

Convex Regularization of Local Volatility Models from Option Prices: Convergence Analysis and Rates

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Joint work with **J. P. Zubelli (IMPA)** and **O. Scherzer (Univ. Vienna)**



Outline

Asset Models and Option Pricing
The Formulation of the Inverse Problem
Properties of F and ill-posedness of the inverse problem
State of the art from the literature
Non-quadratic regularization of calibration problem
Exponential Families
Conclusions

Plan

- 1 Asset Models and Option Pricing
- 2 The Formulation of the Inverse Problem
- 3 Properties of F and ill-posedness of the inverse problem
- 4 State of the art from the literature
- 5 Non-quadratic regularization of calibration problem
 - Convergence
 - Convergence rates
- 6 Exponential Families
- 7 Conclusions



Derivative Contracts

European Call Option: a forward contract that gives the holder the right, but not the obligation, to buy one unit of an underlying asset for an agreed *strike price* K on the *maturity* date T .



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European Call Option: a forward contract that gives the holder the right, but not the obligation, to buy one unit of an underlying asset for an agreed *strike price* K on the *maturity* date T .

Its payoff is given by

$$h(X_T) = \begin{cases} X_T - K & \text{if } X_T > K, \\ 0 & \text{if } X_T \leq K. \end{cases}$$

Fundamental Question *How to price such an obligation given today's information?*



Main Contributions

- L. Bachelier (Paris)
- P. Samuelson
- F. Black
- M. Scholes
- R. Merton

recognized by the Nobel prize in
Economics award to R. Merton and
M. Scholes



Black-Scholes Market Model

We consider the Black-Scholes equation (see Black-Scholes-1973):

$$U_t + \frac{1}{2}\sigma^2(t, X)X^2U_{XX} + (r - q)XU_X = rU, \quad (1)$$

$$U^{t,S}(t = T, X) = \max(X - K, 0) \quad \text{European Call} \quad (2)$$

Here, $X = X(t)$ denotes the spot price, K is called strike, T the maturity, r is the interesting rate, q the dividends and $\sigma(t, X)$ is the local volatility.



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Note 2 Final Value Problem

Remark Constant volatility model - Nobel Prize: Robert Merton and Myron Scholes



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Limitations ...



Local Volatility Models

Idea Assume that the volatility is given by

$$\sigma = \sigma(t, x)$$

i.e.: it depends on time and the asset price.

The Direct Problem

Given $\sigma = \sigma(t, x)$ and the payoff information, determine

$$U = U(t, x, T, K; \sigma)$$



The Inverse Problem

Given a set of observed prices

$$\{U = U(t, x, T, K; \sigma)\}_{(T, K) \in \mathcal{S}}$$

find the volatility $\sigma = \sigma(t, x)$.

The set \mathcal{S} is taken typically as $[T_1, T_2] \times [K_1, K_2]$.

In Practice Very limited and scarce data



The Smile Curve and Dupire's Equation

Assuming that there exists a local volatility function $\sigma = \sigma(S, t)$

Dupire(1994) showed that the call price satisfies

$$\begin{cases} \partial_T U - \frac{1}{2} \sigma^2(K, T) K^2 \partial_K^2 U + rS \partial_K U = 0, & S > 0, t < T \\ U(K, T = 0) = (S - K)^+, \end{cases} \quad (3)$$

Theoretical way of evaluating the local volatility



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$$\sigma(K, T) = \sqrt{2 \left(\frac{\partial_T U + rK \partial_K U}{K^2 \partial_K^2 U} \right)} \quad (4)$$

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Early Results

Bouchoev-Isakov Uniqueness and “Stability”

Consider the case of **time-independent volatility** and working with $y = \log(K/S(0))$ $\tau = T - t$. Suppose $U(y, \tau)$ and $a(y) = \sigma(K)$ satisfies (3) with

$$U(y, 0) = S(0)(1 - e^y)^+, y \in \mathbb{R} \quad (5)$$

$$U(y, \tau^*) = U^*(y), y \in I \quad (6)$$

where I is a sub-interval of \mathbb{R} . Then, we have

- Uniqueness of the volatility
- Stability of the volatility in the Hölder λ -norm w.r.t. to variations of the data on the $2 + \lambda$ -norm. (i.e., one needs TWO extra derivatives of the data).



