

# Non-parametric calibration of jump-diffusion models

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(joint work with Rama Cont)

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## Exponential Lévy models

$$S_t = S_0 e^{rt + X_t},$$

where  $(X_t)$  is a Lévy process on  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{0 \leq t \leq T}, P)$ ,  $T < \infty$ .

$$E[e^{iuX_t}] = e^{t\psi(u)}$$

$$\psi(u) = iu\gamma - \frac{\sigma^2 u^2}{2} + \int \nu(dx) (e^{iux} - 1 - iux1_{|x| \leq 1})$$

Jump-diffusion case:  $\sigma > 0$ ,  $\nu(\mathbb{R}) < \infty$ .

No arbitrage opportunity  $\Leftrightarrow \exists Q \sim P : e^{X_t}$  is a  $Q$ -local martingale.

$$\frac{\sigma^2}{2} + \gamma + \int (e^x - 1 - x1_{|x| \leq 1}) \nu(dx) = 0.$$

Option prices:

$$C^Q(t, K) = e^{-rt} E^Q[(S_0 e^{rt + X_t} - K)^+]$$

## Examples of parametric exp-Lévy models

- Merton's model (Merton (1976)):

$$\sigma > 0, \quad \nu(x) = \frac{\lambda}{\delta\sqrt{2\pi}} e^{-\frac{(x-\theta)^2}{2\delta^2}}.$$

- Variance gamma (Madan, Milne (1991)):

$$\sigma = 0, \quad \nu(x) = \frac{Ae^{-\eta+x}}{x} \mathbf{1}_{x>0} + \frac{Ae^{-\eta-|x|}}{|x|} \mathbf{1}_{x<0}.$$

- Tempered stable (Carr, Geman, Madan, Yor (2002)):

$$\sigma = 0, \quad \nu(x) = \frac{A_+ e^{-\eta+x}}{x^{1+\alpha}} \mathbf{1}_{x>0} + \frac{A_- e^{-\eta-|x|}}{|x|^{1+\alpha}} \mathbf{1}_{x<0}.$$

## The calibration problem

- Retrieve an exponential Lévy model from prices of traded options.

$\mathcal{M}_L = \{\text{risk-neutral probabilities } Q : (X, Q) \text{ is a Lévy process}\}$

- Calibration problem for exact data, consistent with the model:  
given market prices  $C_M(T_i, K_i)$ ,  $i \in I$ , find  $\mathcal{Q}^E \subseteq \mathcal{M}_L$ :

$$\forall Q \in \mathcal{Q}^E, C_M(T_i, K_i) = C^Q(T_i, K_i) \quad \text{for all } i \in I. \quad (E)$$

- If the market data are known exactly, but are not necessarily consistent, we want our model to reproduce them in the best possible way: find  $\mathcal{Q}^{LS} \subseteq \mathcal{M}_L$ :

$$\forall Q^* \in \mathcal{Q}^{LS}, \|C_M - C^{Q^*}\|_w^2 = \inf_{Q \in \mathcal{M}_L} \|C_M - C^Q\|_w^2, \quad (LS)$$

where

$$\|C_M - C^Q\|_w^2 := \sum_{i \in I} w_i (C_M(T_i, K_i) - C^Q(T_i, K_i))^2.$$

## Ill-posedness of least squares calibration

- Lack of identification
- The problem (LS) need not have a solution
- Even if a solution does exist, it may not be continuous with respect to market data
- The solution is hard to find numerically due to non-convexity of the pricing error

# Lack of identification in least squares calibration

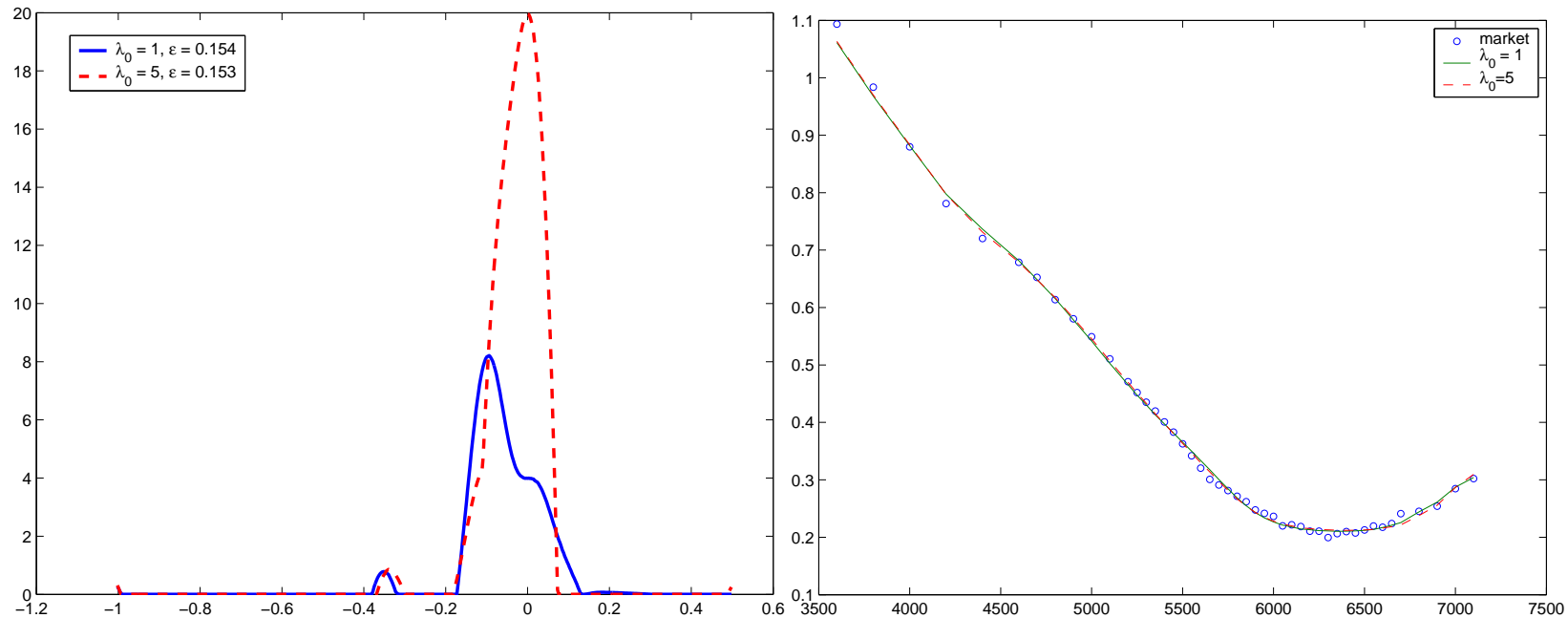


Figure 1: Left: Lévy measures calibrated by least squares, using Merton models with different intensities as initializers. Right: implied volatility smiles corresponding to these measures.

