Pricing Kernel Puzzles

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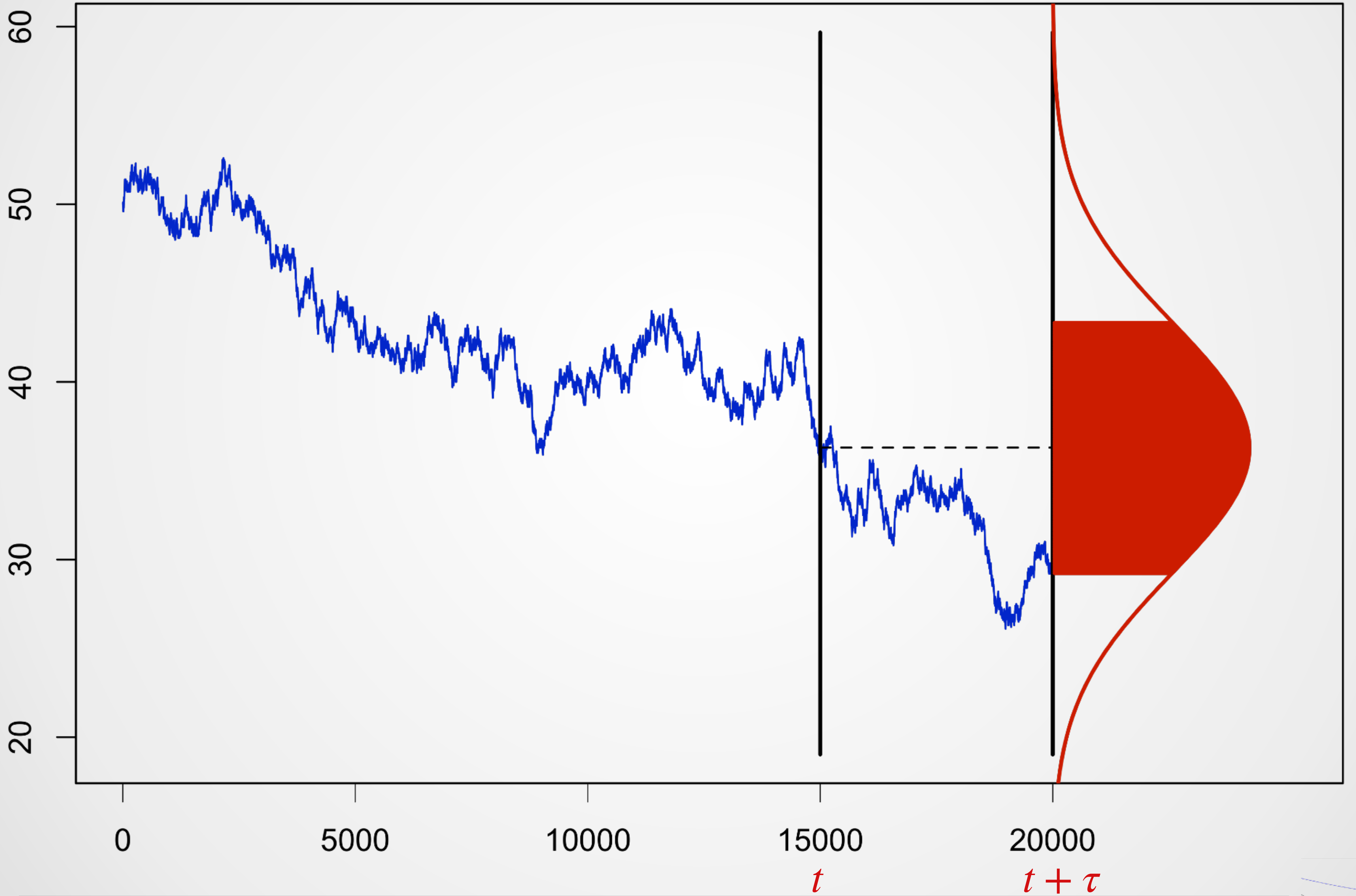
Stock, Prices, Options



Pricing Kernel

$K(x)$: Pricing kernel (PK)

- Risk neutral valuation principle for pay-offs

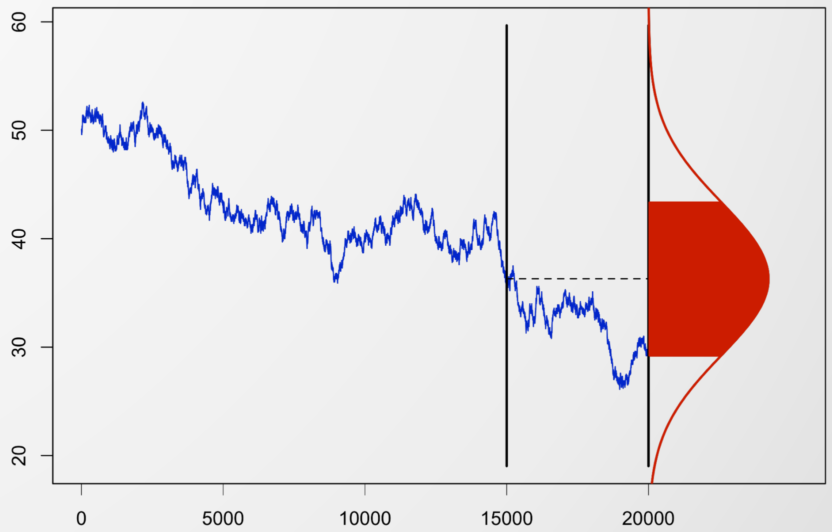
$$p = \mathsf{E}_Q\{e^{-r\tau}\psi(S_T)\} = \int_0^\infty e^{-r\tau}\psi(x)q(x)dx = \int_0^\infty e^{-r\tau}\psi(x)\frac{q(x)}{p(x)}p(x)dx$$

$$= \int_0^\infty e^{-r\tau}\psi(x)K(x)p(x)dx = \mathsf{E}_P\{e^{-r\tau}\psi(S_T)K(S_T)\}$$

  - $p(\cdot)$ historical density of stock S_T under measure P
  - $q(\cdot)$ risk-neutral density of stock S_T under measure Q
  - $\psi(S_T)$ pay-off, r interest rate, τ time to maturity

- Law of one price and absence of arbitrage

  K exists and $K > 0$



Pricing Puzzle

- „Risk aversion“ enforces $\hat{K}$ to be non-increasing
- Empirically, $\hat{K}$ is often non monotone
- Against economic principles:
  - Local „humps“ reveal preference for higher risk (or lower returns) in some return regions
  - Additional factors yield large risk premium (Chabi-Yo et al, 2007)
  - Investors without risk-averse preference (Ziegler, 2007)
  - Biased beliefs (Bakshi et al, 2010)
  - Flaws in existing estimators (Linn et al. 2018, RFS)

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JOURNAL ARTICLE

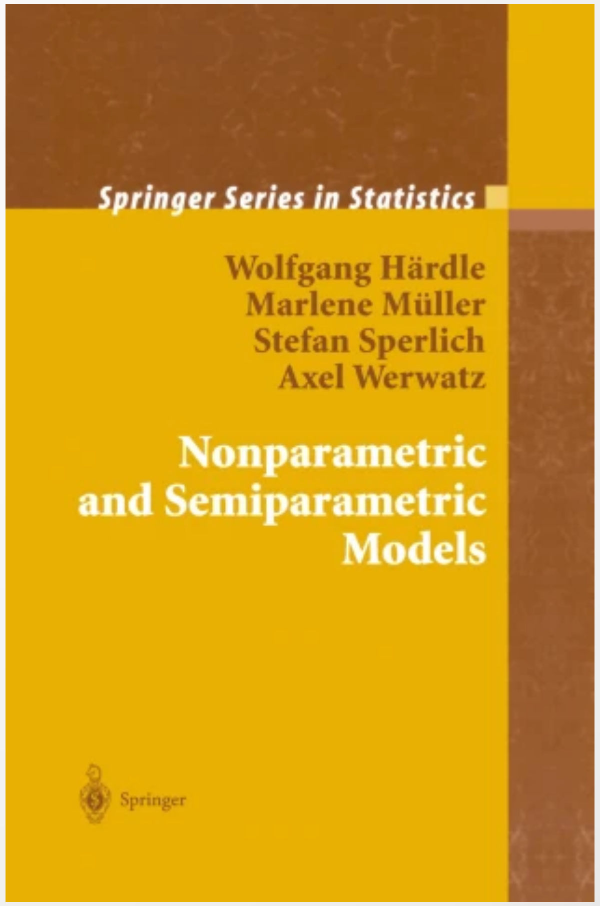
Pricing Kernel Monotonicity and Conditional Information Get access ›

Matthew Linn, Sophie Shive, Tyler Shumway

The Review of Financial Studies, Volume 31, Issue 2, February 2018, Pages 493–531, https://doi.org/10.1093/rfs/hhx095
Published: 21 August 2017

Pricing kernel for BTC options

- Bitcoin market is different
  - Volatility
  - Expected utility (Grith et al., 2017)
- Pricing kernel (PK) puzzle in Bitcoin (BTC) option markets
  - Classical estimation is not monotonically decreasing
  - Will the monotonicity claim by Linn et al (2018) still hold?
- PK estimation for BTC options
  - Bandwidth h, canonical kernel
  - Moments and knots

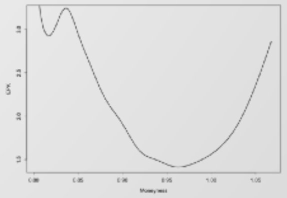


Pricing kernel for BTC options

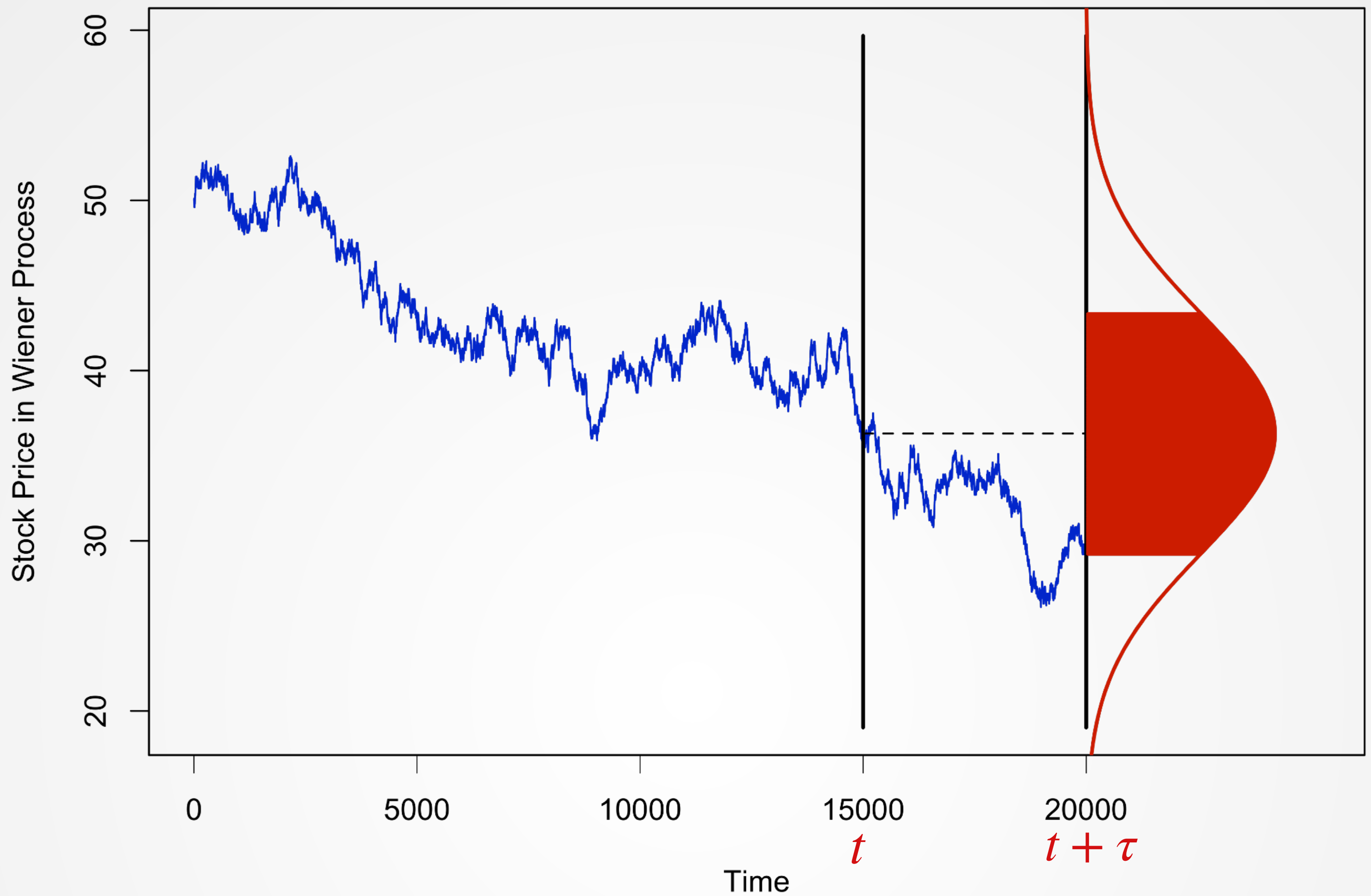
- Analyse BTC option data
- Estimate the PK using classical method (Rookley, 1997)
  - Estimate Q density and P density separately
  - Pricing kernel calculated using Q density and P density
- Estimate PK using CDI method (Linn et al, 2018 CDI)
  - Estimate Q density, same as the classical method
  - Do not need to estimate the P density
- Compare **classical PK results** with **CDI method**
- Confidence bands

