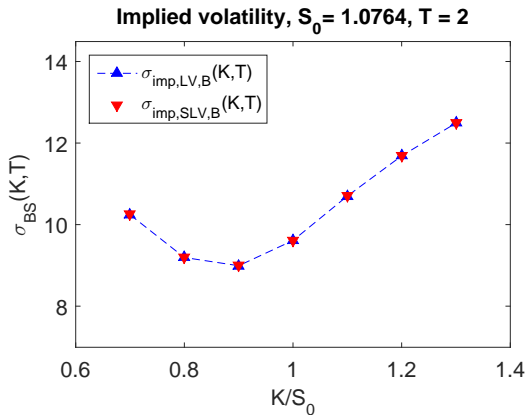


## European call prices, Case 2





## Implied vols (in %), Case 2





## Numerical results

Absolute implied vol error:  $|\sigma_{imp,LV,B}(K, T) - \sigma_{imp,SLV,B}(K, T)|$

$x$ -direction: 100 points,  $v$ -direction: 50 points,  $\Delta\tau = 1/100$

$K/S_0$	0.7	0.8	0.9	1.0	1.1	1.2	1.3
$\sigma_{imp,LV,B}$	10.23	9.19	8.99	9.61	10.70	11.68	12.49
Case 1	$4e-3$	$3e-3$	$2e-3$	$1e-3$	$1e-3$	$2e-3$	$2e-3$
Case 2	$2e-3$	$4e-3$	$2e-4$	$5e-3$	$5e-3$	$4e-3$	$3e-4$





## Calibration time

- ▶ Calibration time  $\sim$  desired accuracy LV discretization
- ▶ Calibration time  $\sim$  desired accuracy  $v$ -direction
- ▶  $x$ -direction: 100 points,  $v$ -direction: 50 points, time steps: 100  
→ Calibration time  $\approx 1s$

(Matlab code, Intel Core i7-3540M 3.00GHz, 8GB RAM)



## Conclusions










- ▶ Adjoint calibration for exact match between semidiscrete LV and SLV model
- ▶ Time stepping and inner iteration for full discretization
- ▶ Fully discrete match upto temporal discretization error
- ▶ Spatial error  $\gg$  temporal error
- ▶ (1) Control discretization error within LV model  
    (2) De facto exact calibration of the SLV model



**Thank You!**



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