## Lack of identification: parametric case

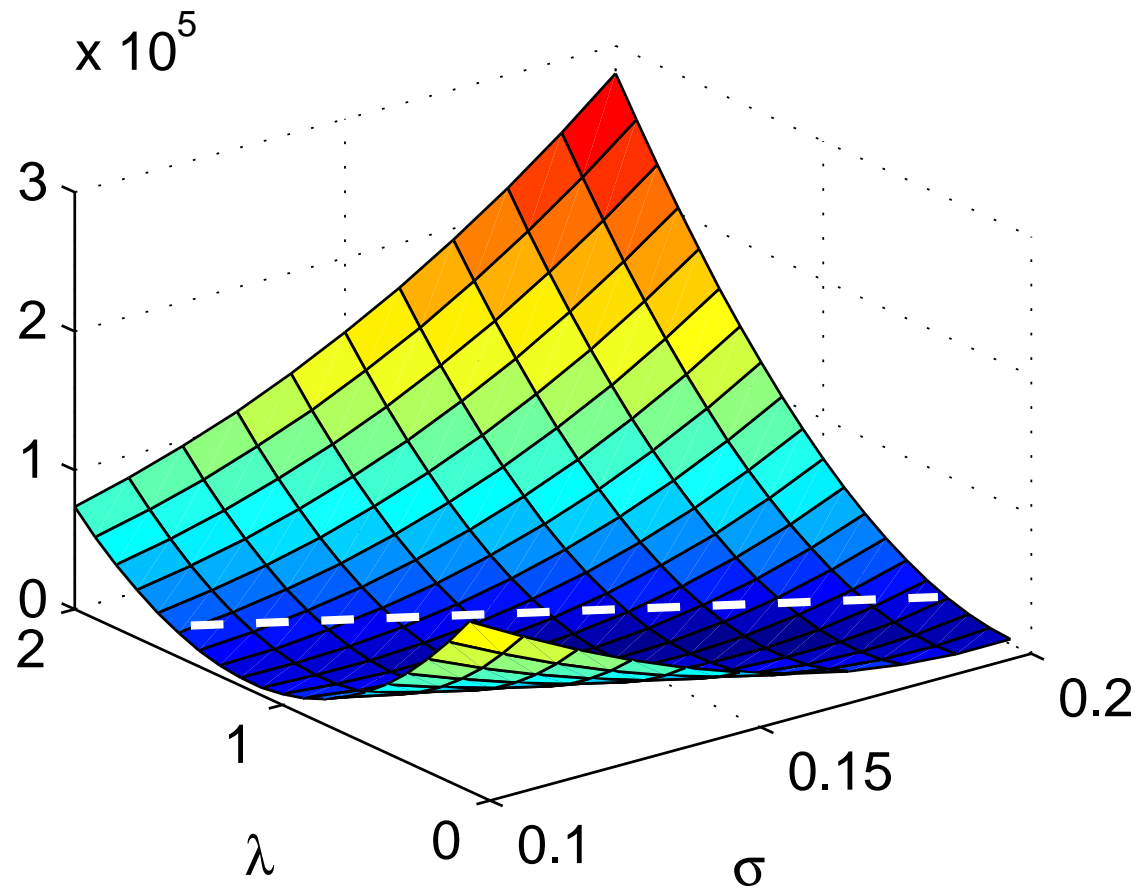


Figure 2: Error surface for Merton model: ill-posedness of the calibration problem may lead to a flat valley in error landscape

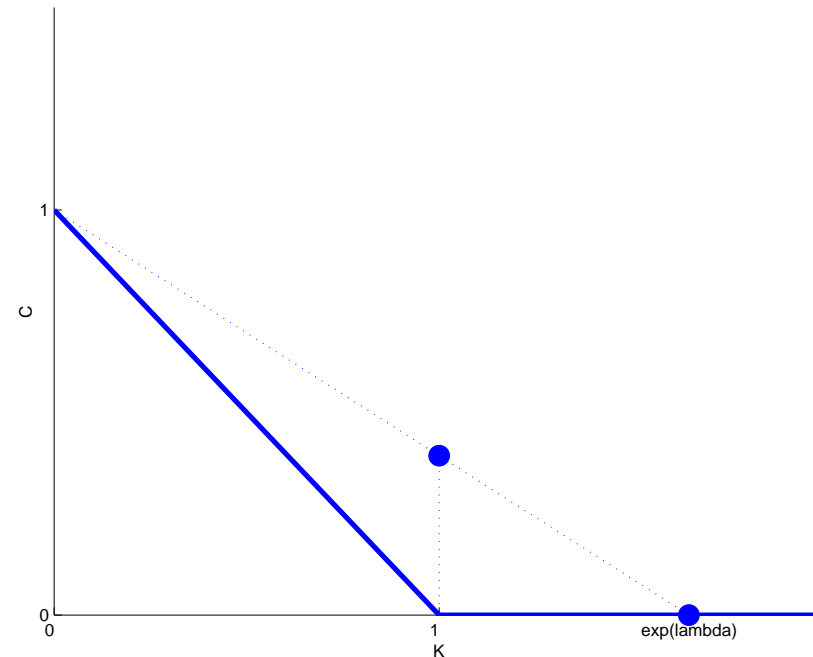
## Example of data set for which the problem (LS) has no solution

$$\begin{cases} C_M(T = 1, K = 1) = 1 - e^{-\lambda} \\ C_M(T = 1, K = e^\lambda) = 0. \end{cases}$$

From absence of arbitrage:

$$C_M(K) = (1 - Ke^{-\lambda})^+.$$

$$\Rightarrow P[S_1 \leq K] = e^{-\lambda} \mathbf{1}_{K \leq e^\lambda}.$$



$\Rightarrow$  No Lévy process is compatible with these prices

However, for the process  $X_t^n := -nN_t + \lambda t(1 - e^{-n})$ ,

$$\lim_{n \rightarrow \infty} E[(e^{X_t^n} - K)^+] = (1 - Ke^{-\lambda t})^+.$$

## Existence of solution of least squares calibration

**Theorem 1.** *Let  $\mathcal{M}_B$  denote the set of all risk-neutral probabilities  $Q$  such that  $(X, Q)$  is a Lévy process satisfying  $|\Delta X_t| \leq B$  for all  $t$ . If there exists  $Q_0 \in \mathcal{M}_B$  with*

$$\|C^{Q_0} - C_M\|_w < \sqrt{w_0}(S_0 - C_M(T_0, K_0)),$$

*then the problem (LS) has a solution in  $\mathcal{M}_B$ .*

Proof:

- The pricing error functional  $\|C_M - C^Q\|_w^2$ , is weakly continuous with respect to  $Q \in \mathcal{M}_B$ .
- The set of risk-neutral Lévy processes  $Q \in \mathcal{M}_B$  satisfying  $C^Q(T, K) \leq C < S_0$  is relatively weakly compact in  $\mathcal{M}_B$ .

## Continuity of solutions with respect to the data

**Definition 1.** *The solutions of a calibration problem are said to depend continuously on input data at the point  $C_M$  if for every sequence of data sheets  $\{C_M^n\}_{n \geq 0}$  such that  $\|C_M^n - C_M\|_w \xrightarrow[n \rightarrow \infty]{} 0$ , if  $Q_n$  is a solution of the calibration problem with data  $C_M^n$  then*

1.  $\{Q_n\}_{n \geq 1}$  has a weakly convergent subsequence  $\{Q_m\}_{m \geq 1}$ .
2. The limit  $Q$  of every convergent subsequence of  $\{Q_n\}_{n \geq 1}$  is a solution of the calibration problem with data  $C_M$ .

## Non-convexity of the pricing error functional

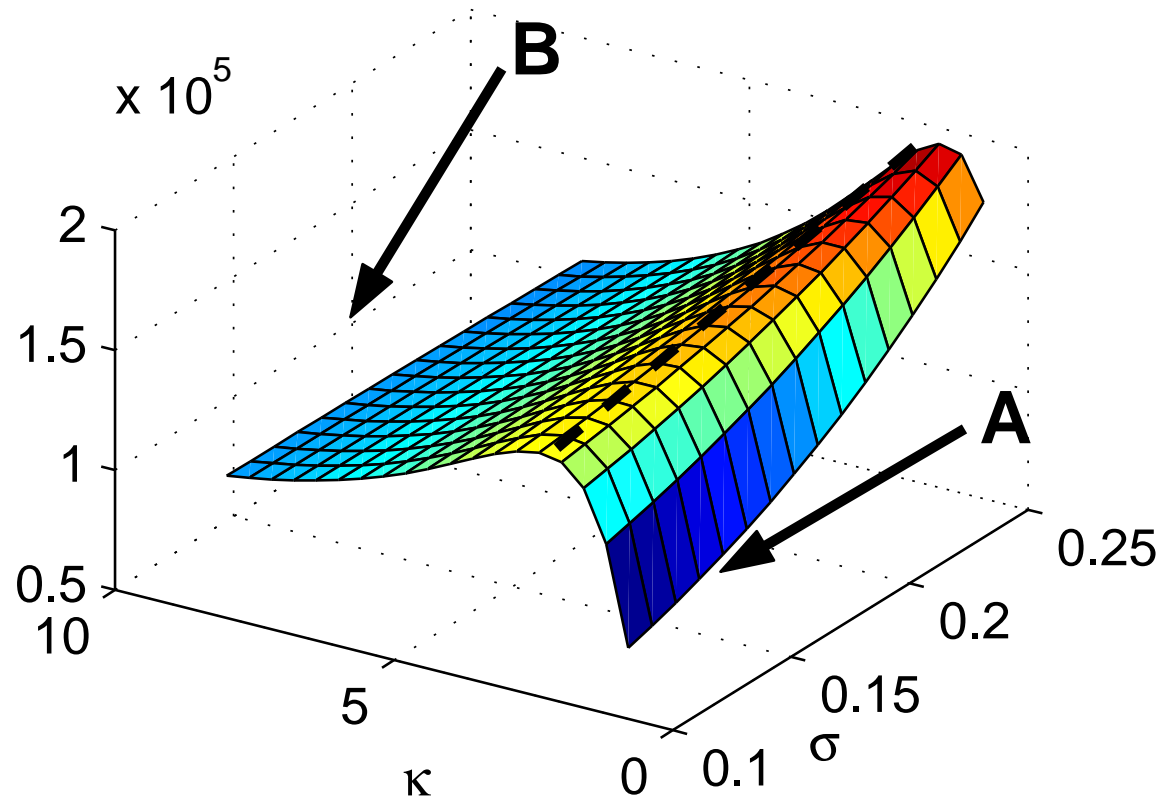


Figure 3: Error surface for variance gamma model: the error function may have distinct local minima

