## Computational Recovery of the Time-Dependent Volatility of Volatility in a Heston Model

Slavi G. Georgiev ${ }^{1,2}$ Lubin G. Vulkov ${ }^{2}$

${ }^{1}$ Department of Informational Modeling, Institute of Mathematics and Informatics, Bulgarian Academy of Sciences sggeorgiev@math.bas.bg
${ }^{2}$ Department of Applied Mathematics and Statistics, Faculty of Natural Sciences and Education, University of Ruse sggeorgiev@uni-ruse.bg, lvalkov@uni-ruse.bg

International Conference on Computational Finance, 2-5 April 2024, Amsterdam

## Contents

(1) Introduction and Formulation of the Problems

- Stochastic volatility models
- Definitions
- Inverse Problem Formulation
(2) Solution to the Direct Problem
- Finite Difference Scheme
- Well-posed Boundary Conditions
(3) Solution to the Inverse Problem
- Observations Definition
- Algorithm
(4) Experiments
- Direct Problem
- Implied Volatility of Volatility
(5) Conclusion


## Heston model

The two-factor model introduces two sources of uncertainty by incorporating a stochastic variance:

$$
\begin{aligned}
& \mathrm{d} x_{t}=\left(r_{d}-r_{f}-\frac{v_{t}}{2}\right) x_{t} \mathrm{~d} t+\sqrt{v_{t}} \mathrm{~d} W_{t}^{1} \\
& \mathrm{~d} v_{t}=k(t)\left(\theta(t)-v_{t}\right) \mathrm{d} t+\xi(t) \sqrt{v_{t}} \mathrm{~d} W_{t}^{2}
\end{aligned}
$$

where $x_{t}$ is the $\log$-spot price $x_{t}=\log S_{t}, v_{t}$ is the instantaneous variance, $k(t)$ is the speed of mean reversion, $\theta(t)$ is the long-term mean of the variance, and $\xi(t)$ is the volatility of the variance.

The Wiener processes $W_{t}^{i}$ are correlated with instantaneous correlation $\rho(t)$, i. e.

$$
\mathbb{E}\left[\mathrm{d} W_{t}^{1} \mathrm{~d} W_{t}^{2}\right]=\rho(t) \mathrm{d} t
$$

Stochastic volatility models

## Related Sources

## Related Sources

- P. Carr, A. Itkin, D. Muravey, Semi-analytical pricing of barrier options in the time-dependent Heston model, arXiv:2202.06177 [q-fin.PR], (2022).
- A. Clevenhaus, C. Totzeck, M. Ehrhardt, A gradient based calibration method for the Heston model, Int. J. Comp. Math., (2024).
- S. Georgiev, L. Vulkov, Computational recovery of time-dependent volatility from integral observations in option pricing, J. Comput. Sci., 39, 101054, (2019).
- D. Guterding, W. Boenkost, The Heston stochastic volatility model with piecewise constant parameters - efficient calibration and pricing of window barrier options, J. Comput. Appl. Math., $343,353-362$, (2018).
- Y. Jin, J. Wang, S. Kim, Y. Heo, C. Yoo, Y. Kim, J. Kim, D. Jeong, Reconstruction of the time-dependent volatility function using the Black-Scholes model, Discr. Dyn. Nat. Soc., vol. 2018, ID 3093708, (2018).


## Heston Model

We consider the two-dimensional general Heston equation for pricing European call option

$$
\begin{align*}
\frac{\partial C}{\partial \tau} & -\frac{v}{2} \frac{\partial^{2} C}{\partial x^{2}}-\frac{\xi^{2}(\tau)}{2} v \frac{\partial^{2} C}{\partial v^{2}}-\xi(\tau) \rho(\tau) v \frac{\partial^{2} C}{\partial x \partial v} \\
& -\left(r_{d}-r_{f}-\frac{v}{2}\right) \frac{\partial C}{\partial x}-k(\tau)(\theta(\tau)-v) \frac{\partial C}{\partial v}+r_{d} C=0 \tag{1}
\end{align*}
$$