Outline

1. Motivation ✓
2. Pricing Kernel and Risk Preferences
3. Classical PK Estimation
4. CDI approach
5. PK of BTC options
6. Classics vs CDI
7. Volatility jumps
8. B-splines and kernels
9. References



Asset prices



$$P(a < W_t < b \,|\, W_s = x)$$

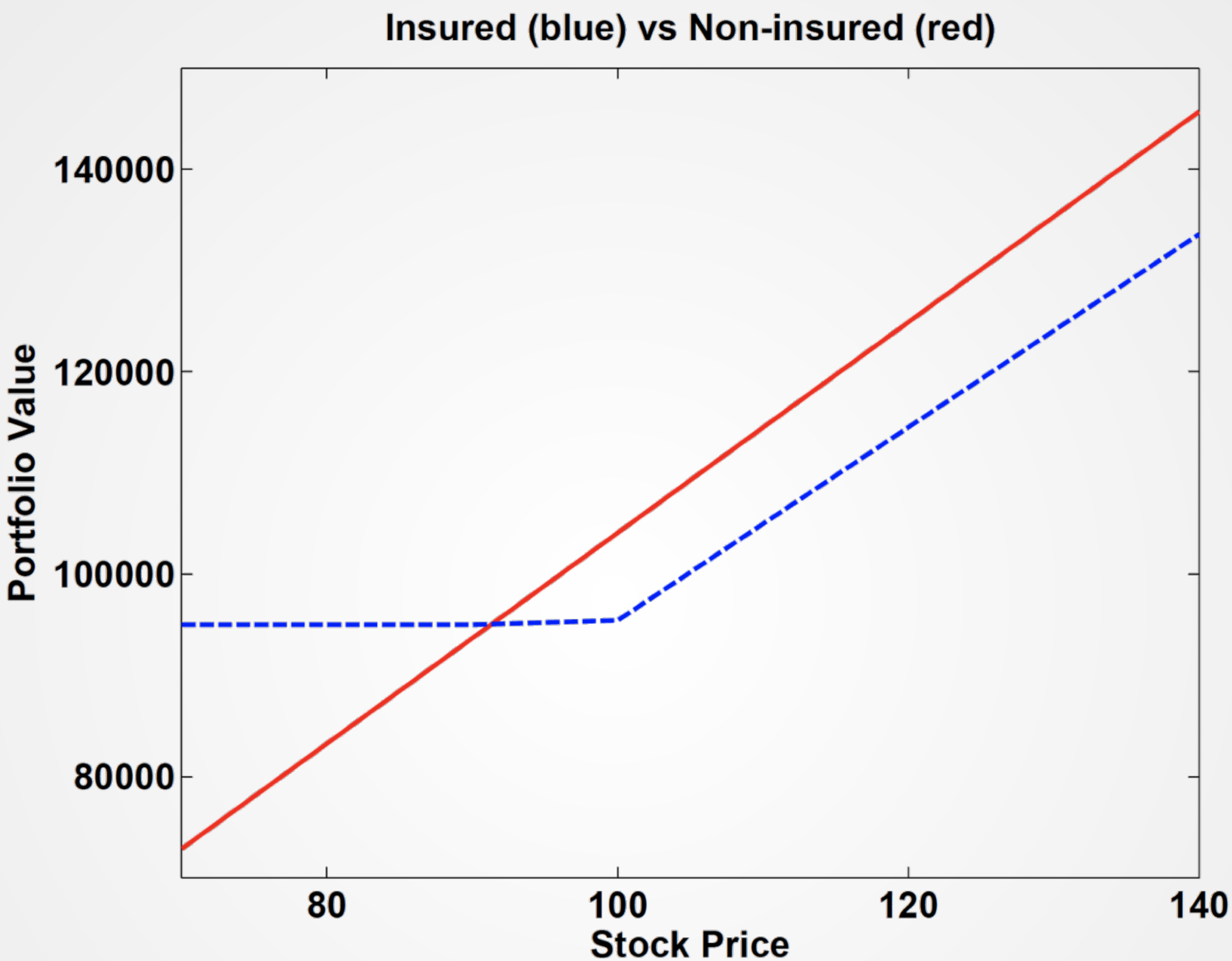
Standard Wiener process $\{W_t; t \geq 0\}$

$E[W_t] = 0$, $\text{Var}[W_t] = t$

$\text{Cov}(W_t, W_s) = s$

Increment $(W_t - W_s) \sim \mathcal{N}(0, t - s)$

SFEwienerdens



Portfolio value: insured, not insured portfolio

SFEoptman

Theoretical PK under the Black-Scholes world

- State Price Density (SPD):

$$q(S_T) = e^{r\tau} \frac{\partial^2 C}{\partial X^2}\Big|_{X=S_T}$$

- Black Scholes framework, European call options

$$C(S_t, X, \tau, r, \sigma^2) = S_t \Phi(d_1) - X e^{r\tau} \Phi(d_2)$$

d_1 and d_2 are known functions of σ^2, τ, X, and S_T

- $q(S_T)$ and $p(S_T)$ are the densities of lognormal distributions:

$$q(S_T) = \frac{1}{S_T\sqrt{2\pi\sigma^2\tau}} \exp[-\frac{\{\log(S_T/S_t) - (r - \sigma^2/2)\tau\}^2}{2\sigma^2\tau}]$$

$$p(S_T) = \frac{1}{S_T\sqrt{2\pi\sigma^2\tau}} \exp[-\frac{\{\log(S_T/S_t) - (\mu - \sigma^2/2)\tau\}^2}{2\sigma^2\tau}]$$

C: call option price
X: strike price
σ: volatility
S_t: stock price at time t
T: maturity
τ: time to maturity
r: interest rate
μ: stock drift

Investor preference analysis

The stock price and bond price follow

$$S_t = S_0 \exp\left\{\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W_t^P\right\}$$

- Risk-free rate r
- Stock volatility σ
- Stock drift μ (under P)
- P-Brownian motion W_t^P

No-arbitrage rule: Use Camerion-Martin-Girsanov and Martingale Representation Theorem to derive risk-neutral measure Q s.t.

$$S_t = S_0 \exp\left\{\left(r - \frac{1}{2}\sigma^2\right)t + \sigma W_t^Q\right\}$$

$$W_t^Q = W_t^P + \gamma t, \quad \gamma = \frac{\mu - r}{\sigma}$$ the market price of risk

Investor preference analysis

Pricing kernel

$$K(S_T) = \frac{q(S_T)}{p(S_T)}$$

BS model consistent with log-normal distribution of S_t.

$$q(S_T) = \frac{1}{S_T\sqrt{2\pi\sigma^2 T}} \exp\left[-\frac{\left\{\log\left(S_T/S_t\right) - \left(r - \sigma^2/2\right) T\right\}^2}{2\sigma^2 T}\right]$$

$$p(S_T) = \frac{1}{S_T\sqrt{2\pi\sigma^2 T}} \exp\left[-\frac{\left\{\log\left(S_T/S_t\right) - \left(\mu - \sigma^2/2\right) T\right\}^2}{2\sigma^2 T}\right]$$

Investor preference analysis

$$K(S_T) = \frac{q(S_T)}{p(S_T)} = \exp\left\{ -\frac{1}{2} \frac{2\log\left(S_T/S_t\right)(\mu - r) + \left(r - \frac{1}{2}\sigma^2\right)^2 T - \left(\mu - \frac{1}{2}\sigma^2\right)^2 T}{\sigma^2} \right\}$$

$$= \left(\frac{S_T}{S_t}\right)^{-\frac{\mu - r}{\sigma^2}} \exp\left\{ \frac{(\mu - r)(\mu - \sigma^2 + r)T}{2\sigma^2} \right\} = a\left(\frac{S_T}{S_t}\right)^{-b}$$

Where $a = \exp\left\{ \frac{(\mu - r)\left(\mu + r - \sigma^2\right)\tau}{2\sigma^2} \right\} = \frac{\mu - r}{\sigma^2}$ and

$b = \frac{\mu - r}{\sigma^2} \geq 0$ constant coefficient of relative risk aversion of a power utility function

If $\mu - r > 0$ then $\gamma > 0$ and we have a risk-averse representative investor

Literature

- Breeden & Litzenberger (1978): Risk neutral density (RND)
  - Second derivative of call option price wrt strike X
- Ait-Sahalia & Lo (2000); Jackwerth (2000)
  - Classical nonparametric Stochastic Discounted Factor (SDF) estimator:

$$\frac{\text{risk-neutral density}}{\text{physical density based on historical return}}$$

  - Decreasing function of market return

Econometric Approach

- Separate estimation of risk-neutral density and physical density

$$\widehat{K}(S_T) = \frac{\widehat{q}(S_T)}{\widehat{p}(S_T)}$$

  - $\widehat{q}$ estimated by option prices ($\partial^2 C / \partial K^2$)
  - $\widehat{p}$ estimated non parametrically using historical returns (e.g. Kernel-Density Est.)

Classical Method

- $dF^P(x_{t+\tau}|\mathscr{F}_t)$ is physical density and $dF^Q(x_{t+\tau}|\mathscr{F}_t)$ is risk-neutral density and x_t is return at time point t
- SDF=PK of Jackwerth (2000) and Ait-Sahalia and Lo (2000)

$$m_t(x_{t+\tau}) = e^{-rs}\frac{dF^Q\left(x_{t+\tau}|\mathscr{F}_t\right)}{dF^P\left(x_{t+\tau}|\mathscr{F}_t\right)}$$

$x_{t+\tau}$: stock return from t to τ

- Estimate risk-neutral and physical densities separately

$$m_t(x_{t+\tau}) = e^{-r\tau}\underbrace{\frac{dF^Q\left(x_{t+\tau}|\mathscr{F}_t\right)}{dx}}_{q(x_{t+\tau})} \Bigg/ \underbrace{\frac{dF^P\left(x_{t+\tau}|\mathscr{F}_t\right)}{dx}}_{p(x_{t+\tau})}$$

- Strong assumption: information set for Q and P density is the same

Estimation Process

Y_i: option price
x_i: stock return
$C()$: Call price function
ε_i: heterogeneity factors

- $q(\,.\,)$ estimated nonparametrically

$$Y_i = C(x_i) + \sigma(x_i)\varepsilon_i, \quad i = 1,\ldots,n$$

- $C(\,.\,)$ approximated by local polynomial

$$C(u,x) = \sum_{j=0}^{d} C_j(x)(x-u)^j$$

$$C_j(x) = C^{(j)}(x)/j!, \;\; j = 0,\ldots,d$$

- Local Gaussian quasi likelihood

$$L\{Y, C(x)\} = -\{Y - C(x)\}^2/\{2\sigma^2(x)\}$$

Estimation Process

- Function $C(\,.\,)$ can be approximated by:

Kernel function

$$\hat{\mathscr{C}}(x) = \arg\max_{\mathscr{C}(x)} n^{-1} \sum_{i=1}^{n} K_h(x_i - x) L\{Y_i, C(x, x_i)\}$$

$$\mathscr{C}(x) = \{C_0(x), C_1(x), \ldots, C_d(x)\}^\top$$

$$K_h(u) = K(u/h)/h$$

- Optimisation ($d = 3$):

$$\mathrm{A}(X) \stackrel{\text{def}}{=} n^{-1} \sum_{i=1}^{n} K_h(x_i - x) \frac{\partial L\{Y_i, C(x, x_i)\}}{\partial C} \mathscr{X}_i = 0$$

$$\mathscr{X}_i \stackrel{\text{def}}{=} (1,\ x_i - x,\ (x_i - x)^2,\ (x_i - x)^3)^\top$$