## Selection using relative entropy

$\mathcal{Q}^{LS}$  will typically contain many elements  $\Rightarrow$  choose the ones with smallest relative entropy with respect to a prior  $P \in \mathcal{M}_L$ :

$$\mathcal{Q}^{MELS} = \{Q^* \in \mathcal{Q}^{LS} : I(Q^*|P) = \inf_{Q \in \mathcal{Q}^{LS}} I(Q|P)\}, \quad (MELS)$$

where

$$I(Q|P) := \begin{cases} \int \frac{dQ}{dP} \log \frac{dQ}{dP} dP, & Q \ll P, \\ +\infty, & \text{otherwise.} \end{cases}$$

- Convex non-negative functional of  $Q$  for fixed  $P$ , equal to zero iff  $\frac{dQ}{dP} = 1$  a.s.
- Easy to express in terms of Lévy measures and to compute
- Well-known in the literature, many results are available (large deviations, information theory, finance, convex duality results)

## The logic of regularization: case of unique minimum entropy solution

- Suppose that for some (hypothetical) exact data  $C_M$ , there exists a unique solution to problem (*MELS*), denoted by  $C^+(C_M)$ .
- Only noisy option prices  $C_M^\delta$ , with  $\|C_M^\delta - C_M\| < \delta$ , are known
- $C^+(C_M^\delta)$  is not a good approximation of  $C^+(C_M)$  because  $C^+$  is not continuous and  $C^+(C_M^\delta)$  may not even exist

The solution: *regularize*  $C^+$ , construct a family of continuous mappings  $R_\alpha$ : for every  $\{\delta_n\}_{n \geq 1}$  with  $\delta_n \rightarrow 0$ ,

$$R_{\alpha_n}(C_M^{\delta_n}) \rightarrow C^+(C_M),$$

where  $\alpha_n$  is chosen appropriately depending on  $\delta_n$  and  $C_M^{\delta_n}$ .

## The logic of regularization: general case

- Suppose that for the exact data  $C_M$ ,  $Q^{MELS}(C_M) \neq \emptyset$ .
- Only noisy option prices  $C_M^\delta$ , with  $\|C_M^\delta - C_M\| < \delta$ , are known
- $Q^{MELS}(C_M^\delta)$  may be very different from  $Q^{MELS}(C_M)$  and may even be empty

The solution: construct a family of calibration problems  $(R_\alpha)_{\alpha>0}$  such that for every  $\{\delta_n\}_{n \geq 1}$  with  $\delta_n \rightarrow 0$ , if for every  $n$ ,  $Q_n$  is a solution of  $(R_{\alpha_n})$  with data  $C_M^{\delta_n}$ , then

- $\{Q_n\}_{n \geq 1}$  has a convergent subsequence and
- the limit of every convergent subsequence is a minimum entropy least squares solution with data  $C_M$ .

## The regularized calibration problem

To regularize problem (*MELS*), we replace it with:

$$Q^R = \arg \inf_{Q \in \mathcal{M}_L} \{ \|C_M - C^Q\|_w^2 + \alpha I(Q|P) \} \quad (R_\alpha)$$

$\Rightarrow$  the entropy is used for *penalization* rather than selection.

- The problem ( $R_\alpha$ ) has at least one solution.
- The solutions of ( $R_\alpha$ ) are continuous with respect to  $C_M$ .
- The solutions of ( $R_\alpha$ ) converge to solutions of (*MELS*) as  $\delta \rightarrow 0$ , if  $\alpha$  is chosen appropriately.
- The problem ( $R_\alpha$ ) can be discretized by taking a discretized prior, and the solutions of discretized problem converge to those of the continuous one.

## Assumptions

We suppose that the prior Lévy process,  $P = P(\sigma^P, \nu^P, \gamma^P)$  satisfies the following assumptions:

1.  $\sigma^P > 0$  and  $\nu^P(\mathbb{R}) < \infty$  (jump-diffusion).
2.  $E^P[e^{X_t}] = 1$  (the probability  $P$  is risk-neutral).
3. The support of  $\nu^P$  is bounded from above:

$$\nu^P([x_0, \infty)) = 0 \text{ for some } x_0 > 0.$$

## Conditions of absolute continuity

**Proposition 1 (Jacod & Shiryaev (2003), Theorem**

**IV.4.39).** *Let  $(X_t)_{t \geq 0}$  be a real-valued Lévy process on  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, Q)$  and on  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, P)$  with characteristic triplets  $(\sigma^Q, \nu^Q, \gamma^Q)$  and  $(\sigma^P, \nu^P, \gamma^P)$ . Then  $Q|_{\mathcal{F}_t} \ll P|_{\mathcal{F}_t}$  for all  $t$  if and only if*

1.  $\sigma^Q = \sigma^P := \sigma$ .

2.  $\nu^Q \ll \nu^P$  with  $\phi := \frac{d\nu^Q}{d\nu^P}$ .

3.  $\int_{-\infty}^{\infty} (\sqrt{\phi(x)} - 1)^2 \nu^P(dx) < \infty$ .

4. If  $\sigma = 0$  then  $\gamma^Q - \gamma^P = \int_{|x| \leq 1} x(\phi(x) - 1) \nu^P(dx)$ .

Under the above assumptions,  $Q|_{\mathcal{F}_t} \ll P|_{\mathcal{F}_t}$  for all  $t$  iff  $\sigma^Q = \sigma^P$ ,  $\nu^Q(\mathbb{R}) < \infty$ , and  $\nu^Q \ll \nu^P$ .

## Computing relative entropy of Lévy processes

**Theorem 2.** *Suppose that the conditions 1–4 of Proposition 1 are satisfied. Then*

$$I(Q|P) = I(Q|_{\mathcal{F}_T}|P|_{\mathcal{F}_T}) = T \int_{\mathbb{R}} \left( \frac{d\nu^Q}{d\nu^P} \log \frac{d\nu^Q}{d\nu^P} + 1 - \frac{d\nu^Q}{d\nu^P} \right) \nu^P(dx) \\ + \frac{T}{2\sigma^2} \left\{ \gamma^Q - \gamma^P - \int_{-1}^1 x(\nu^Q - \nu^P)(dx) \right\}^2 \mathbf{1}_{\sigma \neq 0}$$

*Remark.* If  $Q$  and  $P$  are risk-neutral measures, the second term becomes

$$\frac{T}{2\sigma^2} \left\{ \int_{-\infty}^{\infty} (e^x - 1)(\nu^Q - \nu^P)(dx) \right\}^2$$

$I(Q, P)$  becomes a convex non-negative functional of  $\nu^Q$  for fixed  $\nu^P$ , equal to zero iff  $\frac{d\nu^Q}{d\nu^P} = 1$   $\nu^P$ -a.e.

## Regularized problem in terms of density of Lévy measures

$$J(Q) = \|C_M - C^Q\|_w^2 + \alpha I(Q|P)$$

Since  $J(P) < \infty$ , we can suppose w.l.o.g. that  $Q \ll P$ .

$\Rightarrow Q$  can be parametrized by  $\phi := \frac{d\nu^Q}{d\nu^P}$ .

$$\text{Find } \phi^* \in L^1(\nu^P), \phi^* \geq 0 \quad : \quad J(\phi^*) = \inf_{\phi \in L^1(\nu^P), \phi \geq 0} J(\phi),$$

where

$$J(\phi) = \|C_M - C^{Q(\phi)}\|_w^2 + \alpha(H(\phi) + I(\phi))$$

and

$$H(\phi) = \frac{1}{2\sigma^2} \left( \int (e^x - 1)(\phi(x) - 1)\nu^P(dx) \right)^2,$$

$$I(\phi) = \int (\phi(x) \log \phi(x) + 1 - \phi(x))\nu^P(dx).$$

## Regularized problem: existence of solution

**Proposition 2.** *For all  $\alpha > 0$ , the regularized calibration problem  $(R_\alpha)$  has at least one solution  $Q_\alpha \in \mathcal{M}_L$ .*

*Proof.*

- $H(\phi)$  and  $\|C_M - C^{Q(\phi)}\|_w^2$  are weakly continuous in  $\phi$ .

$$\psi^Q(u) = -\frac{\sigma^2}{2}(u^2 + iu) + \int_{\mathbb{R}} (e^{iux} - 1 - iu - iue^x)\phi(x)\nu^P(dx)$$

- From Teboule and Vajda (1993),  $I(\phi)$  is weakly lower semicontinuous and for every  $r > 0$ ,

$$B_r := \{\phi \in L^1(\nu^P) : \phi \geq 0 \text{ and } I(\phi) \leq r\}$$

is weakly compact.