with $\tau=T-t$ and the initial condition

$$
C(x, v, 0)=\max (\exp (x)-K, 0)
$$

## Definitions

## Heston BC

In the solution to the direct and inverse problems, we use the Heston boundary conditions:

$$
\begin{aligned}
C(-\infty, v, \tau) & =0 \\
C(\infty, v, 0) & =\exp (x)-K \exp \left(-r_{d} \tau\right) \\
\frac{\partial C}{\partial \tau}(x, 0, \tau) & -\left(r_{d}-r_{f}\right) \frac{\partial C}{\partial x}(x, 0, \tau) \\
& -k(\tau) \theta(\tau) \frac{\partial C}{\partial v}(x, 0, \tau)+r_{d} C(x, 0, \tau)=0 \\
C(x, \infty, 0) & =\exp (x)-K \exp \left(-r_{d} \tau\right)
\end{aligned}
$$

The question about well-posed boundary conditions would be regarded henceforward.

## Implied Volatility of Volatility

Assume we know the option price $C$. Then we find that volatility $\xi(\tau)$, for which the theoretical result coincides with the observed quoted price on the market. This volatility is called implied volatility, i. e.

$$
C^{\mathrm{obs}}=C\left(x, t ; K, T, r_{d}, r_{f}, \theta(\tau), k(\tau), \rho(\tau), \xi^{\mathrm{imp}}(\tau)\right)
$$

## Discretization of (1)

Let $f:\left[x_{\text {min }}, x_{\max }\right] \rightarrow \mathbb{R}$ and if $x_{\text {min }}=x_{0}<x_{1}<\ldots<x_{I+1}=x_{\text {max }}$ is the spatial grid, $h_{i}=x_{i}-x_{i-1}, H_{i}=h_{i}+h_{i+1},(1 \leqslant i \leqslant I)$, then the first derivative $f^{\prime}\left(x_{i}\right)$ could be approximated in the following ways:

$$
\begin{align*}
& f^{\prime}\left(x_{i}\right) \approx \frac{f\left(x_{i}\right)-f\left(x_{i-1}\right)}{h_{i}} \equiv \mathrm{D}^{l} f_{i},  \tag{2}\\
& f^{\prime}\left(x_{i}\right) \approx \frac{f\left(x_{i+1}\right)-f\left(x_{i}\right)}{h_{i+1}} \equiv \mathrm{D}^{r} f_{i} \tag{3}
\end{align*}
$$

as well as the second derivative $f^{\prime \prime}\left(r_{i}\right)$ :

$$
\begin{equation*}
f^{\prime \prime}\left(x_{i}\right) \approx \frac{2}{h_{i} H_{i}} f\left(x_{i-1}\right)-\frac{2}{h_{i} h_{i+1}} f\left(x_{i}\right)+\frac{2}{h_{i+1} H_{i}} f\left(x_{i+1}\right) \equiv \mathrm{D}^{2} f_{i} . \tag{4}
\end{equation*}
$$

Applying (2), (3) and (4) to (1), we have an upwind implicit scheme.

Rewriting (1) in terms of the gradient operator gives

$$
\begin{equation*}
\frac{\partial C}{\partial \tau}=\nabla \cdot(A \nabla C)+B^{\top} \cdot \nabla C-r_{d} C \tag{5}
\end{equation*}
$$

where

$$
A=\frac{v}{2}\left[\begin{array}{cc}
1 & \rho \xi \\
\rho \xi & \xi^{2}
\end{array}\right], \quad B=\left[\begin{array}{c}
-\frac{v+\rho \xi}{2}+\left(r_{d}-r_{f}\right) \\
-\frac{\xi^{2}}{2}+k(\theta-v)
\end{array}\right] .
$$

After multiplying (5) by a function $\phi \in H^{1}$, we obtain
$\int_{\Omega} \frac{\partial C}{\partial \tau} \phi \mathrm{~d} \Omega=\int_{\Omega} \nabla \cdot(A \nabla C) \phi \mathrm{d} \Omega-\int_{\Omega} B^{\top} \nabla C \phi \mathrm{~d} \Omega-r_{d} \int_{\Omega} C \phi \mathrm{~d} \Omega$.