Estimation Process

- The physical density $p(x)$ is approximated as follows:

$S_t, \ldots, S_{t+n+\tau-1}$, $(t+n+\tau-1<T)$:

Kernel function

$$\hat{p}(x) = n^{-1}\sum_{j=0}^{n-1} K_h\{x - \log(S_{t+j+\tau}/S_{t+j})\}$$

- The density of log-returns can be estimated as:

$$\hat{p}(x) = S_t \exp(x)\hat{p}\{S_t \exp(x)\}$$

$$\sup_{x\in E} |\hat{p}(x) - p(x)| = \mathcal{O}\{(nh_n/\log n)^{-1/2} + h_n^2\}$$

- EPK: $\hat{K}(x) = \hat{q}(x)/\hat{p}(x)$

$$\sup_{x\in E} |\hat{K}(x) - K(x)| = \sup_{x\in E} \left| \frac{\hat{q}(x)-q(x)}{p(x)} - \frac{\hat{p}(x)-p(x)}{p(x)}\frac{q(x)}{p(x)} - \frac{\{\hat{q}(x)-q(x)\}\{\hat{p}(x)-p(x)\}}{p^2(x)} \right|$$

$$+\mathcal{O}[\max\{(nh_n^{-1/2}) + h_n^2, h_n^{-2}\{nh_n/\log n\}^{-1/2} + h_n^2\}]$$

Conditional density integration (CDI) method

- Since $F(X) \sim U(0,1)$, it follows that

$$\int_{-\infty}^{X_{t+\tau}} dF^P(x_{t+\tau}|\mathscr{F}_t) = \int_{-\infty}^{X_{t+\tau}} \frac{dF^P(x_{t+\tau}|\mathscr{F}_t)}{dF^Q(x_{t+\tau}|\mathscr{F}_t)} dF^Q(x_{t+\tau}|\mathscr{F}_t)$$

Left hand: $F_t^P(X_{t+\tau})$

$$= \int_{-\infty}^{X_{t+\tau}} \left\{ \frac{dF^Q(x_{t+\tau}|\mathscr{F}_t)}{dF^P(x_{t+\tau}|\mathscr{F}_t)} \right\}^{-1} dF^Q(x_{t+\tau}|\mathscr{F}_t)$$

- Uniqueness given by

Recall: PK=dQ/dP

$$\int_{-\infty}^{X_{t+\tau}} g_{t,\tau}(y) dF^Q(y|\mathscr{F}_t) \sim U(0,1)$$

We can view the $F_t^P(X_{t+\tau})$ as a function of $m(X_{t+\tau})$, where $m(u) = \int_{-\infty}^{u} g_{t,\tau}(v) q_t(v) dv$.

CDI & nonparametric regression

$$Y = m(x) + \varepsilon$$

$$Y_i - m(X_i) = \varepsilon_i \sim U(0,1)$$

Observe

t dropped!

$$Y_i = m(X_{i+\tau}) + \varepsilon_i = \int_{-\infty}^{X_{i+\tau}} g_\tau(v)q(v)dv + \varepsilon_i$$

$$Y_i = \int_{-\infty}^{X_{i+\tau}} g_\tau(v)\hat{q}(v)dv$$

$$= q(v) + \eta_i$$

- Employ B-splines to approximate $g_\tau(v)$?

Estimation I

- Assume cubic B-spline

$$g(y) = \sum_{j=1}^{J} \theta_j B_j(y)$$

- Hence,

$$\int_{-\infty}^{X_{t+\tau}} g(y) dF^Q(y|\mathscr{F}_t) = \sum_{j=1}^{J} \theta_j \int_{-\infty}^{X_{t+\tau}} B_j(y) dF^Q(y|\mathscr{F}_t)$$

- Use GMM to get $\hat{\theta}$

$$\hat{\theta} = \underset{\theta \in \mathbb{R}^J}{\operatorname{argmin}} \sum_{i=1}^{m} \left[\frac{1}{T} \sum_{t=1}^{T} \left\{ \sum_{j=1}^{J} \theta_j \int_{-\infty}^{X_{t+\tau}} B_j(y) dF^Q(y|\mathscr{F}_t) \right\}^i - \frac{1}{i+1} \right]^2$$

moments of the uniform distribution

Estimation II

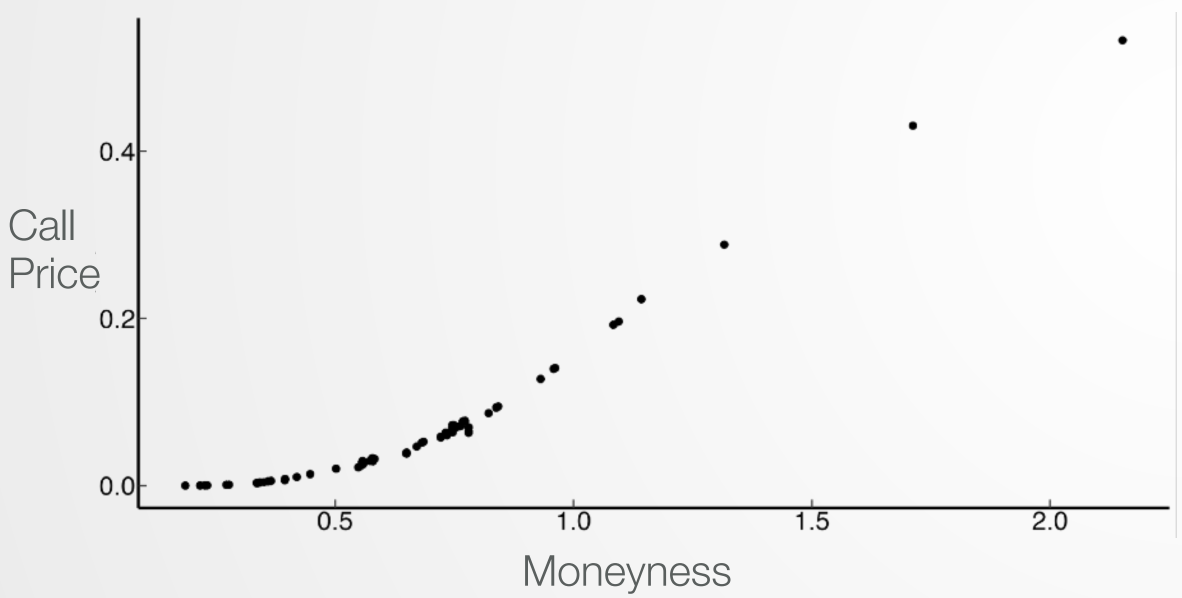
- Plug-in estimate given by

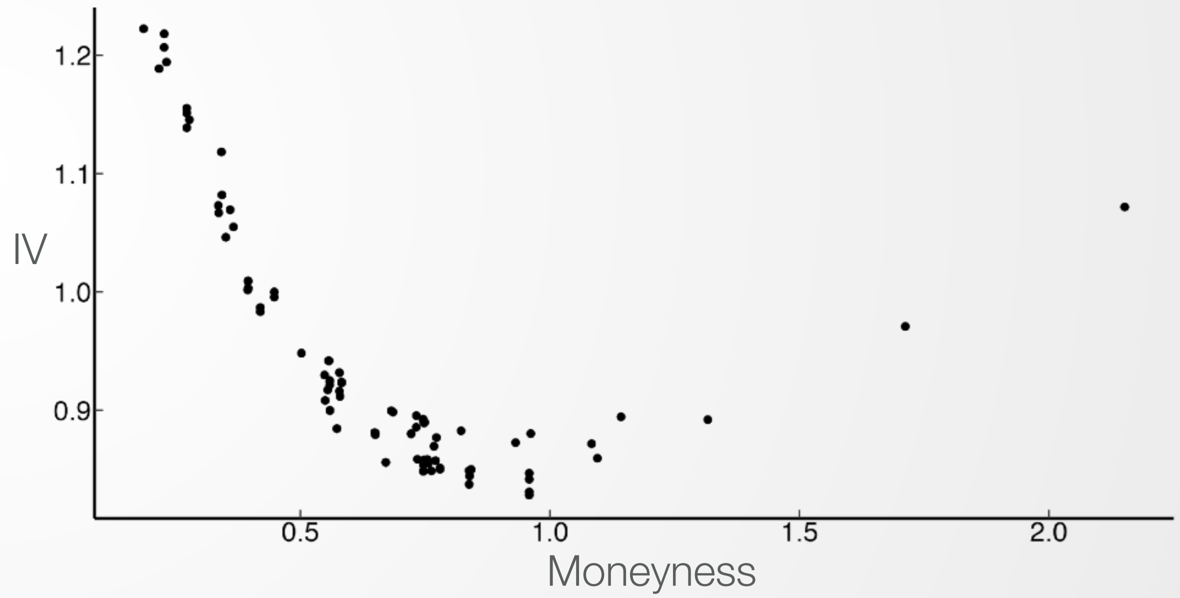
$$\hat{g}(u) = \sum_{j=1}^{J} \hat{\theta}_j B_j(u)$$

- EPK follows as $\widehat{K}(u) = \{\hat{g}(u)\}^{-1}$
- EPK for different number of moments m and basis functions J
  - In Linn et al. (2018), all moments are equally weighted

So let us do it!

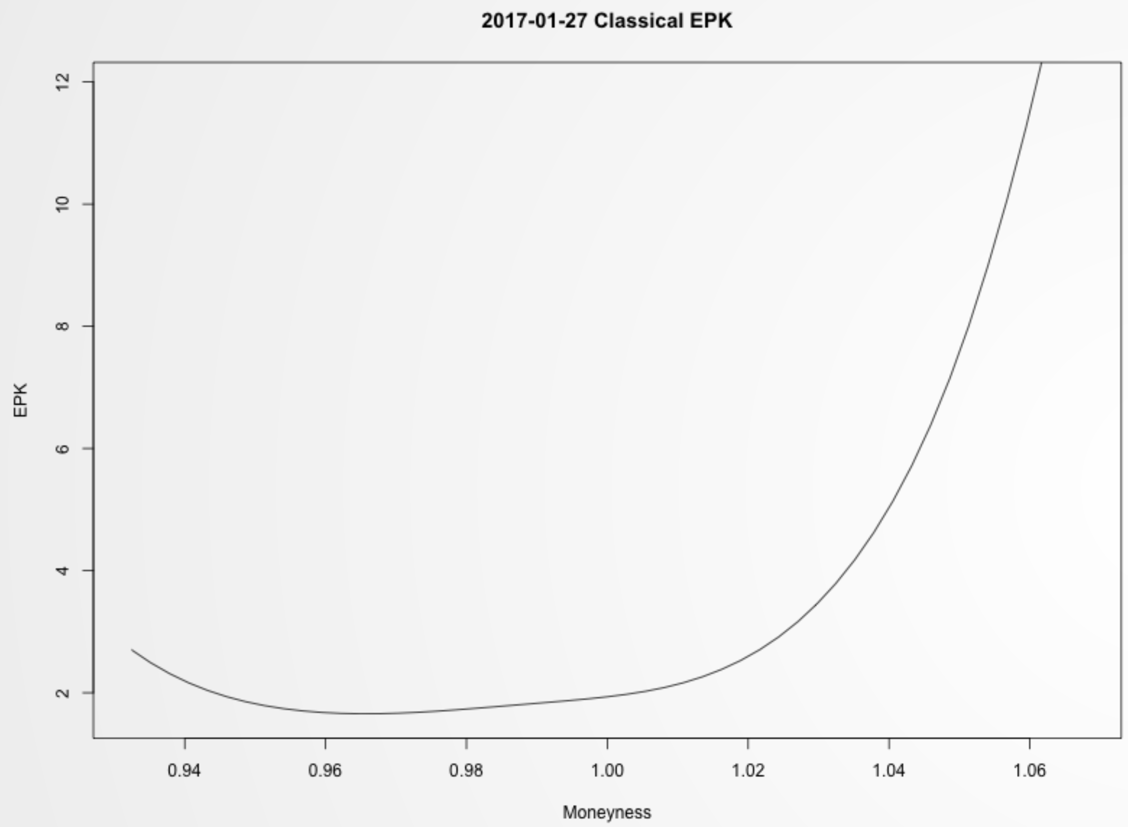
- BTC price 20200801 = 11789.63
- Call options: 53
- Display the IV and Call scatterplots on moneyness and τ



