Energy Markets I: First Models

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Plan of the Course

Commodity Markets

- Production, Transportation, Storage, Delivery
- Spot / Forward Markets

Spread Option Valuation

- Why Spread Options
- First Asset Valuation

Gas and Power Markets

- Physical / Financial Contracts
- Price Formation
- Load and Temperature

Weather Markets

- Weather Exposure
- Temperature Options

More Asset Valuation

- Plant Optionality Valuation
- Financial Valuation
- Valuing Storage Facilities

Emission Markets

No More Utilities monopolies

Vertical Integration of production, transportation, distribution of electricity

Unbundling

Open competitive markets for production and retail (Typically, grid remains under control)

New Price Formation

Constant *supply - demand* balance (Market forces) Commodities form a **separate asset class**!

LOCAL STACK – MERIT ORDER (plant on the margin)

(producer, retailer, utility, investment banks, ...)

Different data analysis

(spot, day-ahead, on-peak, off-peak, firm, non-firm, forward, $\cdots,$ negative prices)

New instrument valuation

- New forms of **hedging** using physical assets Perfected by **GS & MS** (power plants, pipelines, tankers,)
- Marking to market and new forms of **risk** measures

(producer, retailer, utility, investment banks, ...)

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Degradation of credit exacerbated liquidity problems

Credit risk

- Understanding the statistics of credit migration
- Including counter-party risk in valuation
- Credit derivatives and credit enhancement
- Reporting and indexes
- Could clearing be a solution?
 - Exchange traded instruments pretty much standardized, but OTC!
 - Design of a minimal set of instruments for standardization
- Collateral requirements / margin calls
 - **Objective valuation** algorithms widely accepted for frequent Mark-to-Market
 - Netting
 - Challenge of the dependencies (correlations, copulas,)
 - Integrated approach to risk control

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Physical Markets

- Spot (immediate delivery) Markets
- Forward Markets
- Volume Explosion with Financially Settled Contracts
 - Physical / Financial Contracts
 - Exchanges serve as Clearing Houses
 - Speculators provide Liquidity
- In IB, part of Fixed Income Desk
- Seasonality / Storage / Convenience Yield

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• How can it be a challenge?

Just do a PCA !

- "OK" for Crude Oil (backwardation/contango \rightarrow 3 factors)
- Not settled for Gas
- Does not work for Electricity
- Extreme complexity & size of the data (location, grade, peak/off peak, firm/non firm, interruptible, swings, etc)
- Incomplete and inconsistent sources of information
- Liquidity and wide Bid-Ask spreads (smoothing)
- Length of the curve (extrapolation)

• Dynamic models à la HJM:

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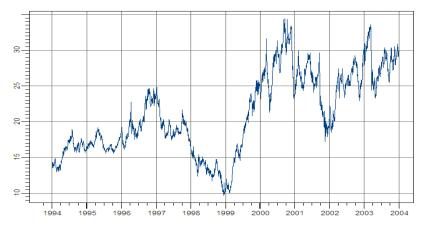
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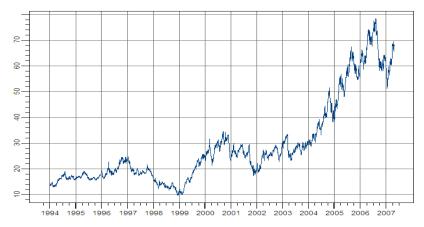
Crude Oil-Brent 1Mth Fwd FOB U\$/BBL before Katrina



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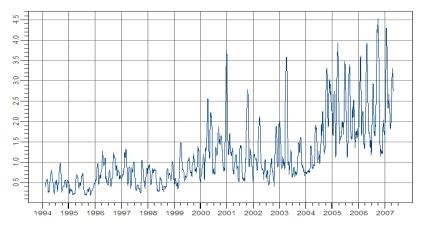
More Crude Oil Data

Crude Oil-Brent 1Mth Fwd FOB U\$/BBL



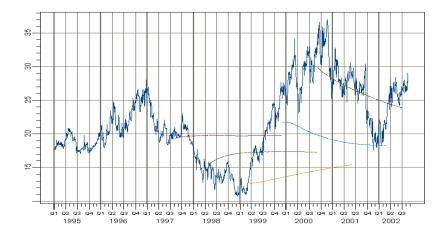
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Crude Oil Spot Volatility

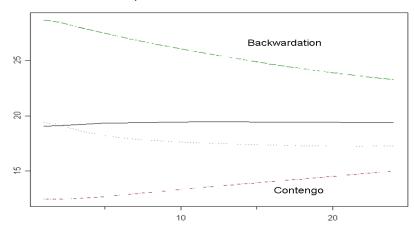


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Is the Forward the Expected Value of Future Spots?