After applying the Green first identity to the diffusion term and choosing $\phi=C$, we get

$$
\begin{array}{r}
\int_{\Omega} \frac{\partial C}{\partial \tau} C \mathrm{~d} \Omega=\int_{\partial \Omega} C(A \nabla C) \cdot \vec{n} \mathrm{~d}(\partial \Omega)-\int_{\Omega} \nabla C^{\top} A \nabla C \mathrm{~d} \Omega+ \\
\int_{\Omega} C B^{\top} \nabla C \mathrm{~d} \Omega-r_{d} \int_{\Omega} C^{2} \mathrm{~d} \Omega
\end{array}
$$

which, rewritten in terms of $L^{2}$ norms and accounting that $A \geqslant 0$, yields

$$
\begin{equation*}
\frac{1}{2} \frac{\mathrm{~d}}{\mathrm{~d} \tau}\|C\|^{2} \leqslant \int_{\partial \Omega} C(A \nabla C) \cdot \vec{n} \mathrm{~d}(\partial \Omega)+\int_{\Omega} C B^{\top} \nabla C \mathrm{~d} \Omega-r_{d}\|C\|^{2} . \tag{6}
\end{equation*}
$$

## Theorem

If the integrals in (6) vanish or are negative, then the correspondin IBVP for eq. (1) is well-posed and the following estimate holds:

$$
\|C(T)\| \leqslant \exp (b T)\|C(0)\|,
$$

where $2 b=\bar{K}-r_{d}, \bar{K}=\max _{\tau \in[0, T]} k(\tau)$.

## Computational Domain



$$
\begin{aligned}
& \Gamma_{l}=\{(x, v): x=-X, v \in(0, V)\}, \\
& \Gamma_{r}=\{(x, v): x=X, v \in(0, V)\}, \\
& \Gamma_{u}=\{(x, v): v=V, x \in(-X, X)\}, \\
& \Gamma_{d}=\{(x, v): v=0, x \in(-X, X)\} .
\end{aligned}
$$

Restricting $x$ and $v$ to a rectangular domain, truncated at $x_{\min }=-X, x_{\max }=X>0, v_{\min }=0, v_{\max }=V>0$, forms four boundaries.

## Diffusion terms

$$
\begin{aligned}
\int_{\partial \Omega} C(A \nabla C) & \cdot \vec{n} \mathrm{~d}(\partial \Omega)=-\left.\frac{1}{2} \int_{0}^{V} v C\left(\rho(t) \xi(\tau) \frac{\partial C}{\partial v}+\frac{\partial C}{\partial x}\right) \mathrm{d} v\right|_{x=-X} \\
+ & \left.\frac{1}{2} \int_{0}^{V} v C\left(\rho(\tau) \xi(\tau) \frac{\partial C}{\partial v}+\frac{\partial C}{\partial x}\right) \mathrm{d} v\right|_{x=X} \\
& +\left.\frac{1}{2} \int_{-X}^{X} v C\left(\xi^{2}(\tau) \frac{\partial C}{\partial v}+\rho(\tau) \xi(\tau) \frac{\partial C}{\partial x}\right) \mathrm{d} x\right|_{v=V}
\end{aligned}
$$

Analogously, the terms from the convection integral follows:

## Convection terms

$$
\begin{aligned}
\int_{\Omega} C B^{\top} \nabla C \mathrm{~d} \Omega & =\frac{1}{2} \int_{\Omega}\left(k(\tau)(\theta(\tau)-v)-\frac{1}{2} \xi^{2}(\tau)\right) \frac{\partial C^{2}}{\partial v} \mathrm{~d} \Omega \\
& +\frac{1}{2} \underbrace{\int_{\Omega}\left(r_{d}-r_{f}\right) \frac{\partial C^{2}}{\partial x} \mathrm{~d} \Omega}_{I_{1}}-\frac{1}{4} \underbrace{\int_{\Omega}(v+\rho(\tau) \xi(\tau)) \frac{\partial C^{2}}{\partial x} \mathrm{~d} \Omega}_{I_{2}}
\end{aligned}
$$

Now, we will define the respective well-posed boundary conditions on the four boundaries.