Early Results

More precisely

Theorem (Bouchouev & Isakov)

Let U_1 and U_2 be solutions of (3-6) with $a = a_1$ and $a = a_2$, resp., and the corresponding final data in Eq. (6) given by U_1^* and U_2^* . Let I_0 be an open interval with $I \supset I_0 \neq \emptyset$. Then,

- 1 If $U_1^* = U_2^*$ on I and $a_1(y) = a_2(y)$ on I_0 then $a_1(y) = a_2(y)$ on I .
- 2 If, in addition, $a_1(y) = a_2(y)$ on $I_0 \cup (\mathbb{R} \setminus I)$ and I is bounded, then $\exists C = C(|a_1|_\lambda(I), |a_2|_\lambda(I), I, I_0, \tau^*)$ s.t.

$$|a_1 - a_2|_\lambda(I) \leq |U_1^* - U_2^*|_{2+\lambda}(I)$$



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Joint work with J.P. Zubelli & O. Scherzer

Start from

$$-U_t + \frac{1}{2}\sigma^2(T, K)K^2 U_{KK} - (r - q)KU_K - qU = 0 \quad (7)$$

$$U^{t,X}(T = t, K) = (X - K)^+, \quad \text{for } K > 0, \quad (8)$$

Setting $K = Xe^y$, $\tau = T - t$, $u(\tau, y) = \exp\left(\int_t^T q(s) ds\right)U(\cdot, T, K)$,
 $b(\tau) = q(\tau) - r(\tau)$ and

$$a(\tau, y) = \frac{1}{2}\sigma^2(\tau; K) \quad (9)$$

yields



$$-u_\tau + a(\tau, y)(u_{yy} - u_y) + b(\tau)u_y = 0 \quad (10)$$

$$u(0, y) = X(1 - e^y)^+. \quad (11)$$

The parameter-to-solution map F is defined by

$$F(a) = u(a), \quad (12)$$

where $u(a)$ is the solution of (10) for $a \in \mathcal{D}(F)$.

We assume noise data u^δ satisfies the inequality

$$\|u^* - u^\delta\|_{L^2(\Omega)} \leq \delta. \quad (13)$$



Properties of F and ill-posedness of the inverse problem

- i) There exists a $p^* > 2$ such that $F : \mathcal{D}(F) \rightarrow W_p^{2,1}(\Omega)$ is continuous and compact for $2 \leq p < p^*$. Moreover, F is weakly (sequentially) continuous and thus weakly closed.
- ii) F is Gateaux differentiable w.r.t. $a \in \mathcal{D}(F)$ in directions h such that $a + h \in \mathcal{D}(F)$, and the derivative $F'(a)$ extends as a linear operator to $H^1(\Omega)$.
- iii) $F'(a)$ is injective and compact. Moreover $\overline{\mathcal{R}(F'(a)^*)} = H^1(\Omega)$.

Proof: see DC & Scherzer & Zubelli (2009) and Egger & Engl (2005) or Crepey (2003).



Ill-posedness in more details

- $\mathcal{D}(F) := \{a \in a_0 + H^1 : \underline{a} \leq a, a_0 \leq \bar{a}\}$.
- $a_k \rightarrow \tilde{a}$ with $u_k = F(a_k) \rightarrow \tilde{u} = F(\tilde{a})$
similar prices u_k and \tilde{u} linked with completely different volatilities

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- Tikhonov regularization

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- source wise condition **equivalent** what we assume know about the inverse solution
- convergence rates to Tikhonov for quadratic penalization $\|a^\delta - a^\dagger\| = O(\sqrt{\delta})$
- **Our approach: convex regularization** $\beta f(\cdot)$ with f convex, positive, etc...

State of the art from the literature

Let the standard choice of regularization parameter $\beta = \beta(\delta) \sim \delta$.