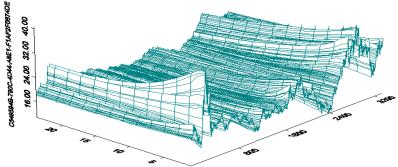


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Examples of Crude Oil Forward Curves

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Spot Forward Relationship

In financial models where one can hold positions at no cost

$$F(t,T) = S(t)e^{r(T-t)}$$

by a simple cash & carry arbitrage argument. In particular

 $F(t,T) = \mathbb{E}\{S(T) \,|\, \mathcal{F}_t\}$

for risk neutral expectations.

Perfect Price Discovery

In general (theory of normal backwardation)

- F(t, T) is a **downward biased** estimate of S(T)
- Spot price exceeds the forward prices

conditional expectation of future values of Spot Price

No cash & carry arbitrage argument

- Is the spot really tradable?
- What are its dynamics?
- How do we risk-adjust them?
- Convenience Yield for storable commodities
 - Natural Gas, Crude Oil, ...
 - Correct interest rate to compute present values
 - Does not apply to Electricity

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Spot-Forward Relationship in Commodity Markets

For **storable** commodities (still same **cash & carry arbitrage** argument)

$$F(t,T) = S(t)e^{(r-\delta)(T-t)}$$

for $\delta \ge 0$ called **convenience yield**. (NOT FOR ELECTRICITY !)

Decompose $\delta = \delta_1 - c$ with

- δ_1 benefit from owning the physical commodity
- c cost of storage

Then

$$f(t, T) = e^{r(T-t)}e^{-\delta_1(T-t)}e^{-c(T-t)}$$

- $e^{r(T-t)}$ cost of **financing** the purchase
- *e^{c(T-t)}* cost of **storage**
- $e^{-\delta_1(T-t)}$ sheer **benefit from owning** the physical commodity

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Backwardation

•
$$T \hookrightarrow F(t,T) = S(t)e^{(r+c-\delta_1)(T-t)}$$
 decreasing if $r + c < \delta_1$

- Low cost of storage
- Low interest rate
- High benefit in holding the commodity

Contango

• $T \hookrightarrow F(t,T) = S(t)e^{(r+c-\delta_1)(T-t)}$ increasing if $r + c \ge \delta_1$

Backwardation

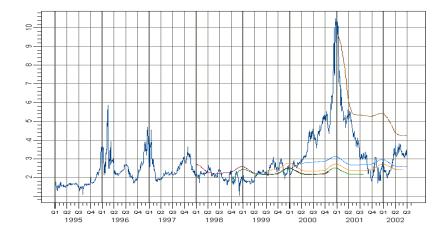
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Natural Gas



Commodity Convenience Yield Models

Gibson-Schwartz Two-factor model

- St commodity spot price
- δ_t convenience yield

Risk Neutral Dynamics

$$dS_t = (r_t - \delta_t)S_t dt + \sigma S_t dW_t^1,$$

$$d\delta_t = \kappa(\theta - \delta_t)dt + \sigma_\delta dW_t^2$$

Major Problems

- Explicit formulae (exponential affine model)
- Convenience yield implied from forward contract prices
- Unstable & Inconsistent (R.C.-M. Ludkovski)

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Lack of Consistency

Exponential Affine Model

$$F(t,T) = S_t e^{\int_t^T r_s ds} e^{B(t,T)\delta_t + A(t,T)}$$

where

$$B(t,T) = \frac{e^{-\kappa(T-t)}-1}{\kappa},$$

$$A(t,T) = \frac{\kappa\theta+\rho\sigma_s\gamma}{\kappa^2}(1-e^{-\kappa(T-t)}-\kappa(T-t)) + \frac{\gamma^2}{\kappa^3}(2\kappa(T-t)-3+4e^{-\kappa(T-t)}-e^{-2\kappa(T-t)}).$$

- For each T, one can imply δ_t from F(t, T)
- Inconsistency in the implied δ_t
- Ignores Maturity Specific effects

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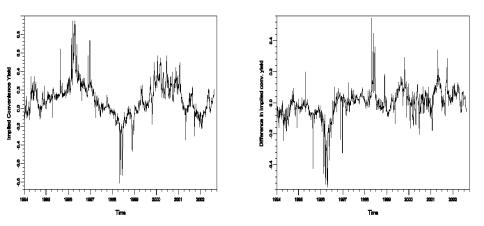
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Crude Oil convenience yield implied by a 3 month futures contract (left) Difference in implied convenience yields between 3 and 12 month contracts.

Convenience Yield Models Revisited

Use forward $F_t = F(t, T_0)$ instead of spot S_t (T_0 fixed maturity) Historical Dynamics

$$dF_t = (\mu_t - \delta_t)F_t dt + \sigma F_t dW_t^1, d\delta_t = \kappa(\theta - \delta_t)dt + \sigma_\delta dW_t^2$$

or more generally

$$d\delta_t = b(\delta_t, F_t)dt + \sigma_{\delta}(\delta_t, F_t)dW_t^2$$

We assume

- *F_t* is tradable (hence observable)
- (Forward) convenience yield δ_t not observable (filtering)

Different from Bjork-Landen's Risk Neutral Term Structure of Convenience Yield

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The Case of Power

Several obstructions

- Cannot store the physical commodity
- Which spot price? Real time? Day-ahead? Balance-of-the-week? month? on-peak? off-peak? etc
- Does the forward price converge as the time to maturity goes to 0?