After integrating by parts we obtain:

$$
\begin{aligned}
I_{1}= & \int_{-X}^{X} \int_{0}^{V}\left(k(\tau)(\theta(t)-v)-\frac{1}{2} \xi^{2}(\tau)\right) \frac{\partial C^{2}}{\partial v} \mathrm{~d} v \mathrm{~d} x \\
& +\int_{-X}^{X}\left(k(\tau)(\theta(t)-V)-\frac{1}{2} \xi^{2}(\tau)\right) C^{2}(V, x, \tau) \mathrm{d} x \\
- & \int_{-X}^{X}\left(k(\tau) \theta(\tau)-\frac{1}{2} \xi^{2}(\tau)\right) C^{2}(0, x, \tau) \mathrm{d} x+k(\tau) \iint_{\Omega} C^{2} \mathrm{~d} \Omega
\end{aligned}
$$

## Well-posed Boundary Conditions

Again, integrating by parts yields:

$$
I_{2}=\left(r_{d}-r_{f}\right) \int_{0}^{V}\left(C^{2}(v, X, \tau)-C^{2}(v,-X, \tau)\right) \mathrm{d} v
$$

and

$$
\begin{aligned}
I_{3}= & \int_{0}^{V}((v
\end{aligned} \quad \begin{aligned}
& \left.(\tau(\tau) \xi(\tau)) \int_{-X}^{X} \frac{\partial C^{2}}{\partial x} \mathrm{~d} x\right) \mathrm{d} v= \\
& \\
& \quad \int_{0}^{V}(v+\rho(\tau) \xi(\tau))\left(C^{2}(v, X, \tau)-C^{2}(v,-X, \tau)\right) \mathrm{d} v .
\end{aligned}
$$

## Convection terms

$$
\begin{aligned}
& \int_{\Omega} C B^{\top} \nabla C \mathrm{~d} \Omega=\frac{1}{2} \int_{-X}^{X}\left(k(\tau)(\theta(\tau)-V)-\frac{1}{2} \xi^{2}(\tau)\right) C^{2}(x, V, \tau) \mathrm{d} x \\
& -\frac{1}{2} \int_{-X}^{X}\left(k(\tau) \theta(\tau)-\frac{1}{2} \xi^{2}(\tau)\right) C^{2}(x, 0, \tau) \mathrm{d} x+\frac{k(\tau)}{2} \iint_{\Omega} C^{2} \mathrm{~d} \Omega \\
& \quad+\frac{1}{2} \int_{0}^{V}\left(\left(r_{d}-r_{f}\right)-\frac{1}{2}(v+\rho(\tau) \xi(\tau))\right) C^{2}(v, X, \tau) \mathrm{d} v \\
& \quad-\frac{1}{2} \int_{0}^{V}\left(\left(r_{d}-r_{f}\right)-\frac{1}{2}(v+\rho(t) \xi(\tau))\right) C^{2}(v,-X, \tau) \mathrm{d} v
\end{aligned}
$$

Left boundary $\Gamma_{l}: x=-X$

$$
\begin{aligned}
-\frac{1}{2} \int_{0}^{V} & {\left[v\left(\rho(\tau) \xi(\tau) \frac{\partial C}{\partial x}(-X, V, \tau)+\frac{\partial C}{\partial v}(-X, V, \tau)\right)\right.} \\
& \left.\quad+\left(\left(r_{d}-r_{f}\right)-\frac{1}{2}(v+\rho(\tau) \xi(\tau))\right) C^{2}(-X, V, \tau)\right] \mathrm{d} v .
\end{aligned}
$$

