

Uniform Confidence for Pricing Kernels

Wolfgang K. Härdle
Okhrin Yarema
Weining Wang

CASE-Center for Applied Statistics and
Economics
Humboldt-Universität zu Berlin



u^b

UNIVERSITÄT
BERLIN

Motivation

- Arbitrage free market; riskless bond with constant interest rate r ; risky derivatives,
- Underlying price process $S_t, t \in [0, T]$,
- How to price the derivative ?



Figure 1: **conditional measure** at time of maturity T built upon a path of the stochastic process for **underlying asset** with information up to time t .



Risk Neutral Price z_t at time t from a payoff $\psi(S_T)$

$$\begin{aligned} z_t &= \int_0^\infty \exp(-r\tau) \psi(S_T) dQ(S_T) | S_t = s_t \\ &= \int_0^\infty \exp(-r\tau) \psi(S_T) \frac{q_t(S_T)}{p_t(S_T)} dP(S_T) | S_t = s_t \end{aligned}$$

where

- $p_t(S_T) \stackrel{\text{def}}{=} p(S_T) | S_t = s_t$ subjective density function,
- $q_t(S_T) \stackrel{\text{def}}{=} q(S_T) | S_t = s_t$ risk neutral density function.



Empirical Pricing Kernel (EPK)

Pricing Kernel (PK) a stochastic discount factor., i.e.

$$\pi_{t,\tau} = \exp(-r\tau) \frac{q_t(S_T)}{p_t(S_T)}$$

EPK is therefore an estimation of PK:

$$\widehat{\pi}_{t,\tau} = \exp(-r\tau) \frac{\widehat{q}_t(S_T)}{\widehat{p}_t(S_T)}$$



Empirical Pricing Kernel

Estimation approach:

- Black-Scholes Model, Black-Scholes(1973)
- GARCH Model, Engle(1982)
- Nonparametric diffusion model, Ait-Sahalia(1997)

All lead to the same paradox.



How true is the EPK Paradoxa?

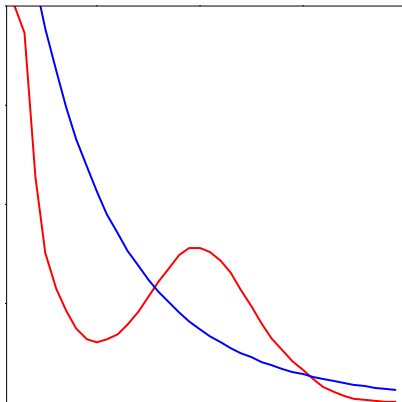


Figure 2: **Empirical** and **theoretical** pricing kernel, DAX 19990205, $\tau = 10$ days.



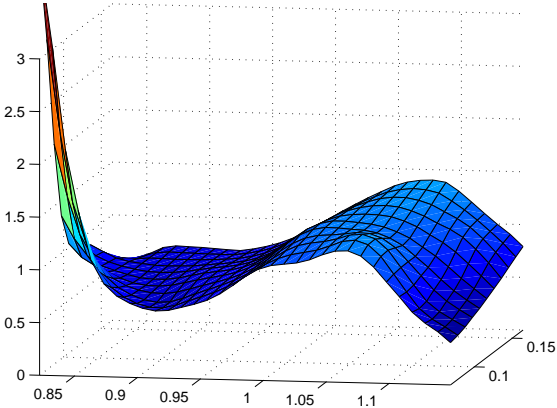


Figure 3: Estimated PK across moneyiness and maturity, DAX on 20010710



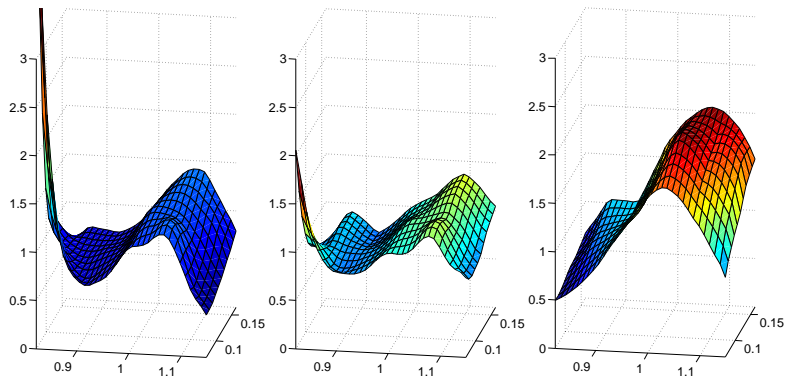


Figure 4: Empirical PK across moneyness and maturity, estimated from DAX on 20010710, 20010904 and 20011130