- $J(1) = \|C_M - C^P\|_w^2 \leq 4S_0^2 < \infty \Rightarrow \phi^* \in B_{J(1)}$ . □

## Regularized problem: continuity of solution with respect to data

**Proposition 3.** *Let  $\{C_M^n\}_{n \geq 0}$  be such that  $\|C_M^n - C_M\|_w \xrightarrow[n \rightarrow \infty]{} 0$  and let  $\phi_n$  be a solution of the regularized problem  $(R_\alpha)$  for some  $\alpha > 0$  with data  $C_M^n$ . Then*

1.  *$\{\phi_n\}$  has a weakly convergent subsequence*
2. *The limit of every convergent subsequence of  $\{\phi_n\}$  is a solution of the regularized problem with data  $C_M$ .*

## Regularized problem: convergence

**Theorem 3.** *Suppose that there exist a solution  $Q$  of problem (LS) with data  $C_M$  such that  $I(Q|P) < \infty$ .*

*If  $\|C_M - C^Q\|_w = 0$ , suppose that  $\alpha(\delta) \rightarrow 0$  and  $\frac{\delta^2}{\alpha(\delta)} \rightarrow 0$  as  $\delta \rightarrow 0$ .*

*Otherwise, suppose that  $\alpha(\delta) \rightarrow 0$  and  $\frac{\delta}{\alpha(\delta)} \rightarrow 0$  as  $\delta \rightarrow 0$ .*

*Let  $\{\delta_k\}_{k \geq 0}$  be such that  $\delta_k \rightarrow 0$ ,  $\{C_M^{\delta_k}\}_{k \geq 1}$  be a sequence of data sets such that  $\|C_M^{\delta_k} - C_M\|_w \leq \delta_k$  and let  $\phi^{\delta_k}$  be a solution of problem  $(R_{\alpha(\delta_k)})$  with data  $C_M^{\delta_k}$ . Then*

- 1. There exists a solution of (MELS) with data  $C_M$ .*
- 2.  $\{\phi^{\delta_k}\}_{k \geq 0}$  has a weakly convergent subsequence.*
- 3. The limit of every convergent subsequence of  $\{\phi^{\delta_k}\}$  is a solution of (MELS) with data  $C_M$ .*
- 4. If such a solution  $\phi^+$  is unique then  $\lim_{\delta \rightarrow 0} \phi^\delta = \phi^+$ .*

## Numerical implementation: computing prices of call options

- European call/put options can be priced using the fast Fourier transform (Carr & Madan)

$$C^Q(T, K) = e^{-rT} E^Q[(S_T - K)^+] = e^{-rT} \int_{-\infty}^{\infty} (e^{rT+x} - e^k)^+ q_T(x) dx$$

- Call price is not integrable  $\Rightarrow$  one cannot compute its Fourier transform directly.
- Possible solution: construct an integrable function by subtracting the intrinsic value:

$$z_T(k) = e^{-rT} E[(e^{rT+X_T} - e^k)^+] - (1 - e^{k-rT})^+$$

$$\zeta_T(v) = \int_{-\infty}^{+\infty} e^{ivk} z_T(k) dk = e^{ivrT} \frac{\Phi_T(v-i) - 1}{iv(1+iv)}$$

## Numerical implementation: discretizing the Lévy measure

- The calibration problem can be discretized by taking a discrete prior:

$$\nu^P(dx) = \sum_{k=1}^N a_k \delta_{\{x_0+k\Delta\}}(dx),$$

In this case, the calibrated measure is also discrete:

$$\nu^Q(dx) = \sum_{k=1}^N b_k \delta_{\{x_0+k\Delta\}}(dx),$$

- The grid must be uniform in order to use the FFT to compute  $\Phi_T(u)$ , the characteristic function of  $X_T$ .
- An explicit representation of the gradient of  $J(Q)$  (minimization functional) allows to use a gradient based optimization method to solve the minimization problem.

## Calibration with entropic regularization

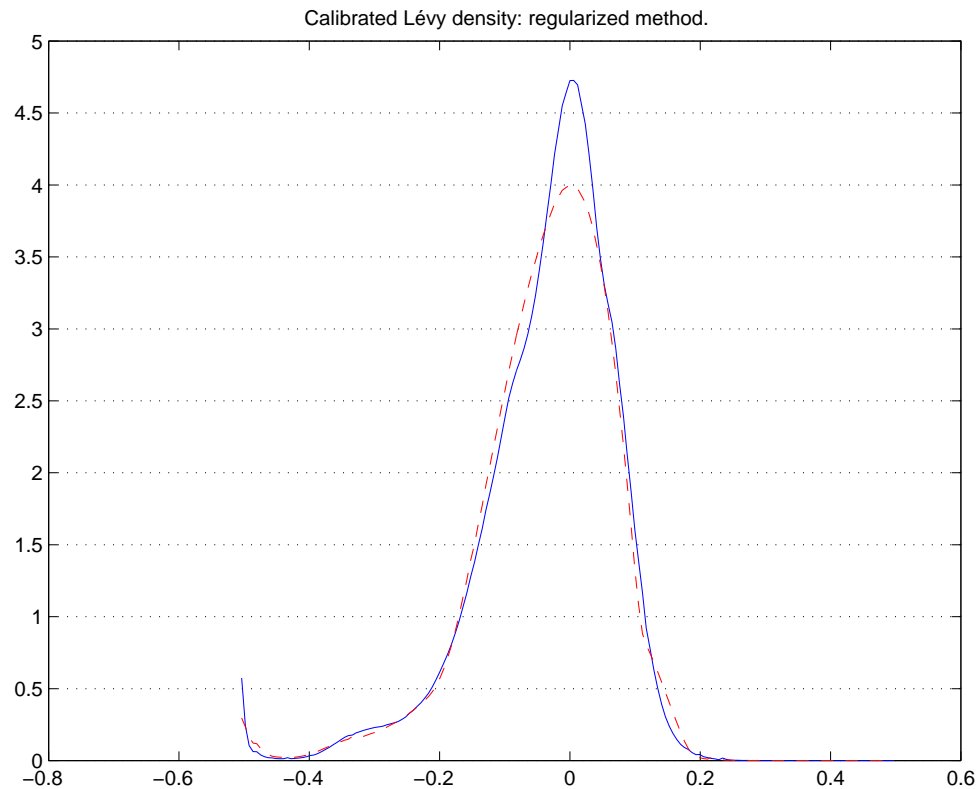


Figure 4: Lévy measure calibrated by entropic regularization. DAX options, 10 May 2001. Maturity 1 month. Again, Merton models with different intensities  $\lambda_1 = 1$  and  $\lambda_2 = 5$  are used as initializers

## Stability of solutions with respect to small changes of the prior measure

**Theorem 4.** *Let  $\nu^P$ ,  $\{\nu_n^P\}_{n \geq 1}$  be positive finite measures on  $(-\infty, x_0]$  such that  $\nu_n^P \Rightarrow \nu^P$ , and for each  $n$  let  $\nu_n^Q$  be a solution of problem  $(R_\alpha)$  with prior  $P(\sigma, \nu_n^P)$  and some  $\alpha > 0$ . Then*

- 1. There exists a weakly convergent subsequence  $\{\nu_{n_k}^Q\} \subseteq \{\nu_n^Q\}$ .*
- 2. The limit  $\nu^Q$  of every convergent subsequence of  $\{\nu_n^Q\}_{n \geq 1}$  is a solution of  $(R_\alpha)$  with prior  $P(\sigma, \nu^P)$ .*

## Numerical implementation: choice of the prior measure

- Based on historical estimation.
- Based on the calibrated measure of the day before.
- Based on the user's views, taking a parametric model with reasonable values of parameters.
- From the same dataset, using precalibration: first calibrate a simple parametric model (i.e. Merton's model) using least squares and then use it as prior.