- (i) If $f(\cdot) = \|\cdot\|_{H^1(\Omega)}^2$, then we have the convergence rate results (Egger & Engl(2005))

$$\|a_{\beta}^{\delta} - a^{\dagger}\|_{H^1(\Omega)} = O(\sqrt{\delta}) \text{ and } \|F(a_{\beta}^{\delta}) - u^{\delta}\|_{L^2(\Omega)} = O(\delta), \quad (14)$$

assuming the source-wise representation $a^* - a^{\dagger} = F'(a^{\dagger})^* w$.

- (ii) In (Hoffman & Kramer (2005)), with

$f(a(\tau)) = \int_I \{a(\tau) \ln \frac{a(\tau)}{\bar{a}(\tau)} + \bar{a}(\tau) - a(\tau)\} d\tau$ the convergence rate results

$$\|a_{\beta}^{\delta} - a^{\dagger}\|_{L^1([0, T])} = O(\sqrt{\delta}) \quad (15)$$

using a source-wise representation $\ln \frac{a^{\dagger}}{a^*} = F'(a^{\dagger})^* w$.



- iii) With $f(\cdot) = \|\cdot\|_{L^2([0, T])}^2$, (Hoffman et al. (2006)) obtained the same rates of (Hoffman & Kramer (2005) (volatility time-dependent only) assuming the source wise representation

$$\xi^\dagger = F'(a^\dagger)^* w \in \partial f(a^\dagger) \quad (16)$$

in terms of Bregman distances.

Our approach

Minimize the functional

$$\mathcal{F}_{\beta, u^\delta}(a) := \frac{1}{2} \|F(a) - u^\delta\|_{L^2(\Omega)}^2 + \beta f(a), \quad (17)$$

where $f : \text{dom}(f) \subset \mathbb{B}_1 \rightarrow [0, \infty]$ is a convex, proper and lower semi-continuous stabilization functional.



Convergence

Theorem (Existence, Stability, Convergence)

Suppose that F , f , $\mathcal{D}(F)$ as above, $\beta > 0$ and (13) holds. Then

- There exists a minimizer of $\mathcal{F}_{\beta, u^\delta}$.
- If $(u_k) \rightarrow u$ in $L^2(\Omega)$, then every sequence (a_k) with

$$a_k \in \operatorname{argmin} \{ \mathcal{F}_{\beta, u_k}(a) : a \in \mathcal{D}(F) \}$$

has a subsequence which weak converges. The limit of every w -convergent subsequence $(a_{k'})$ of (a_k) is a minimizer \tilde{a} of $\mathcal{F}_{\beta, u}$, and $(f(a_{k'}))$ converges to $f(\tilde{a})$.



Theorem (Semi-convergence)

- *If there exists a solution of (12) in $\mathcal{D}(F)$, then there exists an f -minimizing solution of (12).*
- *Assume that (12) has a solution in $\mathcal{D}(F)$ (which implies the existence of an f -minimizing solution) and that $\beta : (0, \infty) \rightarrow (0, \infty)$ satisfies*

$$\beta(\delta) \rightarrow 0 \text{ and } \frac{\delta^2}{\beta(\delta)} \rightarrow 0, \text{ as } \delta \rightarrow 0. \quad (18)$$

Moreover, $(\delta_k) \rightarrow 0$, and that $u_k := u^{\delta_k}$ satisfies $\|\bar{u} - u_k\| \leq \delta_k$. Set $\beta_k := \beta(\delta_k)$. Then, every sequence (a_k) of elements minimizing $\mathcal{F}_{\beta_k, u_k}$, has a subsequence $(a_{k'})$ that is w -convergent. The limit a^\dagger of any w -convergent subsequence $(a_{k'})$ is an f -minimizing solution of (12), and $f(a_k) \rightarrow f(a^\dagger)$.

Lemma

Let $\zeta^\dagger \in \partial f(a^\dagger)$. Then There exists a function $w^\dagger \in L^2(\Omega)$ and a function $r \in H^1(\Omega)$ such that

$$\zeta^\dagger = F'(a^\dagger)^* w^\dagger + r \quad (19)$$

holds. Furthermore, $\|r\|_{H^1(\Omega)}$ can to be taken arbitrarily small.