Mathematical spot?

$$S(t) = \lim_{T \downarrow t} F(t, T)$$

Sparse Forward Data

- Lack of transparency (manipulated indexes)
- Poor (or lack of) **reporting** by fear of law suits
- CCRO white paper(s)

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n-factor forward curve model

$$\frac{dF(t,T)}{F(t,T)} = \mu(t,T)dt + \sum_{k=1}^{n} \sigma_k(t,T)dW_k(t) \qquad t \leq T$$

• $W = (W_1, \ldots, W_n)$ is a *n*-dimensional standard Brownian motion,

- drift μ and volatilities σ_k are deterministic functions of t and time-of-maturity T
- $\mu(t, T) \equiv 0$ for pricing
- $\mu(t, T)$ calibrated to historical data for risk management

$$F(t,T) = F(0,T) \exp\left[\int_0^t \left[\mu(s,T) - \frac{1}{2}\sum_{k=1}^n \sigma_k(s,T)^2\right] ds + \sum_{k=1}^n \int_0^t \sigma_k(s,T) dW_k(s)\right]$$

Forward prices are log-normal (deterministic coefficients)

$$F(t,T) = \alpha e^{\beta X - \beta^2/2}$$

with $X \sim N(0, 1)$ and

$$\alpha = F(0, T) \exp\left[\int_0^t \mu(s, T) ds\right], \quad \text{and} \quad \beta = \sqrt{\sum_{k=1}^n \int_0^t \sigma_k(s, T)^2 ds}$$

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Dynamics of the Spot Price

Spot price left hand of forward curve

$$S(t) = F(t,t)$$

We get

$$S(t) = F(0, t) \exp\left[\int_0^t [\mu(s, t) - \frac{1}{2} \sum_{k=1}^n \sigma_k(s, t)^2] ds + \sum_{k=1}^n \int_0^t \sigma_k(s, t) dW_k(s)\right]$$

and differentiating both sides we get:

$$dS(t) = S(t) \left[\left(\frac{1}{F(0,t)} \frac{\partial F(0,t)}{\partial t} + \mu(t,t) + \int_0^t \frac{\partial \mu(s,t)}{\partial t} ds - \frac{1}{2} \sigma_S(t)^2 - \sum_{k=1}^n \int_0^t \sigma_k(s,t) \frac{\partial \sigma_k(s,t)}{\partial t} ds + \sum_{k=1}^n \int_0^t \frac{\partial \sigma_k(s,t)}{\partial t} dW_k(s) \right) dt + \sum_{k=1}^n \sigma_k(t,t) dW_k(t) \right]$$

Spot volatility

$$\sigma_{S}(t)^{2} = \sum_{k=1}^{n} \sigma_{k}(t, t)^{2}.$$
 (1)
Carmona Energy Markets, Banff

Hence

$$\frac{dS(t)}{S(t)} = \left[\frac{\partial \log F(0,t)}{\partial t} + D(t)\right] dt + \sum_{k=1}^{n} \sigma_k(t,t) dW_k(t)$$

with drift

$$D(t) = \mu(t,t) - \frac{1}{2}\sigma_{s}(t)^{2} + \int_{0}^{t} \frac{\partial\mu(s,t)}{\partial t} ds - \sum_{k=1}^{n} \int_{0}^{t} \sigma_{k}(s,t) \frac{\partial\sigma_{k}(s,t)}{\partial t} ds$$
$$+ \sum_{k=1}^{n} \int_{0}^{t} \frac{\partial\sigma_{k}(s,t)}{\partial t} dW_{k}(s)$$

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Remarks

- Interpretation of drift (in a risk-neutral setting)
 - logarithmic derivative of the forward can be interpreted as a discount rate (*i.e.*, the running interest rate)
 - D(t) can be interpreted as a convenience yield

• Drift generally **not Markovian**

• Particular case n = 1, $\mu(t, T) \equiv 0$, $\sigma_1(t, T) = \sigma e^{-\lambda(T-t)}$

$$D(t) = \lambda [\log F(0,t) - \log S(t)] + rac{\sigma^2}{4}(1-e^{-2\lambda t})$$

$$\frac{dS(t)}{S(t)} = [\mu(t) - \lambda \log S(t)]dt + \sigma dW(t)$$

exponential OU

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exponential OU

time-of-maturity $T \Rightarrow$ time-to-maturity τ

changes dependence upon t

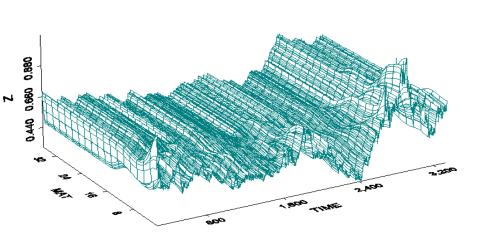
$$t \hookrightarrow F(t,T) = F(t,t+\tau) = \tilde{F}(t,\tau)$$