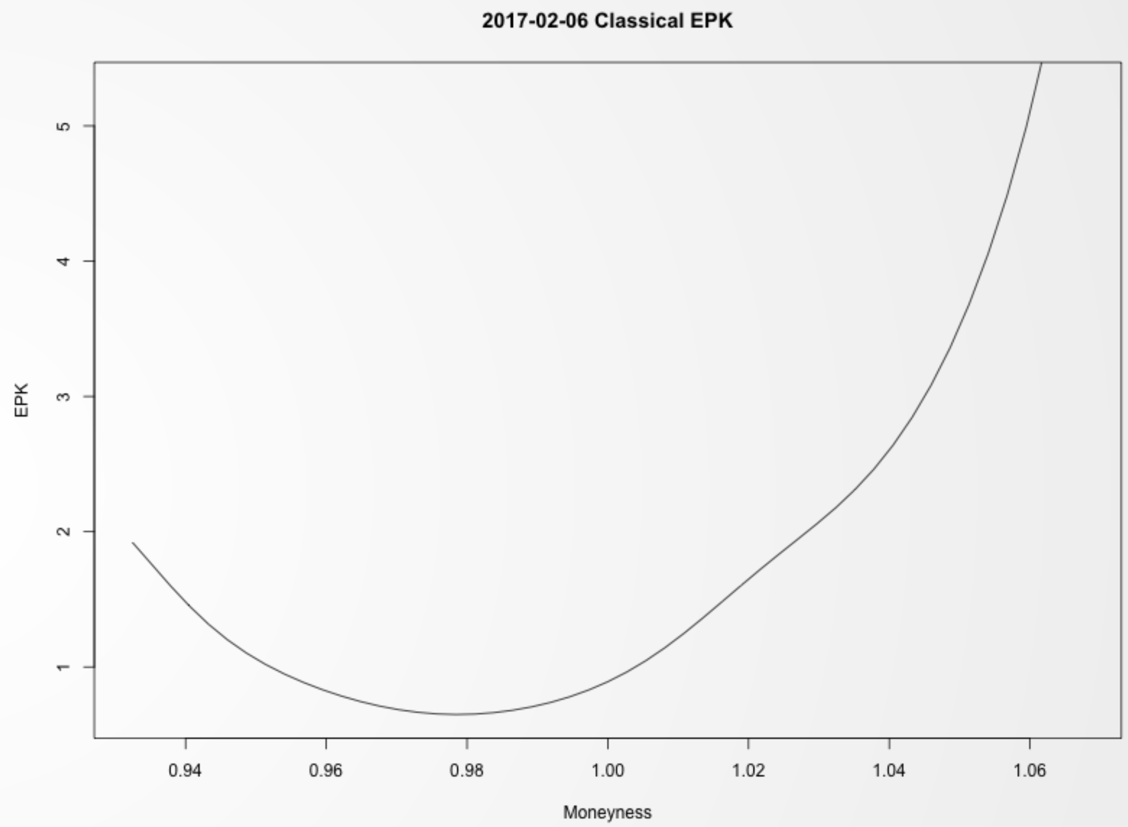


„Pricing Puzzle“ using classical methods

- non monotonicity is discovered



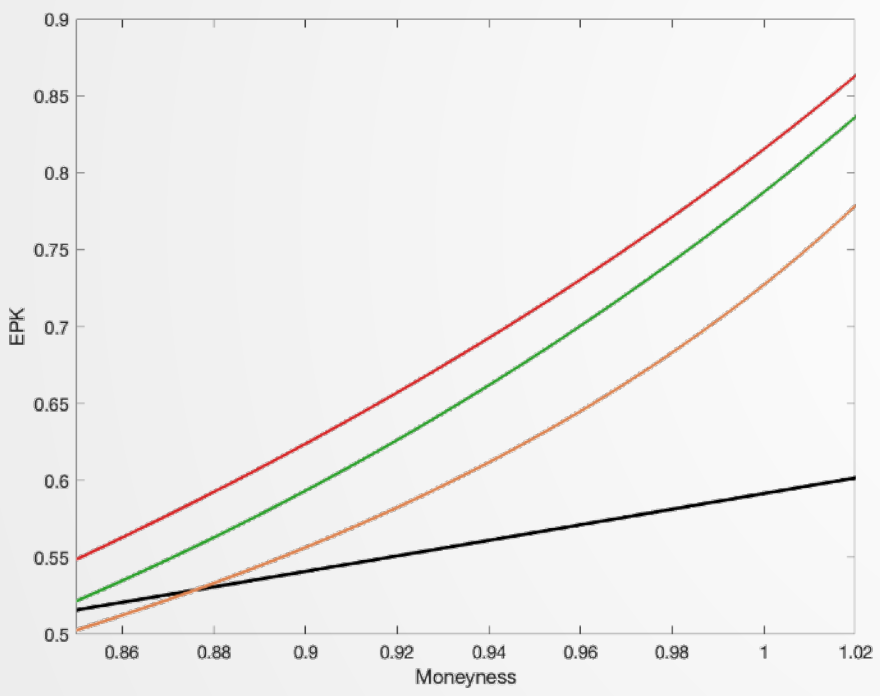
Classical result of S&P 500 Index Option
2017-01-27 $\tau = 32$



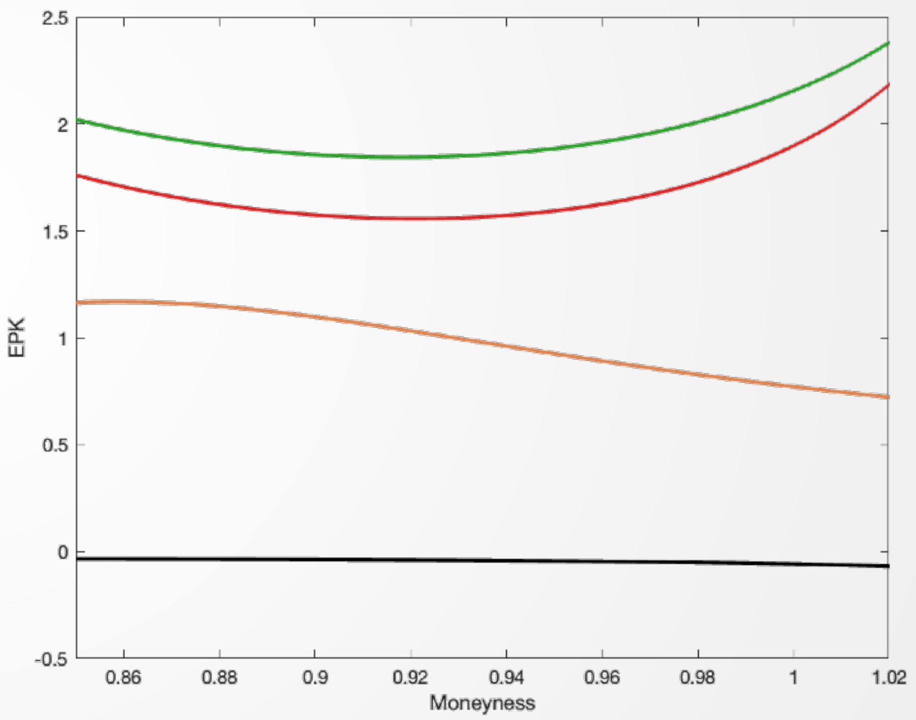
Classical result of S&P 500 Index Option
2022-02-06 $\tau = 39$

Pricing kernel using CDI method

- 2017-01-27 $\tau = 32$, increase monotonically.
- 2018-12-21 $\tau = 26$, monotonicity result is sensitive to the choices of moments and knots



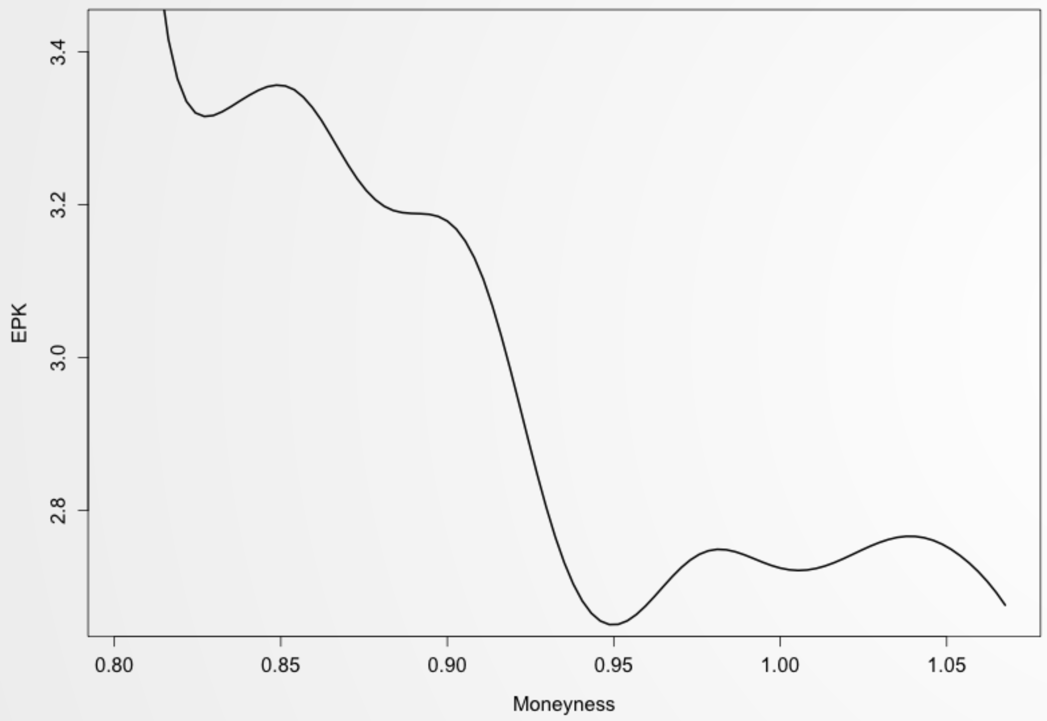
CDI result of S&P 500 Index Option
2017-01-27 $\tau = 32$
4 moments, 4 knots; 5 moments, 5 knots;
6 moments, 6 knots; 7 moments, 7 knots



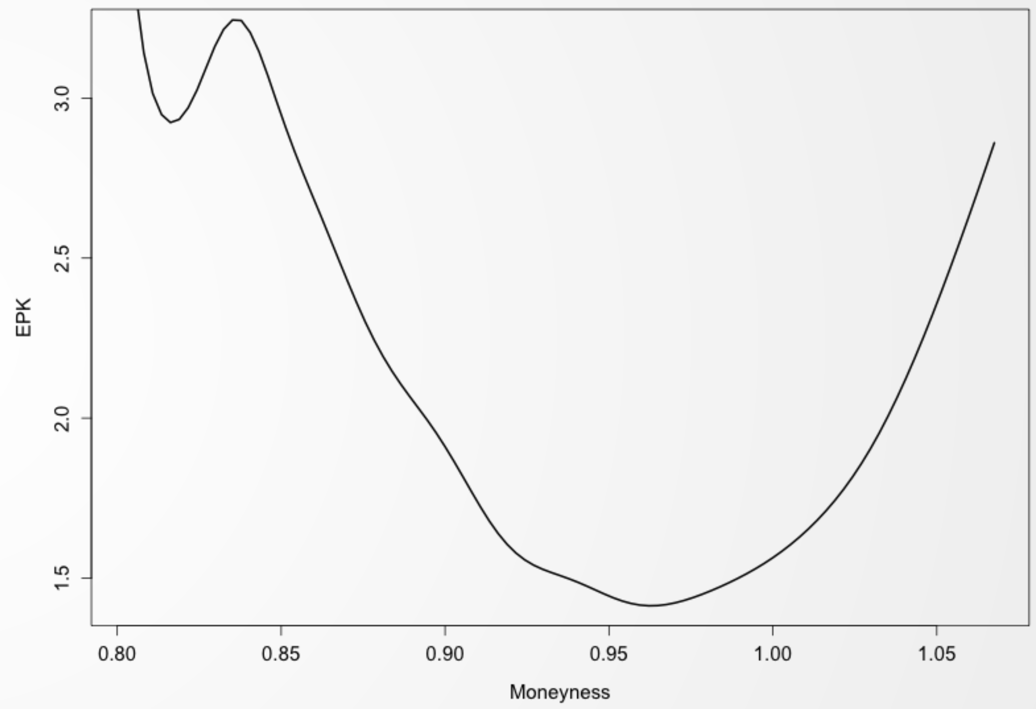
EPK of S&P 500 Index Option
2018-12-21 $\tau = 26$
4 moments, 4 knots; 5 moments, 5 knots;
6 moments, 6 knots; 7 moments, 7 knots