Definition

Let $1 \leq q < \infty$. Moreover, let \tilde{U} be a subset of H^1 . The Bregman distance $D_\zeta(\cdot, \tilde{a})$ of $f : H^1 \rightarrow \mathbb{R} \cup \{+\infty\}$ at $\tilde{a} \in \mathcal{D}_B(f)$ and $\zeta \in \partial f$ is said to be q -coercive with constant $\underline{c} > 0$ if

$$D_\zeta(a, \tilde{a}) \geq \underline{c} \|a - \tilde{a}\|_{\tilde{U}}^q \quad \forall a \in \mathcal{D}(f). \quad (20)$$

Convergence rates

Lemma

Let $\zeta^\dagger \in \partial f(a^\dagger)$ satisfy (19) with w^\dagger and r such that

$$\underline{c}(C\|w^\dagger\|_{L^1(\Omega)} + \|r\|_{L^2(\Omega)}) := \beta_1 \in [0, 1),$$

and the Bregman distance with respect to f is 1 – coercive (as in the Definition 6.1) with $\tilde{U} := H^1(\Omega)$. Then,

$$\langle \zeta^\dagger, a^\dagger - a \rangle \leq \beta_1 D_{\zeta^\dagger}(a, a^\dagger) + \beta_2 \|F(a) - F(a^\dagger)\|_{L^2(\Omega)}, \quad (21)$$

for $a \in \mathcal{M}_{\beta_{max}}(\rho)$, where $\beta_{max}, \rho > 0$ satisfy the relation $\rho > \beta_{max} f(a^\dagger)$.



Theorem (Convergence rates)

Let $\beta : (0, \infty) \rightarrow (0, \infty)$ satisfy $\beta(\delta) \sim \delta$ and (21) satisfied. Then,

$$D_{\zeta^\dagger}(a_\beta^\delta, a^\dagger) = O(\delta), \quad \text{and} \quad \|F(a_\beta^\delta) - u^\delta\|_{L^2(\Omega)} = O(\delta),$$

and there exists $c > 0$, such that $f(a_\beta^\delta) \leq f(a^\dagger) + \delta/c$ for every δ with $\beta(\delta) \leq \beta_{max}$.

Proof: See DC & Scherzer & Zubelli (2009).

Example (q -coercive Bregman distance)

- i) $f(a) := q^{-1} \|a - a^\dagger\|_{\tilde{U}}^q$.
- ii) Let $1 < q \leq 2$. We consider the functional

$$f(a) = \sum_{n=1}^{\infty} |\langle a, \phi_n \rangle|^q,$$

where $\{\phi_n\}$ is an orthonormal basis in $H^1(\Omega)$. The Bregman distance of the functional f satisfies

$$f(a) - f(a^\dagger) - \langle \partial f(a^\dagger), a - a^\dagger \rangle \geq C \sum_{n=1}^{\infty} |\langle a - a^\dagger, \phi_n \rangle|^2 = C \|a - a^\dagger\|_{H^1(\Omega)}^2.$$



Exponential Families

Definition (Regular Exponential Family)

Let $\psi : \mathbb{R} \rightarrow \mathbb{R}_+$ be convex and $p_0 : \mathbb{R} \rightarrow \mathbb{R}_+$ be continuous. The family of functions $p_{\psi, \theta} : \mathbb{R} \rightarrow \mathbb{R}_+$ defined by

$$p_{\psi, \theta}(s) := \exp(s \cdot \theta - \psi(\theta)) p_0(s) \quad (\text{regular exponential family}).$$

Theorem (Banerjee et al. [?])

Let ψ^* the Fenchel transform of ψ (differentiable) and $a(\theta) \in \text{int}(\text{dom}(\psi^*))$. Then,

$$p_{\psi, \theta}(a) = \exp(-D_{\psi^*}(a, a(\theta))) \exp(\psi^*(a)) p_0(a). \quad (22)$$

Exponential Families and Fenchel conjugate

Example (Exponential Families and Fenchel conjugate)

Gaussian distribution $\psi(\theta) = \frac{\sigma^2}{2} \theta^2$, then $\psi^*(a) = \frac{a^2}{2\sigma^2}$. *Poisson distribution* $\psi(\theta) = \exp(\theta)$ we have $\psi^*(a) = a \log(a) - a$.