Our aims

- ▣ Nonparametric estimation for EPK
- ▣ Use uniform confidence band to do simple visual inspection
- ▣ Bootstrap to solve the slow convergence problem



Outline

1. Motivation ✓
2. Uniform Confidence Band
3. Bootstrap
4. Empirical Results



Risk Neutral Density (RND) Estimation

In Breeden and Litzenberger (1978), RND could be estimated from the option prices:

$$q_t(S_T) = \exp(r\tau) \frac{\partial^2 C_t(k, \tau)}{\partial k^2} \Big|_{k=S_T}$$

with option price function $C_t(k, \tau)$; strike price k .

Ait-Sahalia and Lo (1997) purposes to estimate $C_t(k, \tau)$ nonparametrically and then differentiate it twice w.r.t. k .



For RND, fix τ , we have:

$$Y_i = C(k_i) + \varepsilon_i, i = 1, \dots, n_q \quad (1)$$

With call option price function $C(k_i)$ and option price Y_i . ε_i s are i.i.d.

Under some regularity conditions, the estimate for RND is the local polynomial estimate of the second derivative of $C(k_i)$.

For p , the kernel density estimate is based on historical underlying assets prices,

$$\widehat{p}_t(S_T) = n_p^{-1} \sum_{j=1}^{n_p} K_{h_{n_p}}(S - S_j)$$



Convergence Rate

In Stone (1980), under some regularity conditions,

$$\sup_{S_T} |\widehat{p_t(S_T)} - p_t(S_T)| = \mathcal{O}_p\{(n_p / \log n_p)^{-1/(2p+1)}\} = \mathcal{O}_p(b_p),$$

assuming Lipschitz continuous with parameter p .

In Claeskens and Keilegom (2003), under some regularity conditions,

$$\sup_{S_T} |\widehat{q_t(S_T)} - q_t(S_T)| = \mathcal{O}((n_q \log n_q)^{-2/11}) = \mathcal{O}_p(b_q)$$

As in our setting, $\frac{b_p}{b_q} \ll 1$, so we have

$$\left| \frac{\widehat{q_t(S_T)}}{\widehat{p_t(S_T)}} - \frac{q_t(S_T)}{p_t(S_T)} \right| \approx \left| \frac{\hat{q}p - \hat{p}q}{p^2} \right|$$



Uniform Confidence Band

Thus, we have our $(1 - \alpha)100\%$ confidence band for pricing kernel π_τ as

$$[\psi : \sup_{S_T} \{ |2! \widehat{\pi}_\tau(S_T) - \psi_\tau(S_T)| \widehat{\text{Var}}(\hat{q})^{-0.5} \} \leq L_\alpha]$$

where

$$L_\alpha = 2! \hat{p}(n_q h_{n_q}^5)^{-0.5} \left[(-2 \log h_{n_q})^{0.5} + (-2 \log h_{n_q})^{-0.5} \{ x_\alpha + \log(C/2\pi) \} \right]$$

and

$$x_\alpha = -\log\{-0.5 \log(1 - \alpha)\}$$



Challenge 1: Extend to τ direction (or higher dimension.)

- Make the ratio of the EPKs bounded by a function of τ , reparametrize?
- Single index model?



Challenge 2: Convexification of $\widehat{q}_t(S_T)$

- Numerical approach to clean data?
- Restricted optimization?



Bootstrap Confidence Band

The convergence rate to the limiting distribution is quite slow.
Bootstrap method remedies this problem:

- Bootstrap Estimation of the leading term
- Bootstrap Method: Smooth Bootstrap or Wild Bootstrap