Pricing kernel- Bitcoin option data

- Classical EPK in Bitcoin option market



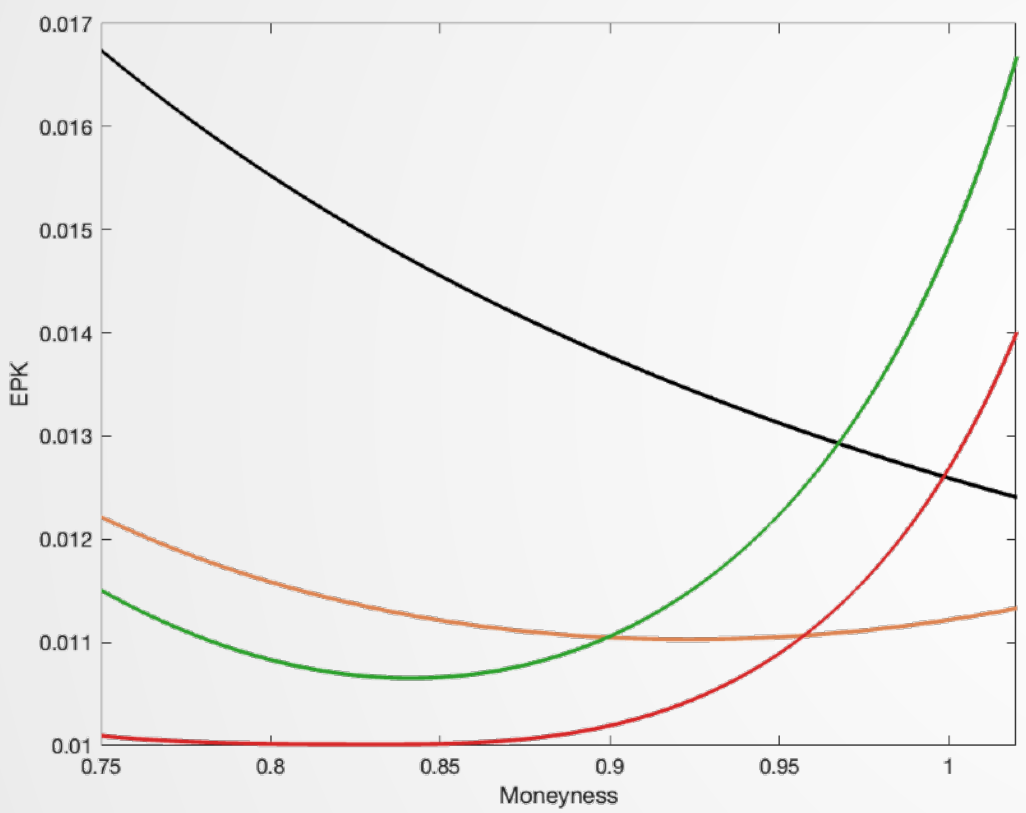
Classical result of Bitcoin Option
2022-11-17 $\tau = 8$



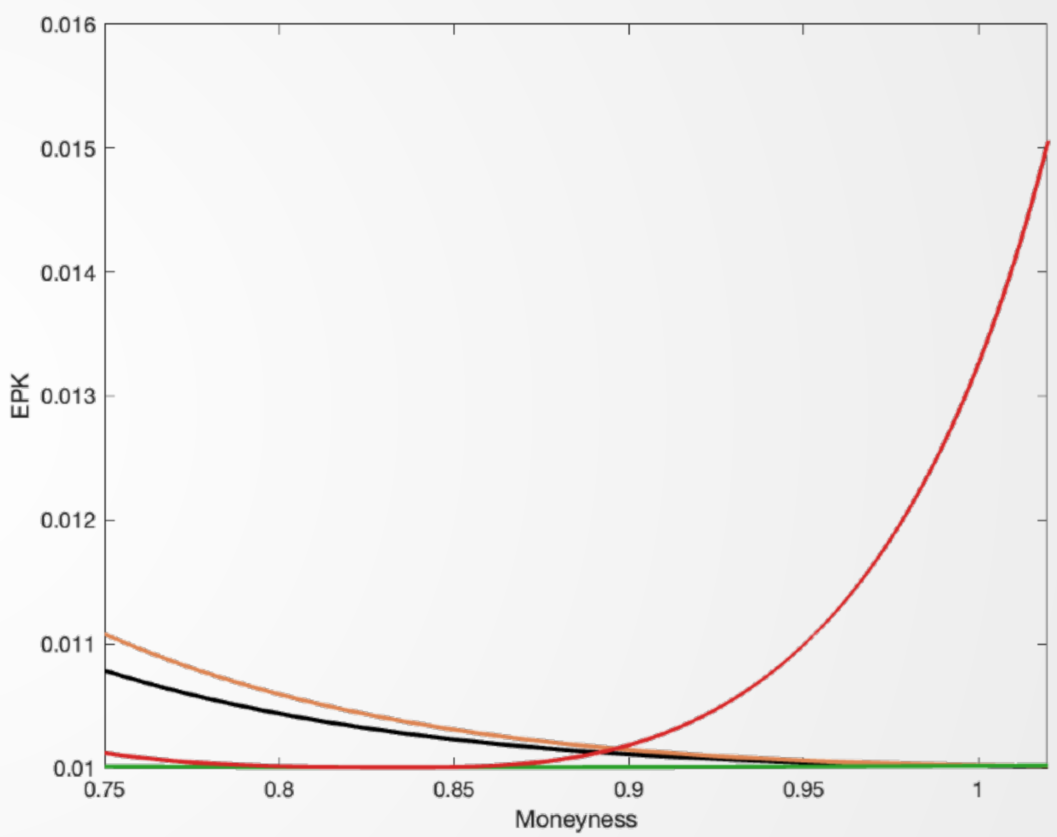
Classical result of Bitcoin Option
2022-10-29 $\tau = 13$

Pricing kernel- Bitcoin option data

- Monotonic decreasing does not always hold in this market



CDI result of of Bitcoin Option
2022-11-17 $\tau = 8$
4 moments, 4 knots; 5 moments, 5 knots;
6 moments, 6 knots; 7 moments, 7 knots



CDI result of of Bitcoin Option
2022-10-29 $\tau = 13$
4 moments, 4 knots; 5 moments, 5 knots;
6 moments, 6 knots; 7 moments, 7 knots

Potential reason of non-monotonic appearance

- Volatility is not constant in different trading dates
- Sensitive to the choice of moments and knots parameters in CDI
- To avoid inconsistent methodology problems, kernel estimation should replace B-spline

It's the vola, stupid!

Simulated volatility regimes

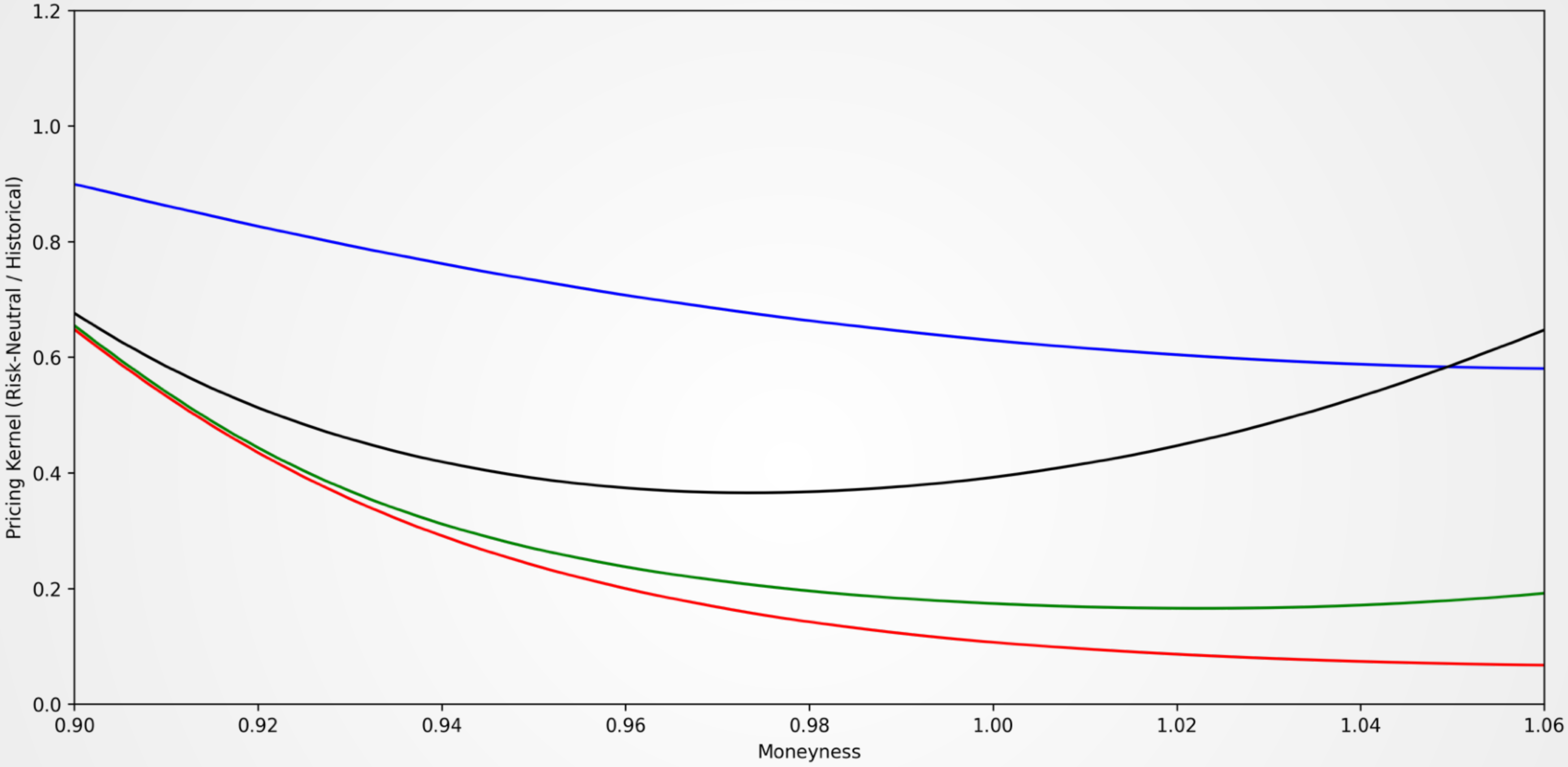
1 Constant volatility

2 Volatility jump in the *past*

3 Volatility jump in the *future*

- Analyze the impact of volatility regime switches on the two proposed PK estimations, we examine the PKs at the same point in time under different overall volatility regime scenarios.
- The classical PK estimation relies on historical returns. It is to be assumed that a volatility jump in the past influences the kernel, while a volatility jump in the future does not.
- In contrast, the CDI PK estimation uses forward-looking returns. In theory past regime switches have no effect on the pricing kernel compared to future regime switches.