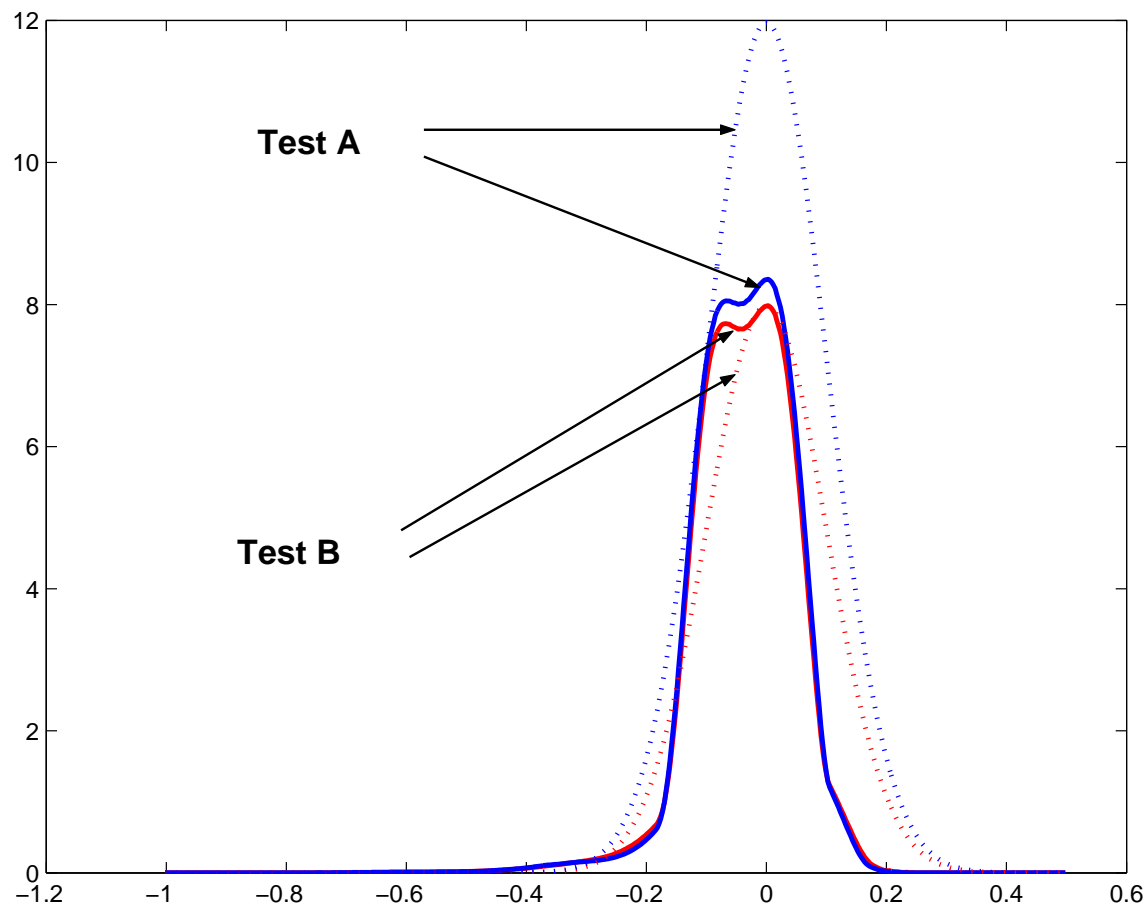


Figure 5: Sensitivity of calibrated measures to minor variations in the parameters of the prior model

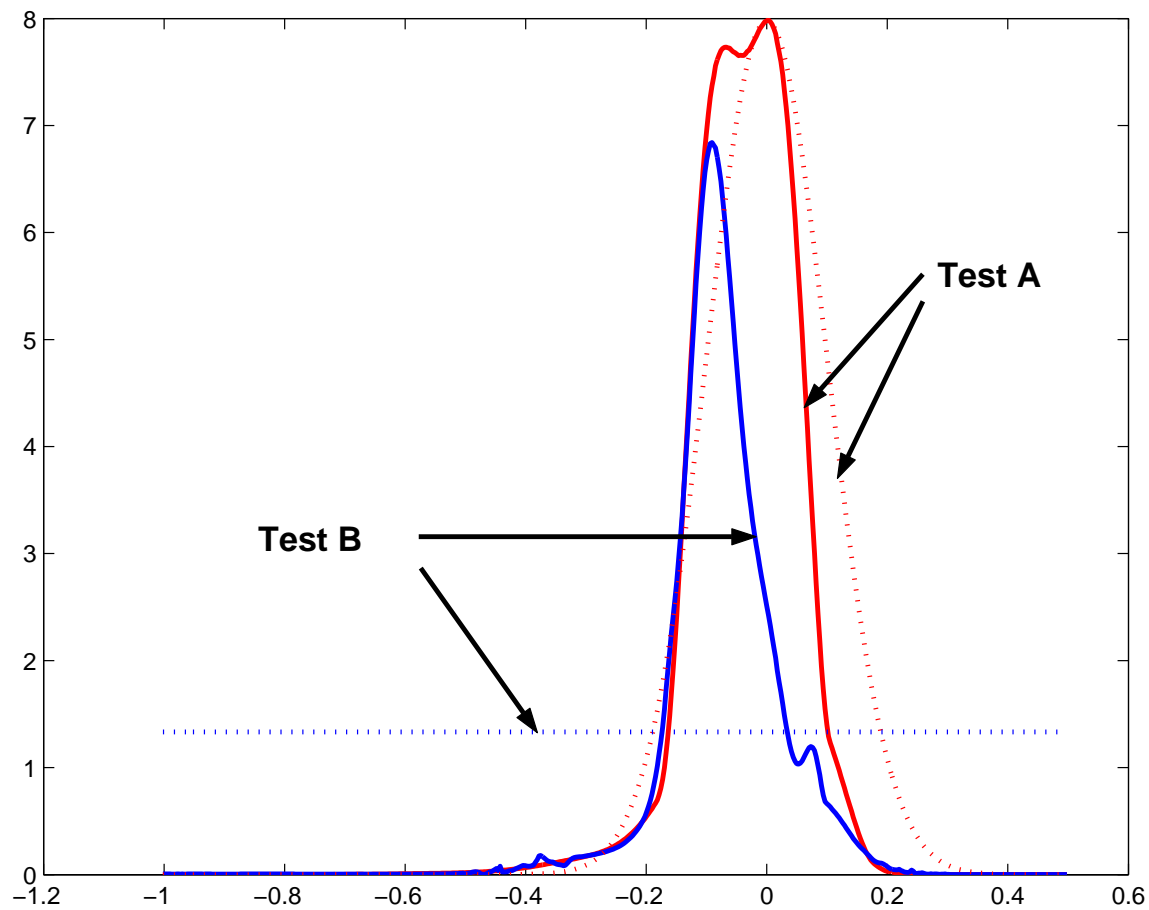


Figure 6: Sensitivity of calibrated measures to qualitative change of the prior model

## Tests on simulated data

Model 1: Kou's model (compound Poisson)

$$\nu(x) = \lambda[p\alpha_1 e^{-\alpha_1 x} 1_{x>0} + (1-p)\alpha_2 e^{-\alpha_2 |x|} 1_{x<0}]$$

Option prices were computed for 21 equidistant strikes, ranging from 6 to 14 (the money being at 10).

The Merton's model (with symmetric Gaussian jumps) was used as prior.