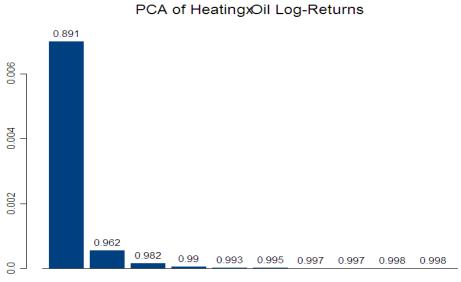
Fixed Domain $[0,\infty)$ for $\tau \hookrightarrow \tilde{F}(t(\tau))$

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2

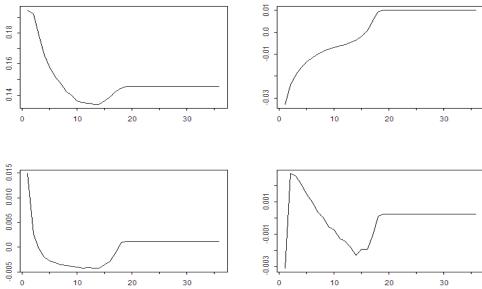
Heating Oil Forward Surface



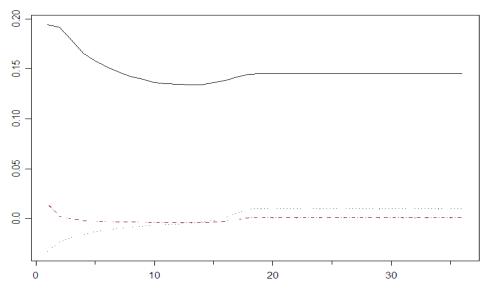


Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8 Comp.9Comp.10



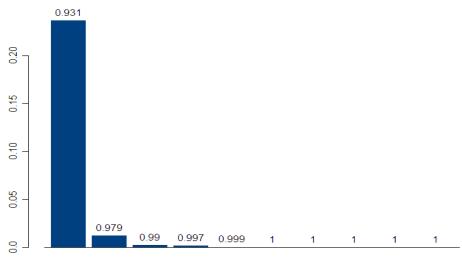


HO Loadings on their Importance Scale



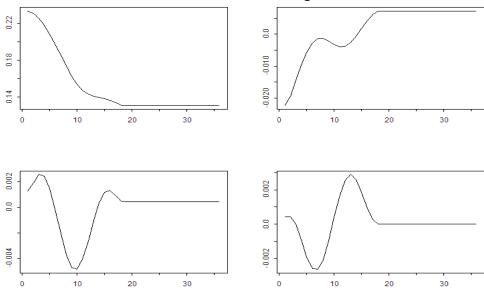
Plain Forward HO PCA

PCA of Heating Oil Forwards

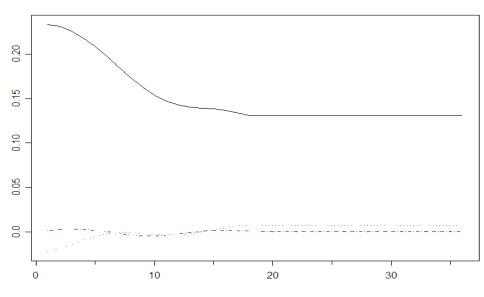


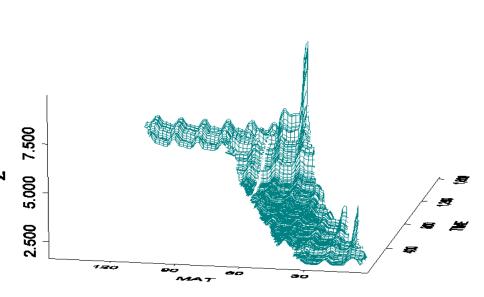
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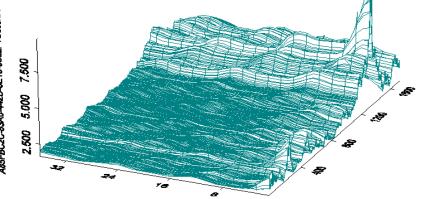
HO PCA Loadings



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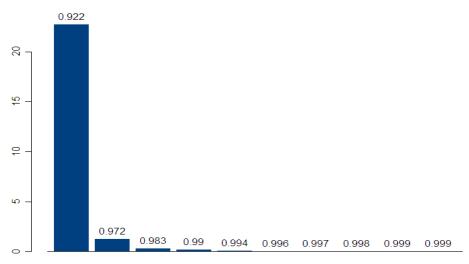






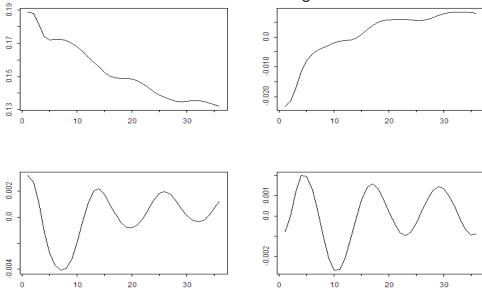
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PCA of Henry Hub Natural Gas Forward Prices