Case 1: CDI Pricing Kernel of Constant Volatility

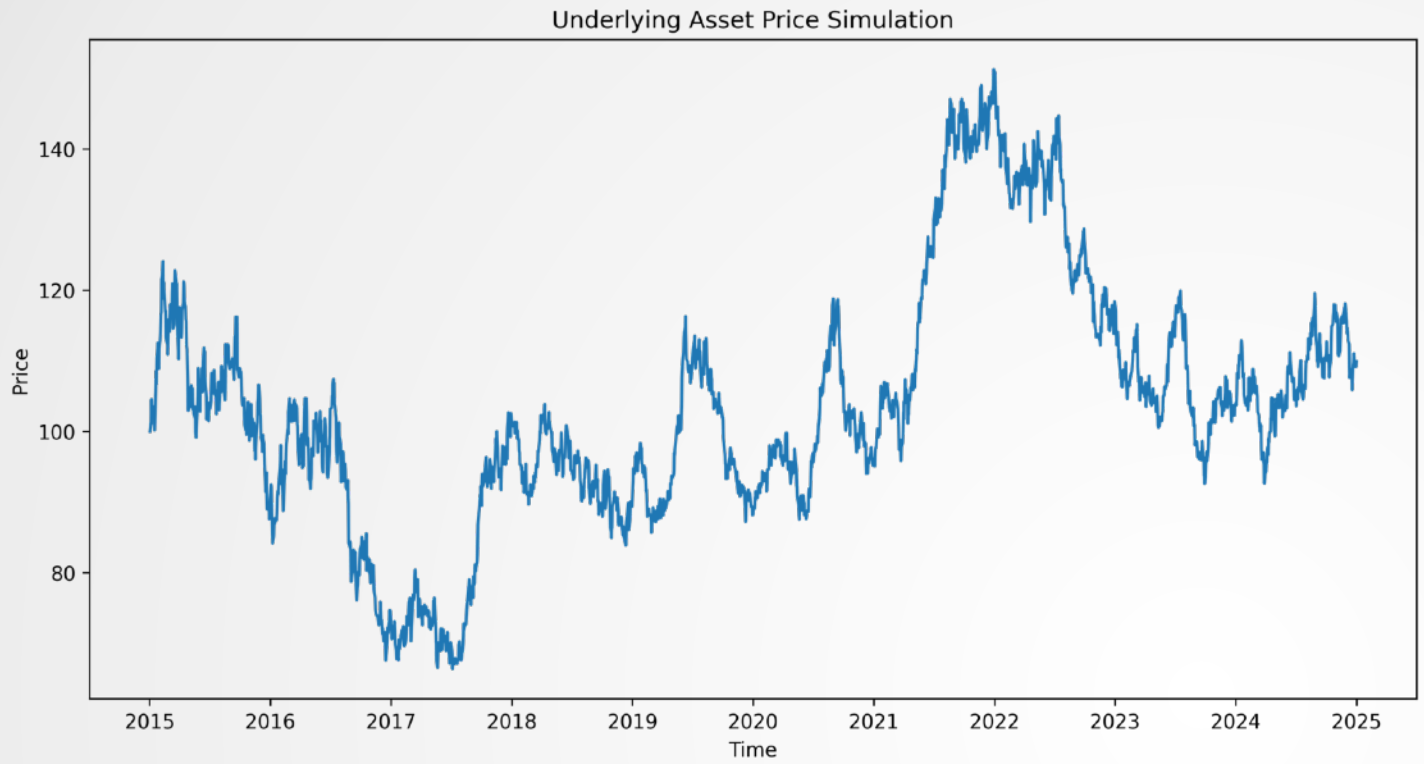


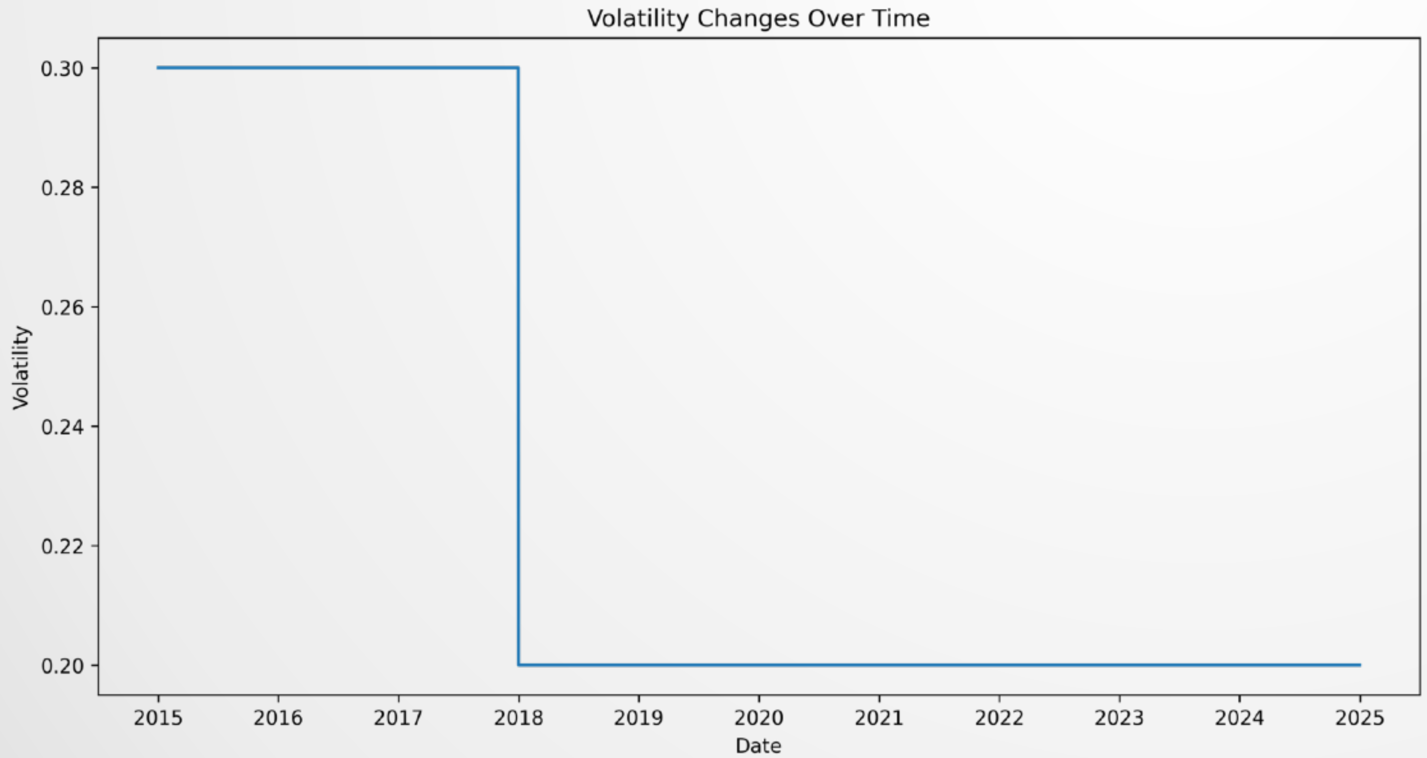
4 bases/moments, 5 bases/moments,

6 bases/moments, 7 bases/moments

Steps: 0.001

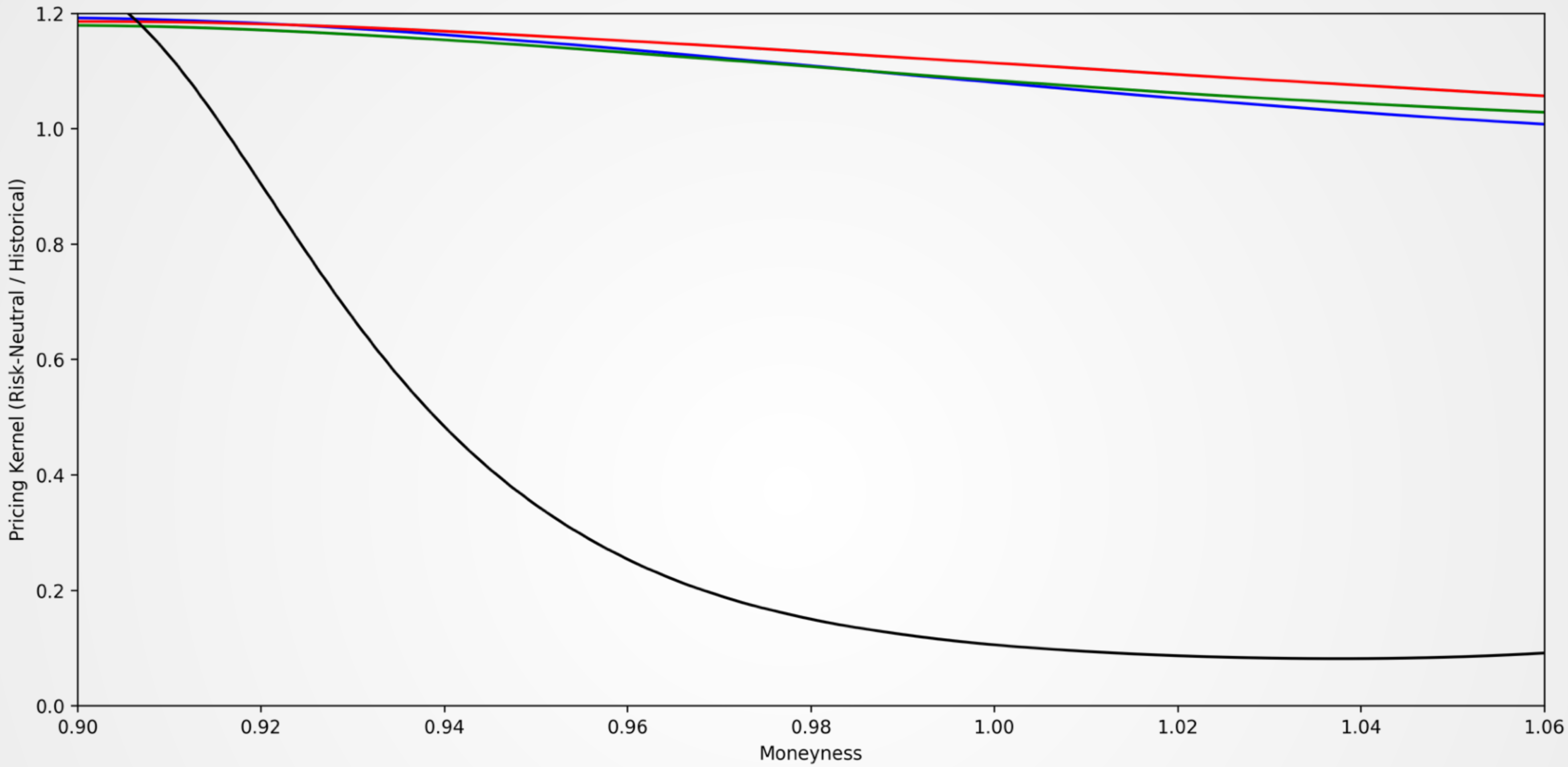
Case 2: Volatility jump in the *past*





- Simulate a volatility regime shift at 2018-01-01
- $$\sigma(t) = \begin{cases} 0.3 & \text{für } t < 2018, \\ 0.2 & \text{für } t \geq 2018. \end{cases}$$