## Tests on simulated data

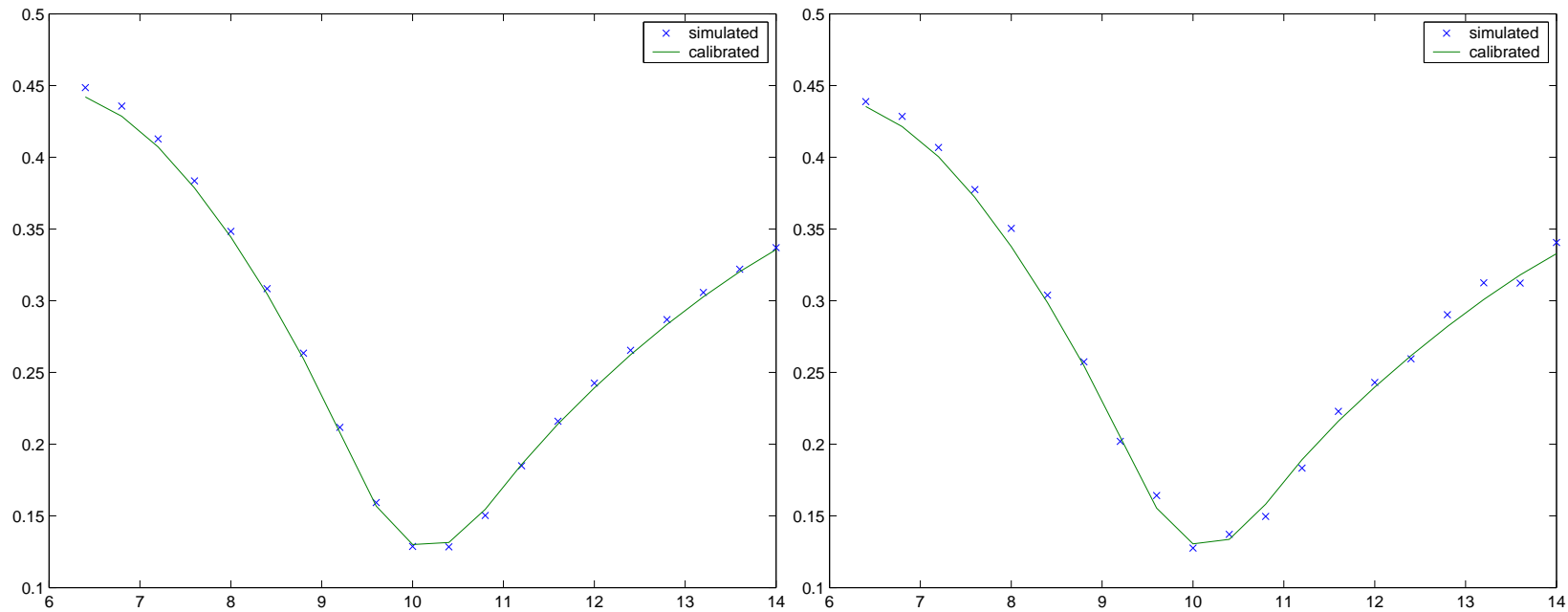


Figure 7: Calibration quality for Kou's jump diffusion model. Left: no perturbations. Right: 1% perturbations were added to the data

## Tests on simulated data

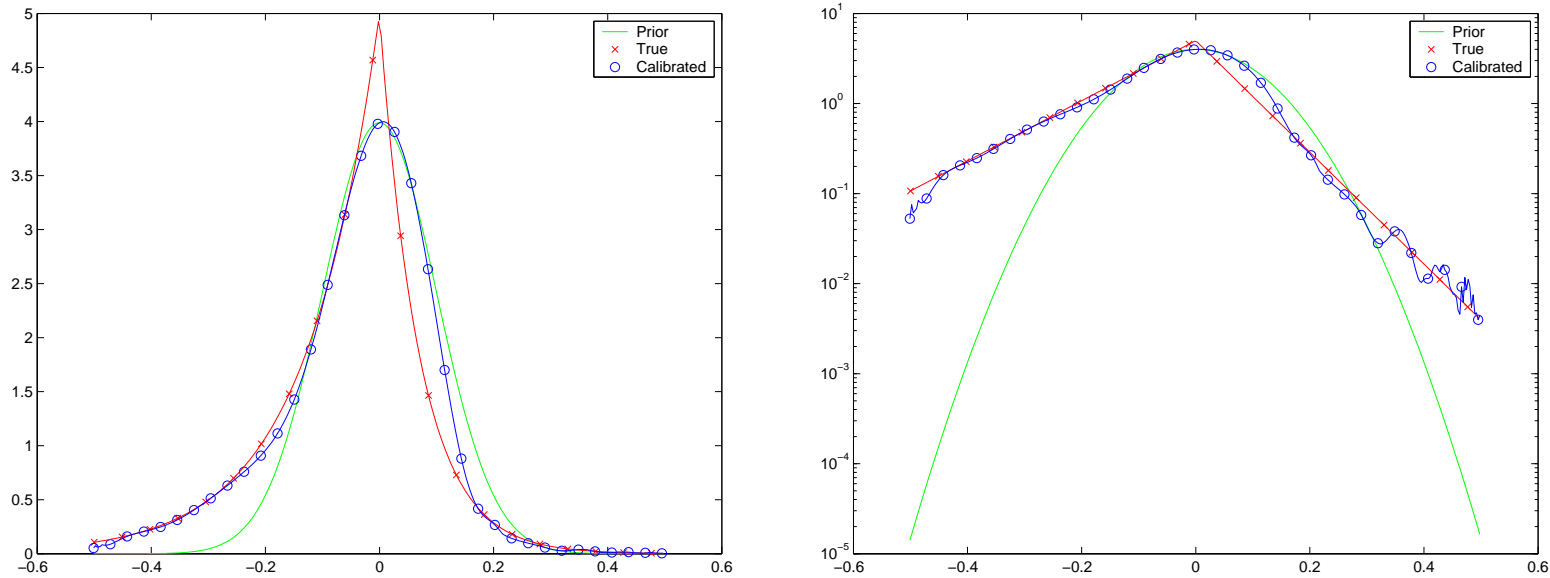


Figure 8: Lévy measure calibrated to option prices simulated from Kou's jump diffusion model with  $\sigma_0 = 10\%$ . No perturbations were added.

## Tests on simulated data

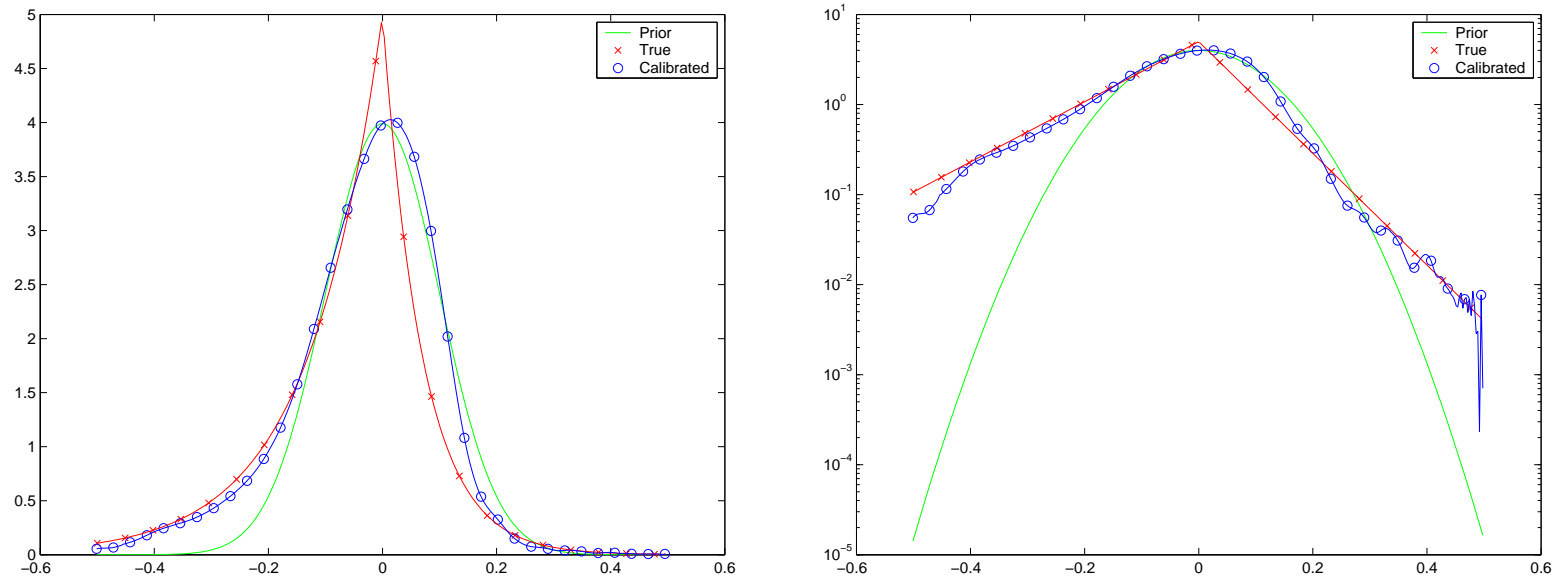


Figure 9: Lévy measure calibrated to option prices simulated from Kou's jump diffusion model with  $\sigma_0 = 10\%$ . 1% perturbations were added to the data.