Well-posed Boundary Conditions
Down boundary $\Gamma_{d}: v=0$

$$
\frac{1}{2} \int_{-X}^{X}\left(k(\tau) \theta(\tau)-\frac{1}{2} \xi^{2}(\tau)\right) C^{2}(x, 0, \tau) \mathrm{d} x
$$

Well-posed Boundary Conditions

## Right boundary $\Gamma_{r}: x=X$

$$
\begin{aligned}
& \frac{1}{2} \int_{0}^{V}\left(\rho(\tau) \xi(\tau) \frac{\partial C}{\partial x}(X, v, \tau)+\frac{\partial C}{\partial v}(X, v, \tau)\right) \mathrm{d} v \\
& \quad+\frac{1}{2} \int_{0}^{V}\left(\left(r_{d}-r_{f}\right)-\frac{1}{2}(v+\rho(\tau) \xi(\tau))\right) C^{2}(X, v, \tau) \mathrm{d} v .
\end{aligned}
$$

## Up boundary $\Gamma_{u}: v=V$

$$
\begin{aligned}
& \frac{v}{2} \int_{-X}^{X}\left(\xi^{2}(\tau)\right. \\
& \left.\quad \frac{\partial C}{\partial x}(x, V, \tau)+\rho(\tau) \xi(\tau) \frac{\partial C}{\partial v}(x, V, \tau)\right) \mathrm{d} x \\
& \quad+\frac{1}{2} \int_{-X}^{X}\left(k(\tau)(\theta(t)-V)-\frac{1}{2} \xi^{2}(\tau)\right) C^{2}(x, V, \tau) \mathrm{d} x .
\end{aligned}
$$

Observations Definition

## Reconstruction Problem

## Reconstruction Problem

We have a set of market measurements $\left\{\omega_{\beta}^{\alpha}\right\}$, where $\omega_{\beta}^{\alpha}$ is the quoted price of an option with maturity $T_{\alpha}, \alpha=1, \ldots, M_{T}$ and strikes $K_{\beta}, \beta=1, \ldots, N$, assuming that $T_{1} \leqslant \ldots \leqslant T_{M_{T}}$.

## Reconstruction Problem

We have a set of market measurements $\left\{\omega_{\beta}^{\alpha}\right\}$, where $\omega_{\beta}^{\alpha}$ is the quoted price of an option with maturity $T_{\alpha}, \alpha=1, \ldots, M_{T}$ and strikes $K_{\beta}, \beta=1, \ldots, N$, assuming that $T_{1} \leqslant \ldots \leqslant T_{M_{T}}$.

We minimize the following

## Cost Function

$$
\begin{aligned}
& \Gamma_{\alpha}(\xi)=\frac{1}{N} \sum_{\beta=1}^{N}\left[c_{\beta}\left(\xi_{\alpha}\left(\tau_{\alpha}\right) ; K_{\beta}, T_{\alpha}\right)-\omega_{\beta}^{\alpha}\right]^{2} \chi_{\beta}^{\alpha} \\
& \\
& \tau_{\alpha} \in\left(0, T_{\alpha}\right], \quad \alpha=1, \ldots, M_{T}
\end{aligned}
$$

where $c_{\beta}\left(\xi_{\alpha}\left(\tau_{\alpha}\right) ; K_{\beta}, T_{\alpha}\right)$ is the numerical solution of (1) with strike $K_{\beta}$ and expiry time $T_{\alpha}$.

Algorithm

## Step 1

## Step 1

## Step 1.1

We find $\mu_{1}$ that minimizes the cost function

$$
\Gamma_{1}(\xi)=\frac{1}{N} \sum_{\beta=1}^{N}\left[c_{\beta}\left(\xi_{1}\left(\tau_{1}\right) ; K_{\beta}, T_{1}\right)-\omega_{\beta}^{1}\right]^{2} \chi_{\beta}^{1},
$$

$\tau_{1} \in\left(0, T_{1}\right]$.