Case 2: CDI Pricing Kernel of Jump in the Past

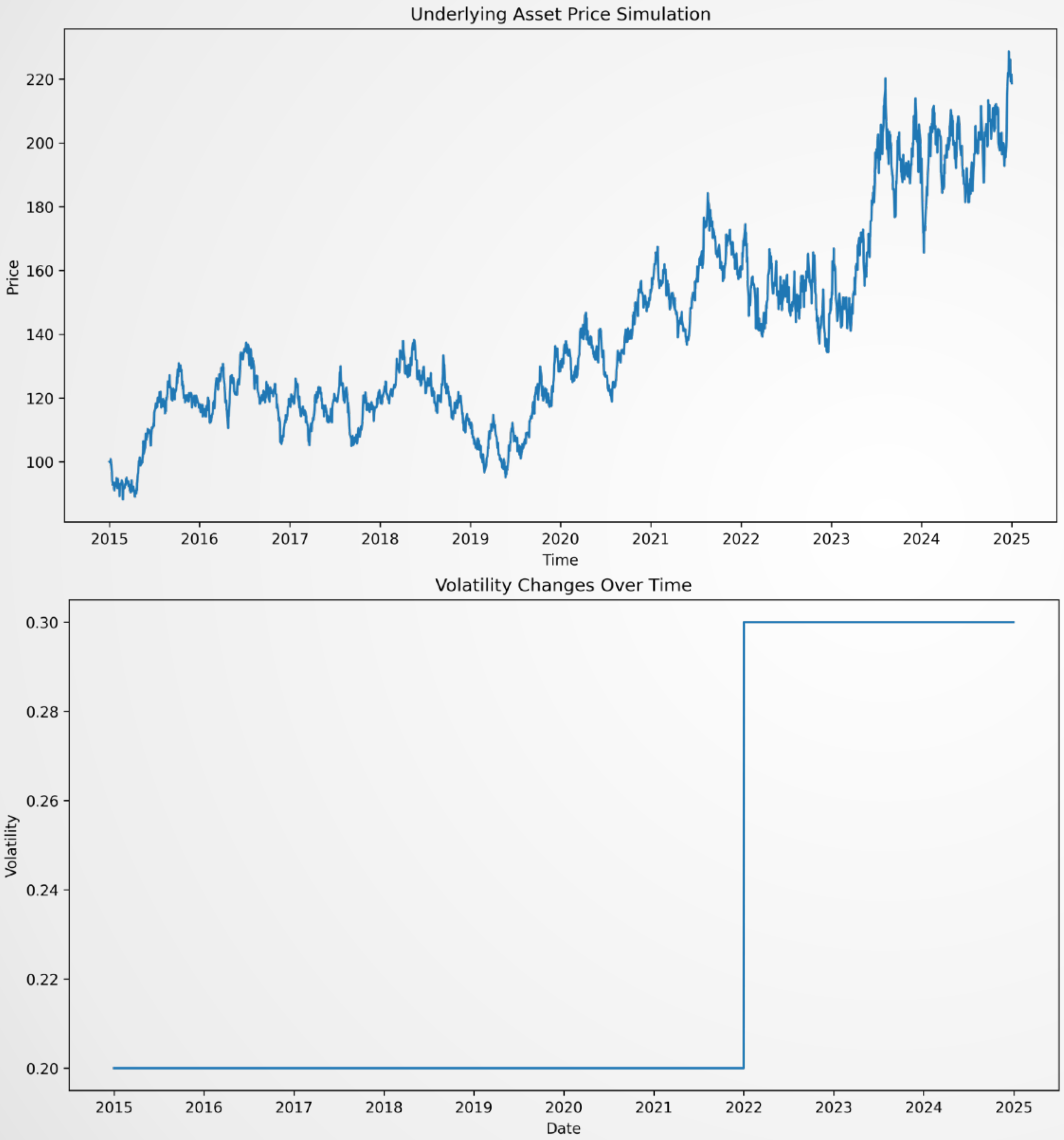


4 bases/moments, 5 bases/moments,

6 bases/moments, 7 bases/moments

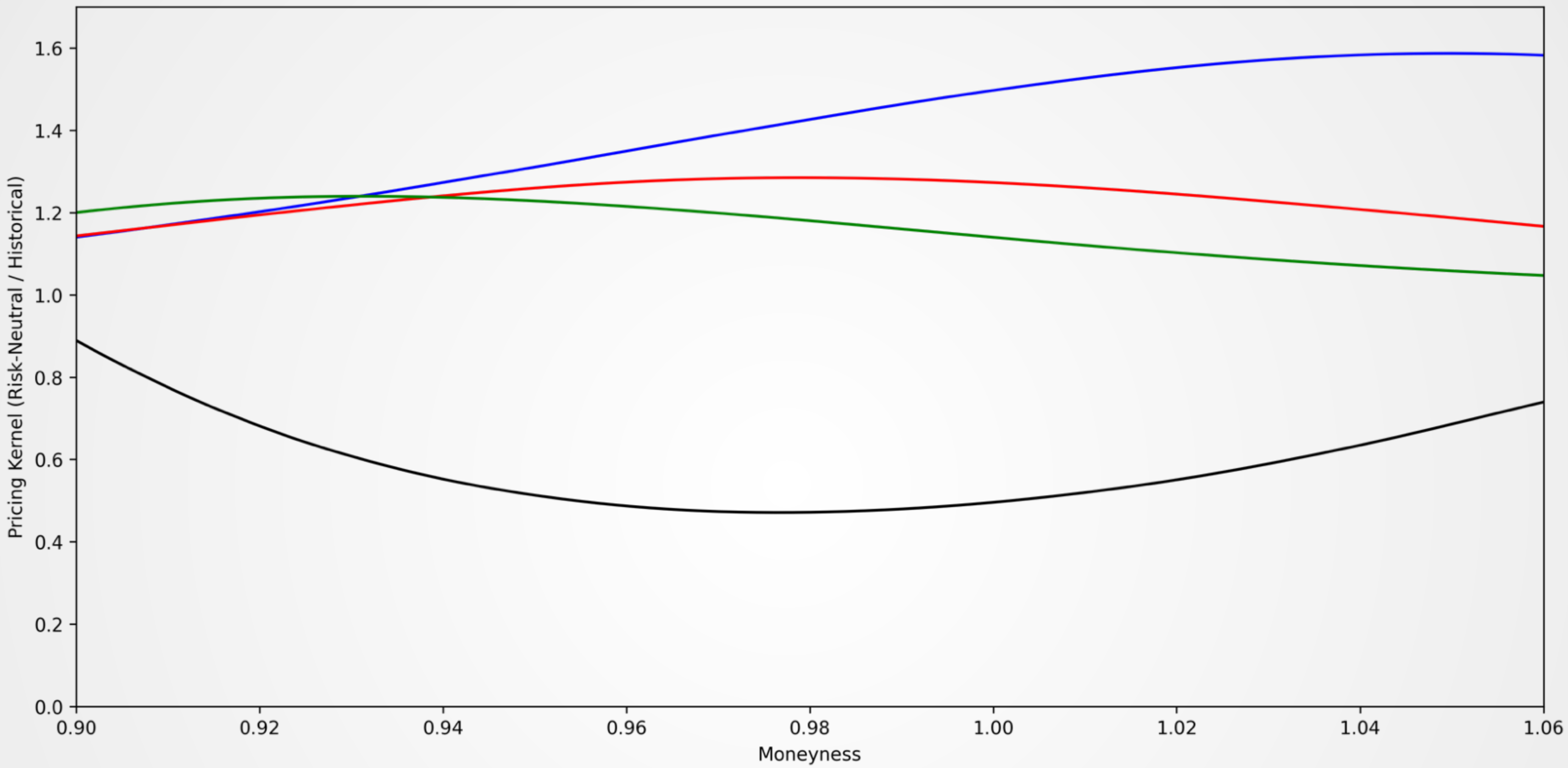
Steps: 0.001

Case 3: Volatility jump in the "future"



- Simulate a volatility regime shift at 2022-01-01
- $$\sigma(t) = \begin{cases} 0.2 & \text{für } t < 2022, \\ 0.3 & \text{für } t \geq 2022. \end{cases}$$

Case 3: CDI Pricing Kernel



4 bases/moments, 5 bases/moments,

6 bases/moments, 7 bases/moments

Steps: 0.001

Highlights

- Previous literature compares mismatched information sets
- The CDI approach is a nonparametric estimation technique using B-Splines for the pricing kernel by using GMM minimization
  - Requires daily returns and risk-neutral density as input
  - It includes forward looking returns as upper bound within the integral
  - Asymptotic distribution theory of Empirical Pricing Kernel (EPK) is lacking
  - Test for (non)monotone shape is impossible. Alternatively: *Uniform confidence band* of EPK
- CDI averages a period of time
- # knots in the B-spline should be carefully selected

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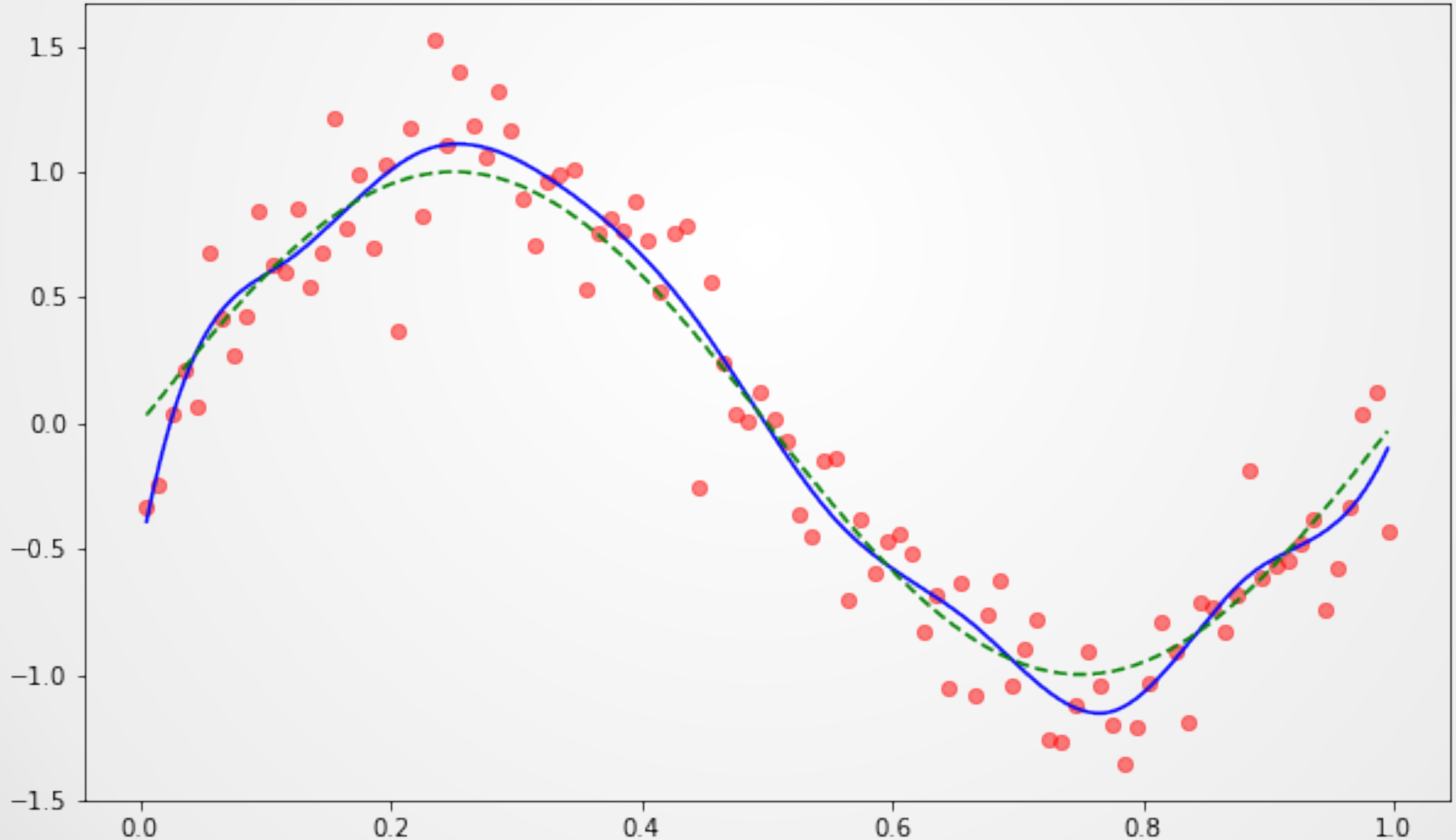
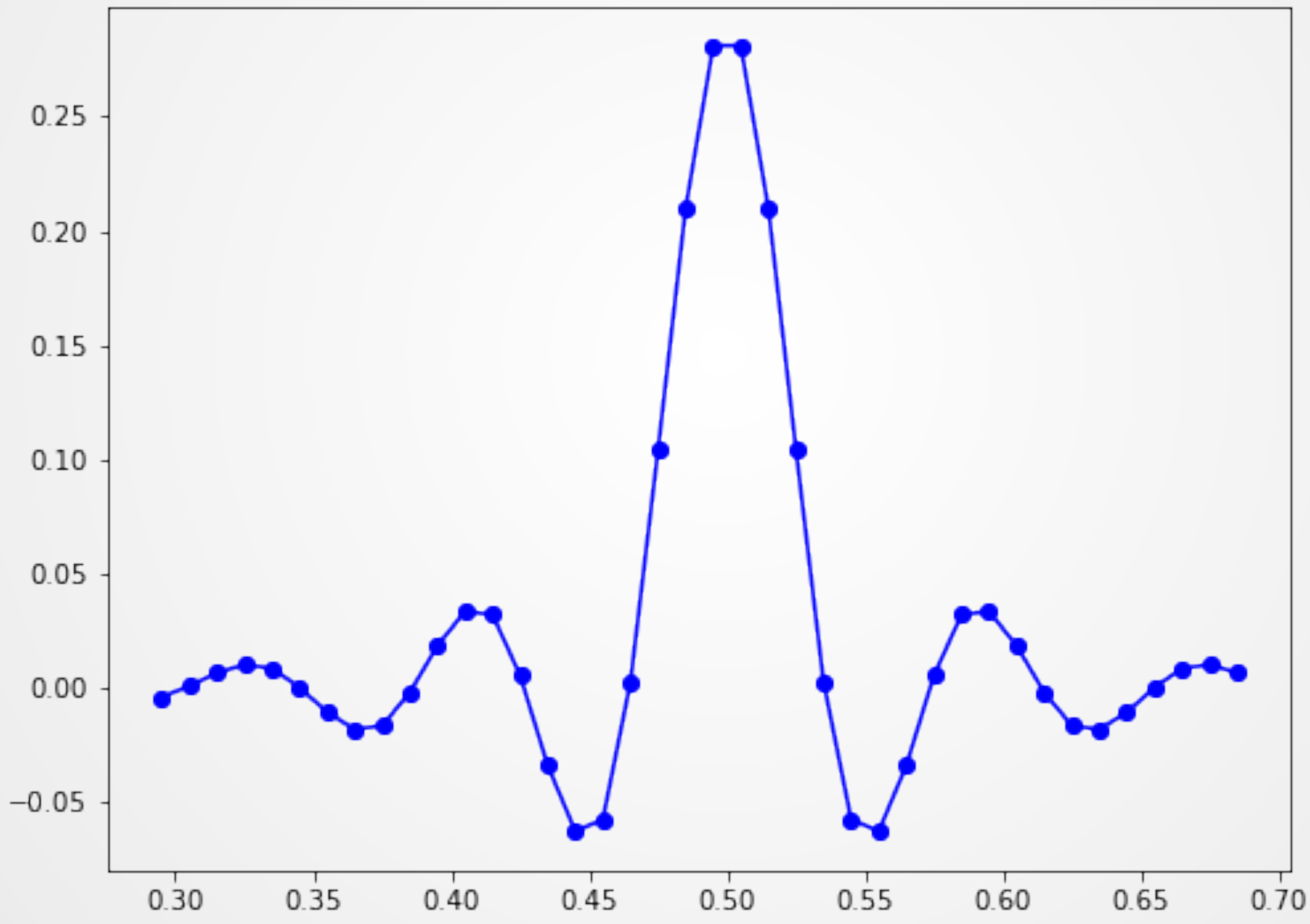
- B-spline (deg=3, k=10) smooth on $\sin(2\pi x)$ with noise (sig=0.2)