## Empirical results (one maturity)

- The calibrated Lévy measures are strongly asymmetric: the distribution of jump sizes is skewed towards negative values.
- Most of the calibrated measures are bimodal with one mode (at zero) corresponding to regular activity and the second one corresponding to a large negative jump
- A small intensity of jumps  $\lambda$  can be sufficient for explaining the shape of the implied volatility: empirically  $\lambda \sim 1$

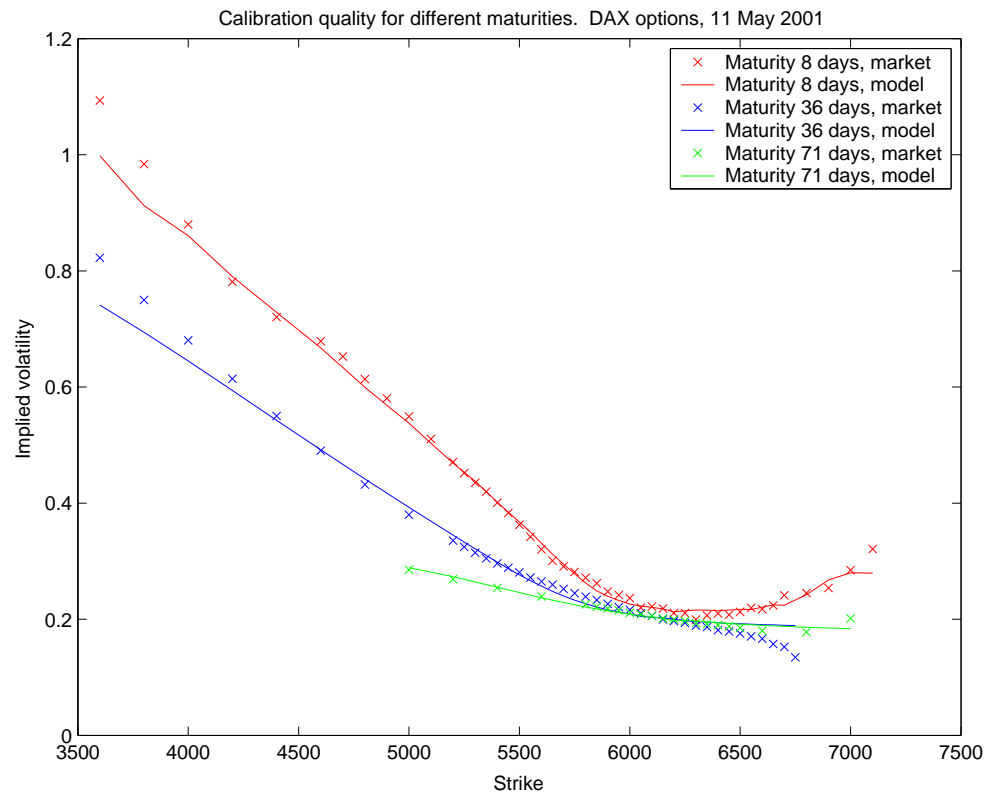


Figure 10: Calibration quality for different maturities: market implied volatilities for DAX options against model implied volatilities. Each maturity has been calibrated separately.

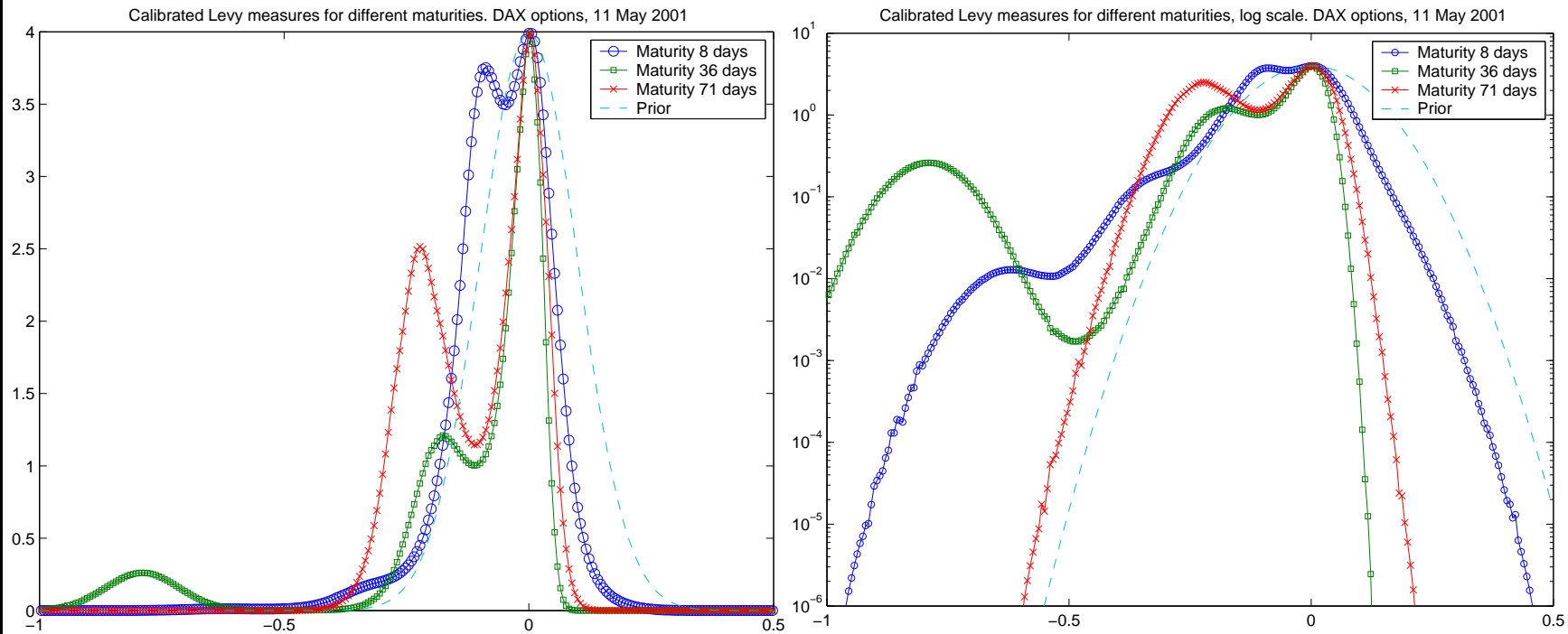


Figure 11: Lévy measures calibrated to DAX option prices for three different maturities, linear and logarithmic scale.