## Step 1

## Step 1.1

We find $\mu_{1}$ that minimizes the cost function

$$
\Gamma_{1}(\xi)=\frac{1}{N} \sum_{\beta=1}^{N}\left[c_{\beta}\left(\xi_{1}\left(\tau_{1}\right) ; K_{\beta}, T_{1}\right)-\omega_{\beta}^{1}\right]^{2} \chi_{\beta}^{1},
$$

$$
\tau_{1} \in\left(0, T_{1}\right]
$$

## Step 1.2

We assume that the volvol function on $\left(0, T_{1}\right]$ is constant, defined as $\left\{\xi_{1}(\tau)\right\}=\mu_{1}$. Then we have

$$
\xi(\tau)=\xi_{1}(\tau) \quad \text { for } \tau \in\left[0, T_{1}\right]
$$

## Algorithm



Figure: $\xi_{1}(\tau)$

## Step 2

## Step 2

## Step 2.1

We find $\mu_{2}$ that minimizes the cost function

$$
\Gamma_{2}(\xi)=\frac{1}{N} \sum_{\beta=1}^{N}\left[c_{\beta}\left(\xi_{2}\left(\tau_{2}\right) ; K_{\beta}, T_{2}\right)-\omega_{\beta}^{2}\right]^{2} \chi_{\beta}^{2},
$$

$\tau_{2} \in\left(0, T_{2}\right]$.

## Step 2

## Step 2.1

We find $\mu_{2}$ that minimizes the cost function

$$
\Gamma_{2}(\xi)=\frac{1}{N} \sum_{\beta=1}^{N}\left[c_{\beta}\left(\xi_{2}\left(\tau_{2}\right) ; K_{\beta}, T_{2}\right)-\omega_{\beta}^{2}\right]^{2} \chi_{\beta}^{2},
$$

$$
\tau_{2} \in\left(0, T_{2}\right]
$$

## Step 2.2

We assume that the volvol function on $\left(0, T_{1}\right]$ is linear, defined as $\xi_{2}(\tau)=a \tau+b$. Then we have

$$
\xi(\tau)=\xi_{2}(\tau) \quad \text { for } \tau \in\left[0, T_{2}\right]
$$

## Algorithm



Figure: $\xi_{2}(\tau)$

## Step 3

Step 3 is repeated from $\alpha=3$ to $\alpha=M_{T}$.

## Step 3

Step 3 is repeated from $\alpha=3$ to $\alpha=M_{T}$.

## Step 3.1

We find $\mu_{\alpha}:=\left\{\xi_{\alpha}\right\}$ that minimizes the cost function

$$
\Gamma_{\alpha}(\xi)=\frac{1}{N} \sum_{\beta=1}^{N}\left[c_{\beta}\left(\xi_{\alpha}\left(\tau_{\alpha}\right) ; K_{\beta}, T_{\alpha}\right)-\omega_{\beta}^{\alpha}\right]^{2} \chi_{\beta}^{\alpha},
$$

$$
\tau_{\alpha} \in\left(0, T_{\alpha}\right]
$$

## Step 3

Step 3 is repeated from $\alpha=3$ to $\alpha=M_{T}$.

## Step 3.1

We find $\mu_{\alpha}:=\left\{\xi_{\alpha}\right\}$ that minimizes the cost function

$$
\Gamma_{\alpha}(\xi)=\frac{1}{N} \sum_{\beta=1}^{N}\left[c_{\beta}\left(\xi_{\alpha}\left(\tau_{\alpha}\right) ; K_{\beta}, T_{\alpha}\right)-\omega_{\beta}^{\alpha}\right]^{2} \chi_{\beta}^{\alpha}
$$

$$
\tau_{\alpha} \in\left(0, T_{\alpha}\right]
$$

## Step 3.2

We define the linear volvol function $\xi_{\alpha}(\tau)$ on $\left[T_{\alpha-3 / 2}, T_{\alpha}\right]$ as

$$
\xi_{\alpha}(\tau)=\frac{\mu_{\alpha}-\mu_{\alpha-1}}{T_{\alpha}-T_{\alpha-3 / 2}}\left(\tau-T_{\alpha}\right)+\mu_{\alpha}
$$