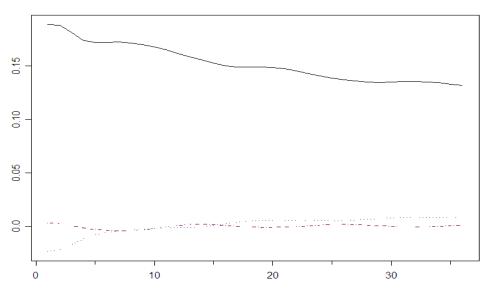


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HH PCA Loadings



HH Loadings on their Absolute Importance Scale



time-of-maturity $T \Rightarrow$ time-to-maturity τ

changes dependence upon t

$$t \hookrightarrow F(t,T) = F(t,t+\tau) = \tilde{F}(t,\tau)$$

For pricing purposes

• For T fixed, $\{F(t, T)\}_{0 \le t \le T}$ is a martingale

• For τ fixed, $\{\tilde{F}(t,\tau)\}_{0 \le t}$ is NOT a martingale

 $\tilde{F}(t,\tau) = F(t,t+\tau),$ $\tilde{\mu}(t,\tau) = \mu(t,t+\tau),$ and $\tilde{\sigma}_k(t,\tau) = \sigma_k(t,t+\tau),$ In general dynamics become

$$d\tilde{F}(t,\tau) = \tilde{F}(t,\tau) \left[\left(\tilde{\mu}(t,\tau) + \frac{\partial}{\partial \tau} \log \tilde{F}(t,\tau) \right) dt + \sum_{k=1}^{n} \tilde{\sigma}_{k}(t,\tau) dW_{k}(t) \right],$$

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PCA with Seasonality

Fundamental Assumption

$$\sigma_k(t,T) = \sigma(t)\sigma_k(T-t) = \sigma(t)\sigma_k(\tau)$$

for some function $t \hookrightarrow \sigma(t)$

Notice

$$\sigma_{\mathcal{S}}(t) = \tilde{\sigma}(\mathbf{0})\sigma(t)$$

provided we set:

$$\tilde{\sigma}(\tau) = \sqrt{\sum_{k=1}^{n} \sigma_k(\tau)^2}.$$

Conclusion

 $t \hookrightarrow \sigma(t)$ is (up to a constant) the **instantaneous spot volatility**

Rationale for a New PCA

- Fix times-to-maturity $\tau_1, \tau_2, \ldots, \tau_N$
- Assume on each day *t*, quotes for the forward prices with times-of-maturity $T_1 = t + \tau_1$, $T_2 = t + \tau_2$, ..., $T_N = t + \tau_N$ are available

$$\frac{d\tilde{F}(t,\tau_i)}{\tilde{F}(t,\tau_i)} = \left(\tilde{\mu}(t,\tau_i) + \frac{\partial}{\partial\tau}\log\tilde{F}(t,\tau_i)\right)dt + \sigma(t)\sum_{k=1}^n \sigma_k(\tau_i)dW_k(t) \qquad i = 1,\dots,N$$
Define $\mathbf{F} = [\sigma_k(\tau_i)]_{i=1}$ we keet $\sigma_k(\tau_i)$

$$d\log \tilde{F}(t,\tau_i) = \left(\tilde{\mu}(t,\tau_i) + \frac{\partial}{\partial \tau_i}\log \tilde{F}(t,\tau_i) - \frac{1}{2}\sigma(t)^2\tilde{\sigma}(\tau_i)^2\right)dt + \sigma(t)\sum_{k=1}^n \sigma_k(\tau_i)dW_k(t)$$

Instantaneous variance/covariance matrix $\{M(t); t \ge 0\}$ defined by:

$$d[\log \tilde{F}(\,\cdot\,, au_i),\log \tilde{F}(\,\cdot\,, au_j)]_t = M_{i,j}(t)dt$$

satisfies

$$M(t) = \sigma(t)^2 \left(\sum_{k=1}^n \sigma_k(\tau_i) \sigma_k(\tau_j) \right)$$

or equivalently

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- Estimate FF* from historical data as the empirical auto-covariance of ln(F(t, ·)) ln(F(t 1, ·)) after normalization by σ(t)
- Instantaneous auto-covariance structure of the entire forward curve becomes time independent
- Do SVD of auto-covariance matrix and get

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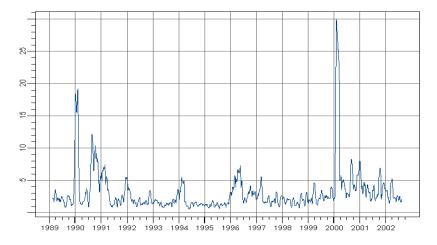
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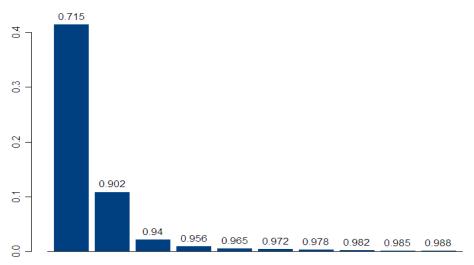
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The Case of Natural Gas