Bregman distance regularization as a log-maximum a-posteriori estimator for an exponential family.

The probability (normally and identically distributed) of observing $u_i^\delta := u^\delta(x_i)$ given $u_i := F(a)(x_i)$ is given by

$$p(u_i^\delta | u_i) = \frac{1}{\varpi \sqrt{2\pi}} \exp\left(-\frac{|u_i^\delta - u_i|^2}{2\varpi^2}\right).$$

where $a_i = a(x_i) \in \mathbb{R}$.



According to Theorem 7

$$p(a) = \exp(-D_{\Psi^*}(\hat{a}, a)) \exp(\Psi^*(\hat{a})) p_0(\hat{a}) .$$

The Log-maximum estimation then consists in minimizing the functional

$$\vec{a} \mapsto \sum_i \left(-\log(p(u_i^\delta | u_i)) - \log(p(a_i)) \right) ,$$

which is equivalent to minimizing the functional

$$\vec{a} \mapsto \sum_i (u_i - u_i^\delta)^2 + \beta \sum_i D_{\Psi^*}(\hat{a}_i, a_i) ,$$

where $\beta = 2\sigma^2$.



Example

Exponential family associated to Poisson distributions, consisting in minimization of

$$a \mapsto \mathcal{F}_{\beta, u^\delta}(a) := \|F(a) - u^\delta\|_{L^2(\Omega)}^2 + \beta KL(\hat{a}, a), \quad (23)$$

where

$$KL(\hat{a}, a) = \int_{\Omega} a \log(\hat{a}/a) - (\hat{a} - a) dx .$$

Lemma

$\Omega \subset \mathbb{R}^2$ bounded and $F : L^1(\Omega) \longrightarrow L^2(\Omega)$ is continuous with respect to the weak topologies, respectively.

1 Let $a, b \in \mathcal{D}(\mathcal{G})$. Then

$$\|a - b\|_{L^1(\Omega)}^2 \leq \left(\frac{2}{3} \|a\|_{L^1(\Omega)} + \frac{4}{3} \|b\|_{L^1(\Omega)} \right) KL(a, b). \quad (24)$$

2 For sequences $(a_k)_k$ and $(b_k)_k$ in $L^1(\Omega)$, such that one of them is bounded: If $KL(a_k, b_k) \rightarrow 0$, then $\|a_k - b_k\|_{L^1(\Omega)} \rightarrow 0$.

3 Let $0 \neq \hat{a} \in \mathcal{D}_B(\mathcal{G})$, $\mathcal{M}_{\beta, u^\delta}(M) := \{a \in \mathcal{D}_B(\mathcal{G}) : \mathcal{F}_{\beta, u^\delta}(a) \leq M\}$ are weak sequentially compact.



Convergence analysis

Using standard results on variational regularization, we have:

Theorem

There exists a minimizer of $\mathcal{F}_{\beta, u^\delta}$ in (23). The minimizers are stable and convergent for $\beta(\delta) \rightarrow 0$ and $\delta^2/\beta(\delta) \rightarrow 0$. Stable means that $\operatorname{argmin} \mathcal{F}_{\beta, u^{\delta_k}} \rightarrow \operatorname{argmin} \mathcal{F}_{\beta, u^0}$ for $\delta_k \rightarrow 0$ and that $\operatorname{argmin} \mathcal{F}_{\beta(\delta_k), u^{\delta_k}}$ converges to a solution of (12) with minimal energy.

Conclusions

- The main novelty
 - i f only requires convexity properties and weak lower-semicontinuity.
 - ii we establish, for Bregman distances, better convergence rates than those available in the literature to this problem,
 - iii Another advantage of the current approach is the requirement of weaker conditions than those previously required in the literature. Namely, we only require (20).
 - iv we prove (19),
 - v and we motivate Bregman distance regularization using exponential families.



Future research

- Future research
 - i numerical implementation.
 - ii investigation of American Options.

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