## Algorithm



Figure: $\xi_{3}(\tau)$

## Step 3

## Step 3

If $\alpha=2$, then the volvol function is linear:

$$
\xi(\tau)=\xi_{2}(\tau) \quad \text { for } \tau \in\left[0, T_{2}\right]
$$

## Step 3

If $\alpha=2$, then the volvol function is linear:

$$
\xi(\tau)=\xi_{2}(\tau) \quad \text { for } \tau \in\left[0, T_{2}\right]
$$

If $\alpha \geqslant 3$, the volvol function is piecewise linear:

$$
\xi(\tau)= \begin{cases}\xi_{2}(\tau) & \text { for } \tau \in\left[0, T_{3 / 2}\right] \\ \xi_{j}(\tau) & \text { for } \tau \in\left[T_{j-3 / 2}, T_{j-1 / 2}\right] \text { for } 2<j<\alpha, \\ \xi_{\alpha}(\tau) & \text { for } \tau \in\left[T_{\alpha-3 / 2}, T_{\alpha}\right]\end{cases}
$$

## Step 3

If $\alpha=2$, then the volvol function is linear:

$$
\xi(\tau)=\xi_{2}(\tau) \quad \text { for } \tau \in\left[0, T_{2}\right]
$$

If $\alpha \geqslant 3$, the volvol function is piecewise linear:

$$
\xi(\tau)= \begin{cases}\xi_{2}(\tau) & \text { for } \tau \in\left[0, T_{3 / 2}\right] \\ \xi_{j}(\tau) & \text { for } \tau \in\left[T_{j-3 / 2}, T_{j-1 / 2}\right] \text { for } 2<j<\alpha, \\ \xi_{\alpha}(\tau) & \text { for } \tau \in\left[T_{\alpha-3 / 2}, T_{\alpha}\right]\end{cases}
$$

Finally, we arrive at the recovered volvol function $\xi(\tau)$ for $\tau \in\left(0, T_{M_{T}}\right]$.

For our synthetic data test we take

- $x_{\text {min }}=-6$
- $x_{\text {max }}=6$
- $v_{\text {min }}=0$
- $v_{\text {max }}=10$
- $T=5$ years
- $r_{d}=0.05$
- $r_{f}=0$
- $\theta(\tau)=0.2$
- $k(\tau)=2$
- $\rho(\tau)=-0.5$
- $\xi(\tau)=0.005+0.004 \log (\tau+1 / 3)$

For our synthetic data test we take

- $x_{\text {min }}=-6$
- $x_{\text {max }}=6$
- $v_{\text {min }}=0$
- $v_{\text {max }}=10$
- $T=5$ years
- $r_{d}=0.05$
- $r_{f}=0$
- $\theta(\tau)=0.2$
- $k(\tau)=2$
- $\rho(\tau)=-0.5$
- $\xi(\tau)=0.005+0.004 \log (\tau+1 / 3)$

When solving the direct problem we take $\triangle \tau=1 / 52$.

## Option Price



Figure: Option price


Figure: True and recovered volvol


Figure: True and recovered volvol with perturbed observations

## Implications

## Implications

The model suits the real market situation.

We adopt a predictor-corrector mechanism. At the first step, we assume the volatility is constant. Further, our algorithm builds a linear forward step, which corrects the volatility at half-backward time level. This is done for all the steps except the last one.

The reconstructed volvol function is piecewise linear.

The method does not require to invert a formula or an equation.

The algorithm is robust since we need to find only scalar parameters at each step.

## Conclusion

## Conclusion

Future research:

## Conclusion

Future research:

- Dupire equation


## Conclusion

Future research:

- Dupire equation
- regularization, e. g. of Tikhonov type


## Conclusion

Future research:

- Dupire equation
- regularization, e. g. of Tikhonov type
- higher order and/or nonstandard finite difference schemes


## Conclusion

Future research:

- Dupire equation
- regularization, e. g. of Tikhonov type
- higher order and/or nonstandard finite difference schemes
- American and exotic options

Thank you for your attention!