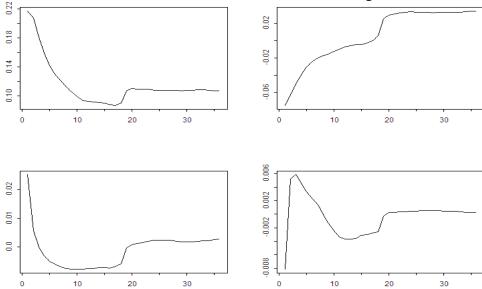
Instantaneous standard deviation of the Henry Hub natural gas spot price computed in a sliding window of length 30 days.

PCA of Henry Hub Natural Gas De-Seasonalized Forward Prices

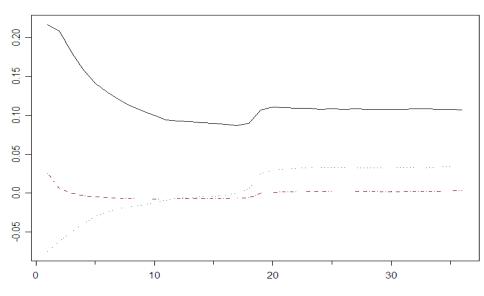


Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8 Comp.9Comp.10

HH De-Seasonalized PCA Loadings



HH De-Seasonalized Loadings on their Absolute Importance Scal



Mean Reversion toward the cost of production

The example of the power prices

- Reduced Form Models
 - Nonlinear effects (exponential OU²)

Mean Reversion toward the cost of production The example of the power prices

Reduced Form Models

- Nonlinear effects (exponential OU²)
- Jumps (Geman-Roncoroni)
- Structural Models
 - Inelastic Demand
 - The Supply Stack

Barlow (based on merit order graph)

- $s_t(x)$ supply at time *t* when power price is *x*
- $d_t(x)$ demand at time t when power price is x

Power price at time t is number S_t such that

$$s(S_t) = d_t(S_t)$$

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Example of a merit graph (Alberta Power Pool, courtesy M. Barlow)

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Barlow's Proposal

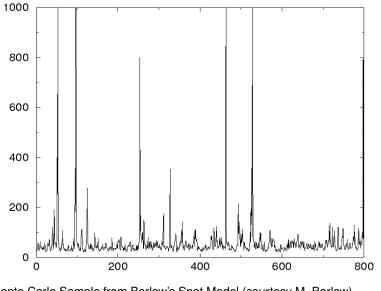
$$\mathcal{S}(t) = egin{cases} f_lpha(X_t) & 1+lpha X_t > \epsilon_0 \ \epsilon_0^{1/lpha} & 1+lpha X_t \leq \epsilon_0 \end{cases}$$

for the non-linear function

$$f_{\alpha}(\mathbf{x}) = \begin{cases} (1 + \alpha \mathbf{x})^{1/\alpha}, & \alpha \neq \mathbf{0} \\ \mathbf{e}^{\mathbf{x}} & \alpha = \mathbf{0} \end{cases}$$

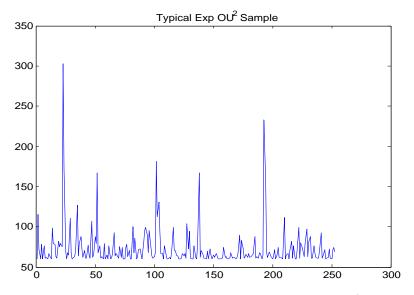
of an **OU** diffusion

$$dX_t = -\lambda(X_t - \overline{x})dt + \sigma dW_t$$



Monte Carlo Sample from Barlow's Spot Model (courtesy M. Barlow)

Cheap Alternative



Example of a Monte Carlo Sample from the Exponential of an OU^2

Carmona Energy Markets, Banff

- Over 3,000 nodes in the transmission network
- Each day, and for each node
 - Real time prices
 - Day-ahead prices
 - Hour by hour load prediction for the following day
- Historical prices
- In 2003 over 100,000 instances of NEGATIVE PRICES
 - Geographic clusters
 - Time of the year (shoulder months)
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- Possible Explanations
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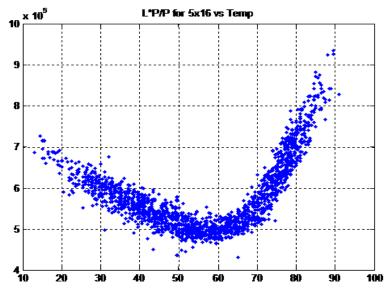
Possible Explanations

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For many contracts, delivery needs to match demand

- Demand for energy highly correlated with temperature
 - Heating Season (winter) HDD
 - Cooling Season (summer) CDD
- Stylized Facts and First (naive) Models
 - Electricity demand = β * weather + α