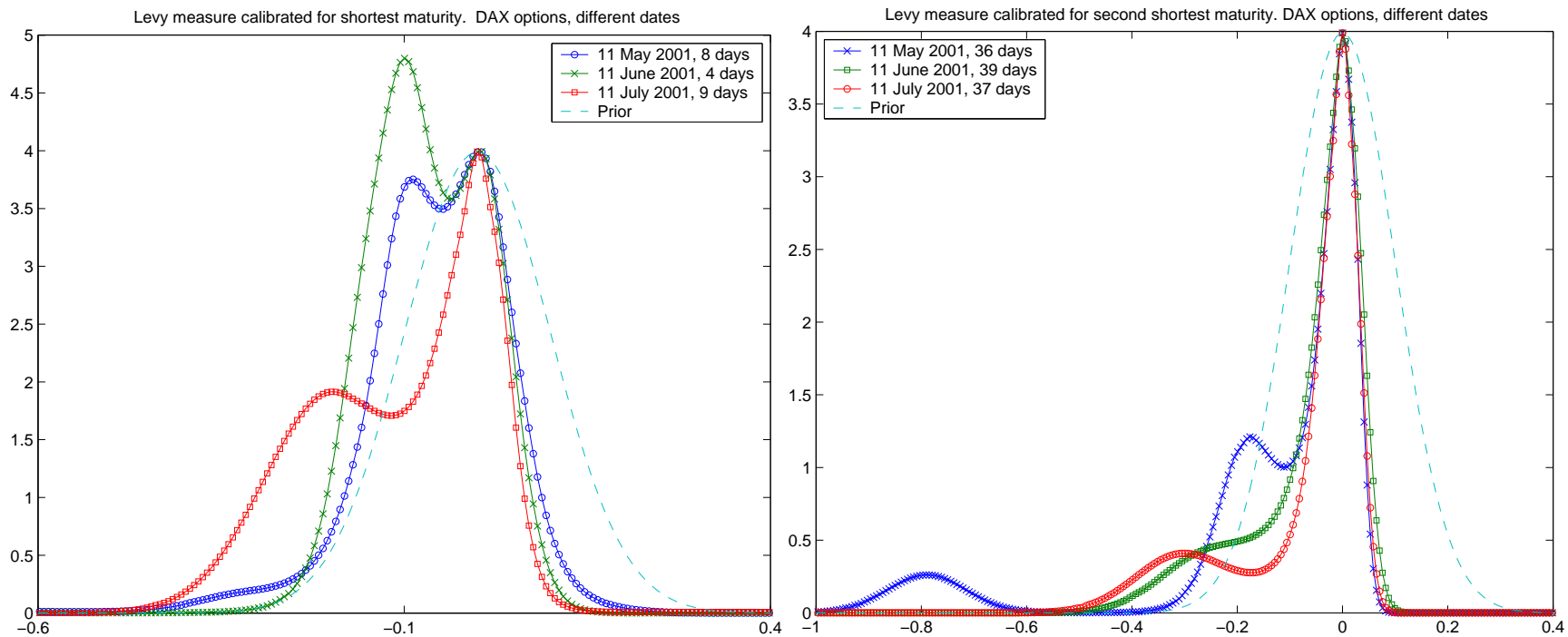


Figure 12: Stability of calibration over calendar dates. Lévy measures have been calibrated at different dates for shortest (left) and second shortest (right) maturity.

## Empirical results (several maturities)

Lévy processes explain the smile for one maturity but perform poorly for several maturities at the same time

- The implied volatility smile flattens too fast
- In Lévy models at the money implied volatility increases with time while the market ATM implied volatility changes little

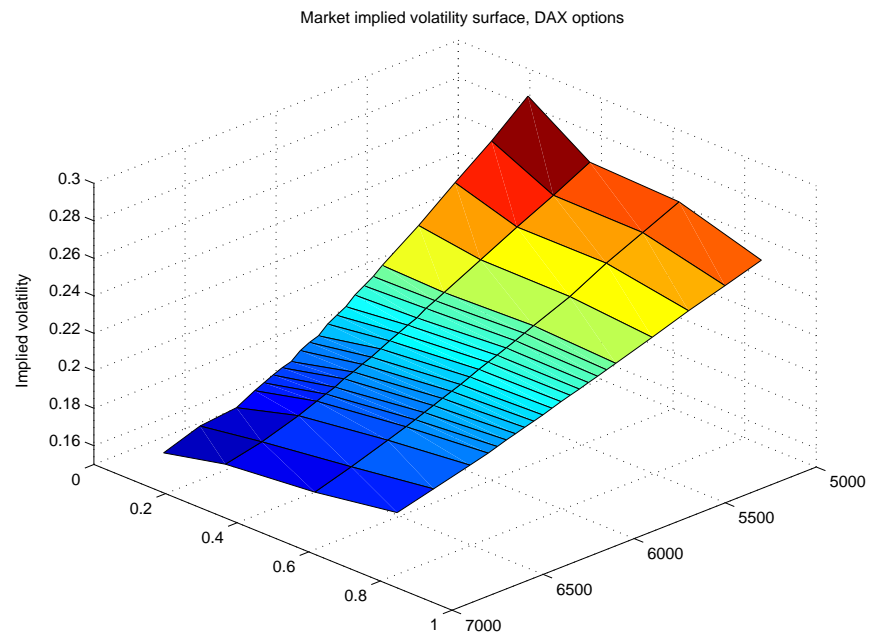


Figure 13: Market implied volatility surface

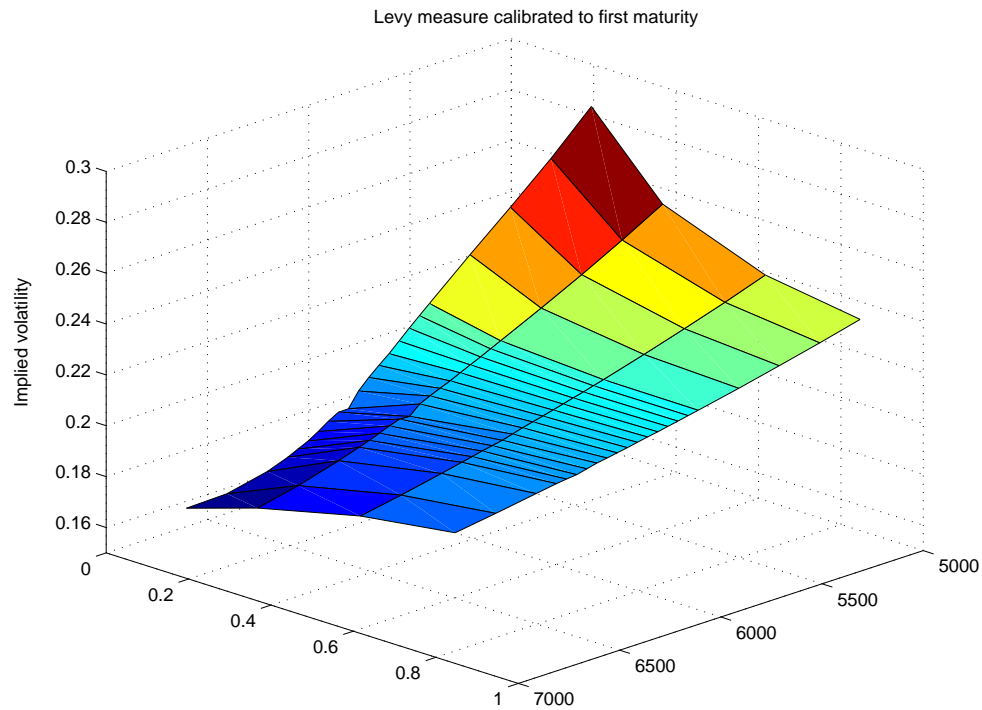


Figure 14: Implied volatilities for all maturities were computed, using the Lévy measure, calibrated to the first maturity

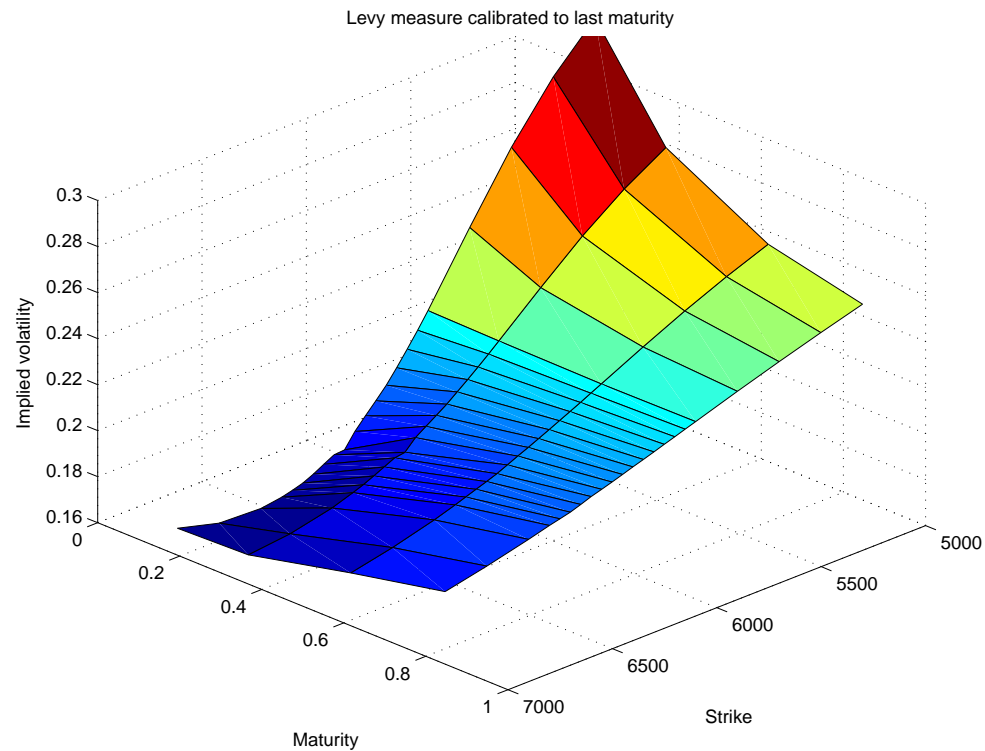


Figure 15: Implied volatilities for all maturities were computed, using the Lévy measure, calibrated to the last maturity