All smoothers are local averages

- B-spline contributions at $x = 0.50$

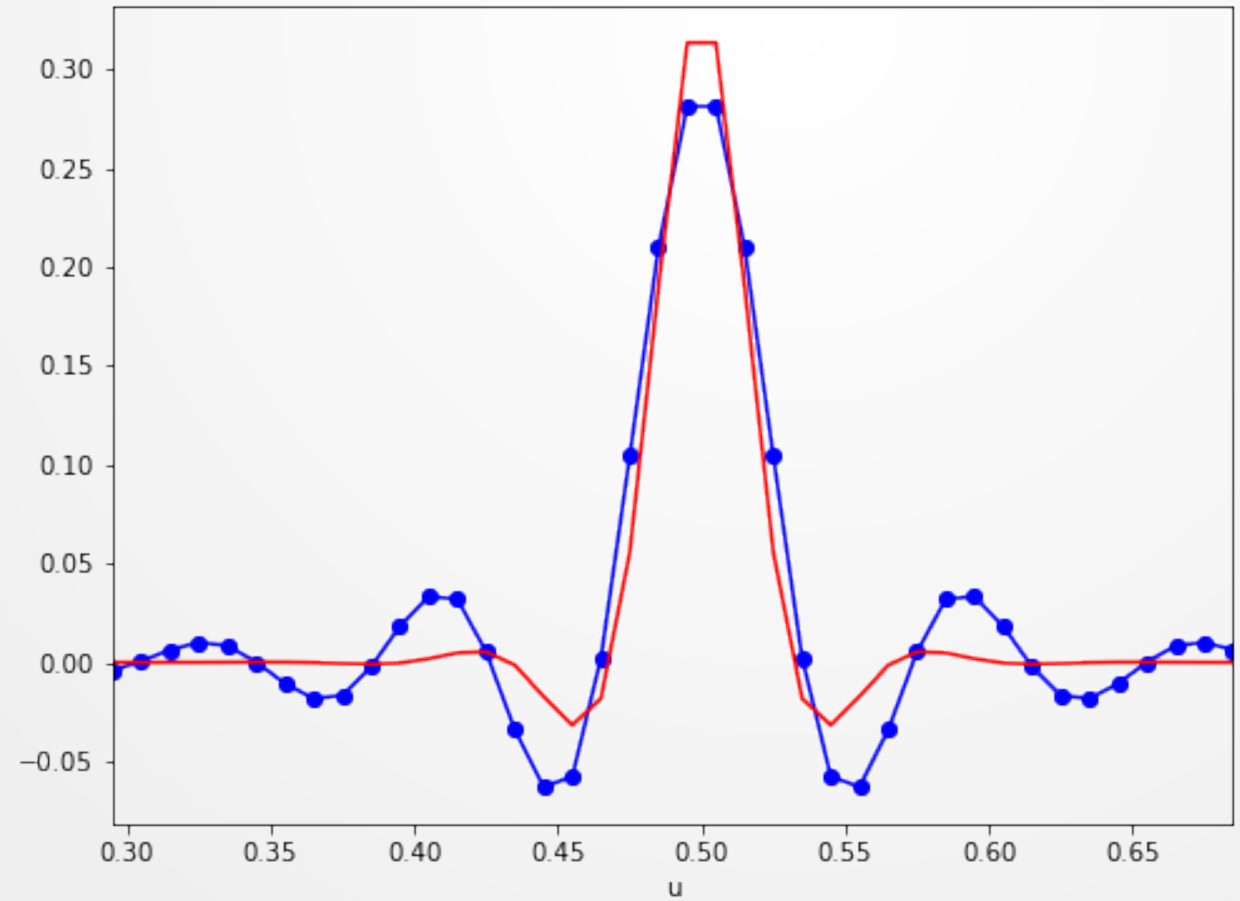


omnes viae Romam ducunt

$$f(u) = \frac{1}{6} \cdot \exp(|u|) + 2 \cdot \exp(-\frac{|u|}{2}) \cdot \sin(\frac{\pi}{6} + \sqrt{3} \cdot \frac{|u|}{2})$$

$G(x, x_i) = f\{(x - x_i)/h\}/h$; h - bandwidth

$$\hat{m}(x) = n^{-1} \sum G(x, x_i) \cdot Y_i$$



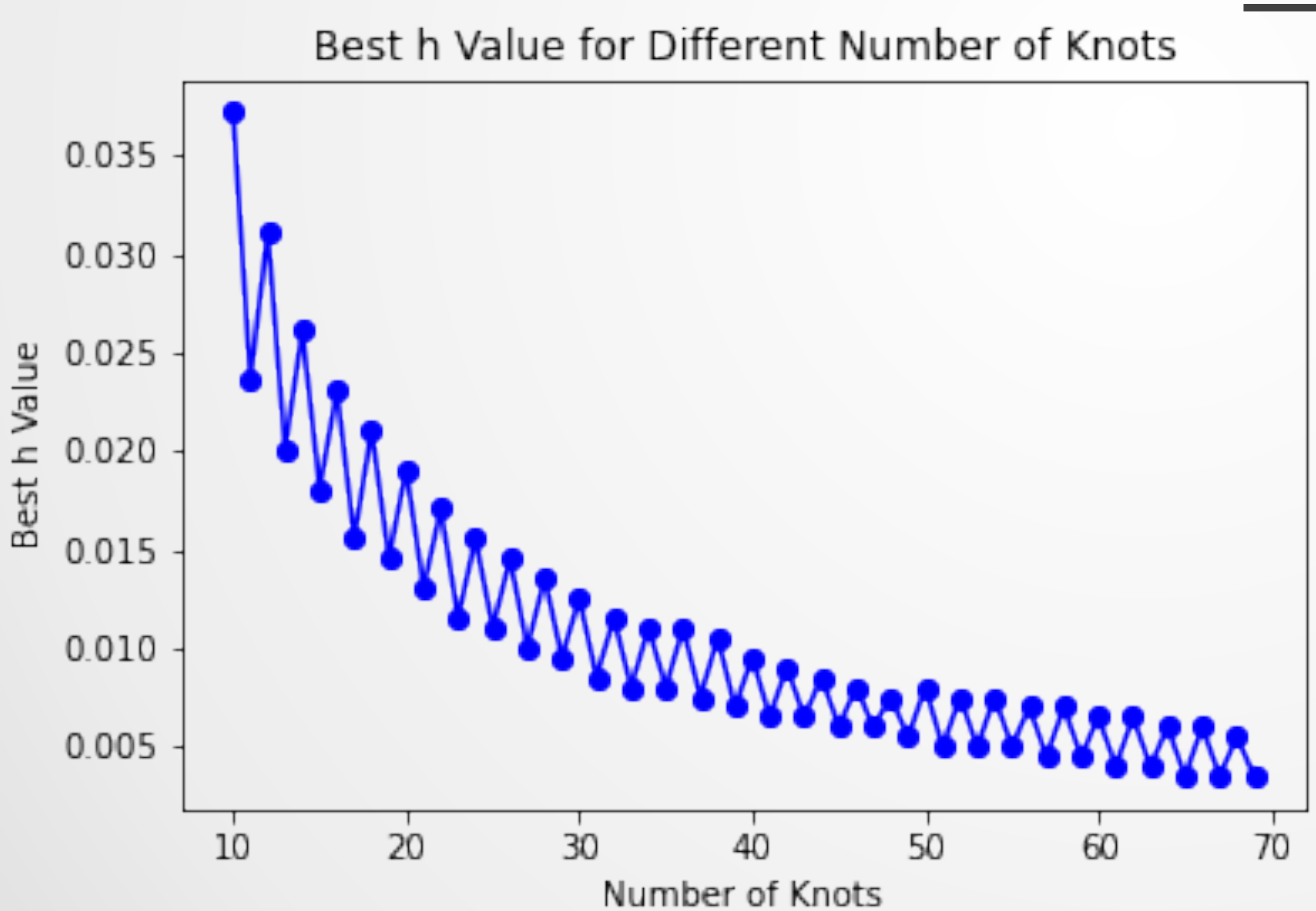
$f(u)$

B-spline

#knots = 1/h

- Given k, find the best h, to minimize the SSE between two smoothed curves
- $\log(k) = \beta_0 + \beta_1 \log(h) + \varepsilon$

Y	log(h)
log(k)	-1.011*** (0.047)
Observations	60
Adj_R^2	0.885



Nonparametric Regression Setting

$$Y = m(x) + \varepsilon$$

- Estimate unknown function $m(x) = \mathsf{E}\left(Y | X = x\right)$
- $\varepsilon \sim N(0,1)$, $x \in \mathbb{R}$ and deterministic
- Use B-spline of order m with knots at $\pm 1/2, \pm 3/2, \ldots$

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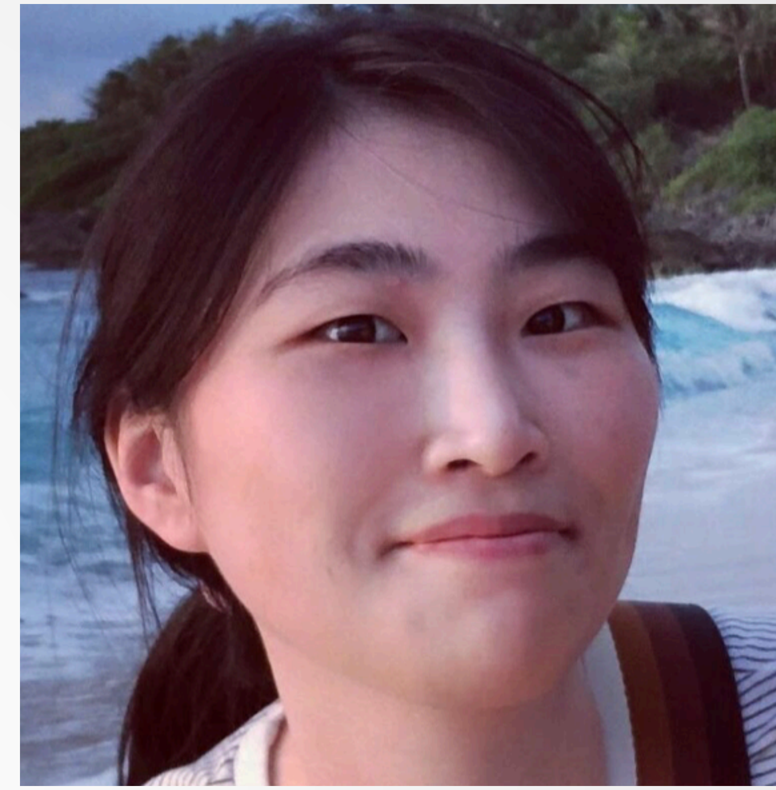
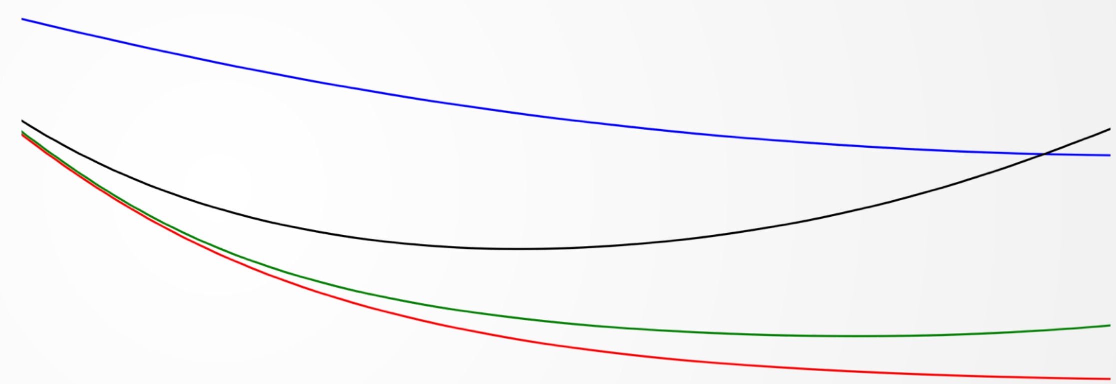
Team





Pricing Kernel Puzzles



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