Load / Temperature



Daily Load versus Daily Temperature (PJM)

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 - Time dependent β by filtering !
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 - Could it be because of heavy tails?
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First Faculty Meeting of New PU President

Princeton University Electricity Budget

2.8 M \$ over (PU is small)

- The University has its own Power Plant
- Gas Turbine for Electricity & Steam
- Major Exposures
 - Hot Summer (air conditioning) Spikes in Demand, Gas & Electricity Prices
 - Cold Winter (heating) Spikes in Gas Prices

Risk Management Solution

- Never Again such a Short Fall !!!
- Student (Greg Larkin) Senior Thesis
- Hedging Volume Risk
 - Protection against the Weather Exposure
 - Temperature Options on CDDs (Extreme Load)
- Hedging Volume & Basis Risk
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Mitigating Volume Risk with Swing Options

Exposure to spikes in prices of

- Natural Gas (used to fuel the plant)
- Electricity Spot (in case of overload)

Proposed Solution

- Forward Contracts
- Swing Options

Pretty standard

Mitigating Volume Risk

Use Swing Options

- Multiple Rights to deviate (within bounds) from base load contract level
- Pricing & Hedging quite involved!
 - Tree/Forest Based Methods
 - Direct Backward Dynamic Programing Induction (à la Jaillet-Ronn-Tompaidis)
 - New Monte Carlo Methods
 - Nonparametric Regression (à la Longstaff-Schwarz) Backward Dynamic Programing Induction

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Mathematics of Swing Contracts: a Crash Course

Review: Classical Optimal Stopping Problem: American Option

- $X_0, X_1, X_2, \cdots, X_n, \cdots$ rewards
- Right to ONE Exercise
- Mathematical Problem

$$\sup_{0 \le \tau \le T} \mathbb{E}\{X_{\tau}\}$$

Mathematical Solution

- Snell's Envelop
- Backward Dynamic Programming Induction in Markovian Case

Standard, Well Understood

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Standard, Well Understood

In its simplest form the problem of Swing/Recall option pricing is an

Optimal Multiple Stopping Problem

- $X_0, X_1, X_2, \cdots, X_n, \cdots$ rewards
- Right to N Exercises
- Mathematical Problem

$$\sup_{0\leq \tau_1<\tau_2<\cdots<\tau_N\leq T}\mathbb{E}\{X_{\tau_1}+X_{\tau_2}+\cdots+X_{\tau_N}\}$$

• **Refraction** period θ

$$\tau_1 + \theta < \tau_2 < \tau_2 + \theta < \tau_3 < \dots < \tau_{N-1} + \theta < \tau_N$$

Part of recall contracts & crucial for continuous time models

Instruments with Multiple American Exercises

Ubiquitous in Energy Sector

- Swing / Recall contracts
- End user contracts (EDF)
- Present in other contexts
 - Fixed income markets (e.g. chooser swaps)
 - Executive option programs
 - Reload \rightarrow Multiple exercise, Vesting \rightarrow Refraction, \cdots
 - Fleet Purchase (airplanes, cars, ···)
- Challenges
 - Valuation
 - Optimal exercise policies
 - Hedging

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Some Mathematical Problems

Recursive re-formulation into a hierarchy of classical optimal stopping problems

- Development of a theory of *Generalized Snell's Envelop* in continuous time setting
- Find a form of Backward Dynamic Programing Induction in Markovian Case
- Design & implement efficient numerical algorithms for finite horizon case

- Perpetual case: abstract nonsense
 R.C.& S.Dayanik (diffusion), R.C.& N.Touzi (GBM)
- Perpetual case: Characterization of the optimal policies R.C.& S.Dayanik (diffusion), R.C.& N.Touzi (GBM)
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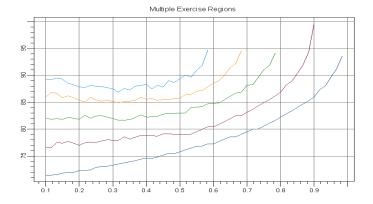
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R.C.-Touzi, (Bouchard)



Exercise regions for N = 5 rights and finite maturity computed by Malliavin-Monte-Carlo.

• Rigorous Analysis of the Dependence between the **Budget Shortfall** and **Temperature** in Princeton

- Use of Historical Data (sparse) & Define of a Temperature Protection
 - Period of the Coverage
 - Form of the Coverage

- La Guardia Airport (LGA)
- Philadelphia (PHL)
- Define a Portfolio of LGA & PHL forward / option Contracts
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Pricing: How Much is it Worth to PU?

Actuarial / Historical Approach

- Burn Analysis
- Temperature Modeling & Monte Carlo VaR Computations
- Not Enough Reliable Load Data

• Expected (Exponential) Utility Maximization (A. Danilova)

- Use Gas & Power Contracts
- Hedging in Incomplete Models
- Indifference Pricing
- Very Difficult Numerics (whether PDE's or Monte Carlo)

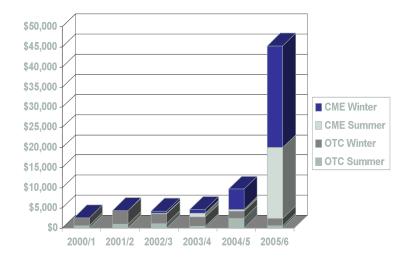
Weather is an essential economic factor

- 'Weather is not just an environmental issue; it is a major economic factor. At least 1 trillion USD of our economy is weather-sensitive' (William Daley, 1998, US Commerce Secretary)
- 20% of the world economy is estimated to be affected by weather
- Energy and other industrial sectors, Entertainment and Tourism Industry, ...

• WRMA

Weather Derivatives as a **Risk Transfer** Mechanism (**El Karoui -Barrieu**)

Size of the Weather Market



Total Notional Value of weather contracts: (in million USD) Price Waterhouse Coopers market survey).

• OTC Customer tailored transactions

- Temperature, Precipitation, Wind, Snow Fall,
- CME (\approx 50%) (Tempreature Launched in 1999)
 - 18 American cities
 - 9 European cities (London, Paris, Amsterdam, Berlin, Essen, Stockholm, Rome, Madrid and Barcelona)
 - 2 Japanese cities (Tokyo and Osaka)

An Example of Precipitation Contract

- Physical Underlying Daily Index:
 - Precipitation in Paris
 - A day is a rainy day if precipitation exceeds 2mm
- Season
 - 2000: April thru August + September weekends
 - 2001: April thru August + September weekends
 - 2002: April thru August + September weekends
- Aggregate Index
 - Total Number of Rainy Days in the Season
- Pay- Off
 - Strike, Cap, Rate

RainFall Option Continued

Who Wanted this Deal?

• A Natural Trying to Hedge RainFall Exposure (Asterix Amusement Park)

Who was willing to take the other side?

- Speculators
- Insurance Companies
- Re-insurance Companies
- Statistical Arbitrageurs
- Investment Banks
- Hedge Funds
- Endowment Funds
-

Other Example: Precipitation / Snow Pack

City of Sacramento

- HydroPower Electricity
- Who was on the other side?
 - Large Energy Companies (Aquila, Enron)

Who is covering for them?

For a given location, on any given day t

 $CDD_t = \max\{T_t - 65, 0\}$ $HDD_t = \max\{65 - T_t, 0\}$

Season

- One Month (CME Contracts)
- May 1st September 30 (CDD season)
- November 1st March 31st (HDD season)

Index

• Aggregate number of DD in the season

$$I = \sum_{t \in \text{Season}} CDD_t$$
 or $I = \sum_{t \in \text{Season}} HDD_t$

Pay-Off

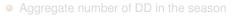
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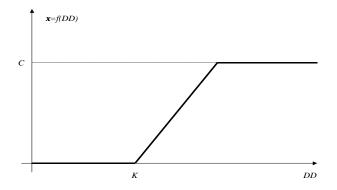
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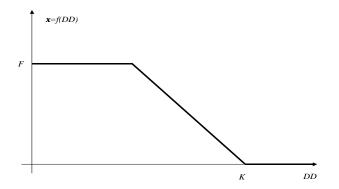


 $Pay-off = \min\{\max\{\alpha * (I - K), 0\}, C\}$

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Put with a Floor

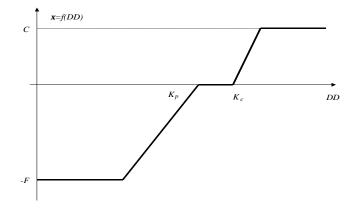


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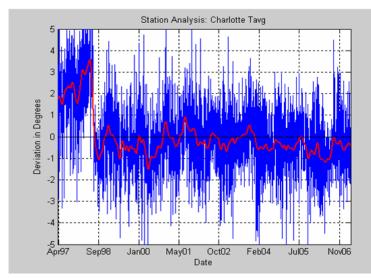
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Collar



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Folklore of Data Reliability



Famous Example of Weather Station Change in Charlotte (NC).

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Stylized Spreadsheet of a Basket Option

- Structure: Heating Degree Day (HDD) Floor (Put)
- Index: Cumulative HDDs
- Term: November 1, 2007 February 28, 2008
- Stations:
 - New York, LaGuardia 57.20%
 - Boston, MA 24.5%
 - Philadelphia, PA 12.00%
 - Baltimore, MD 6.30%
- Floor Strike: 3130 HDDs
- Payout: USD 35,000/HDD
- Limit: USD 12,500,000
- Premium: USD 2,925,000

Weather and Commodity

Stand-alone

- temperature (\approx 80%)
- precipitation (\approx 10%)
- o wind (≈ 5%)
- snow fall (\approx 5%)

In-Combination

- natural gas
- o power
- heating oil
- o propane
- Agricultural risk (yield, revenue, input hedges and trading)
- Power outage contingent power price options

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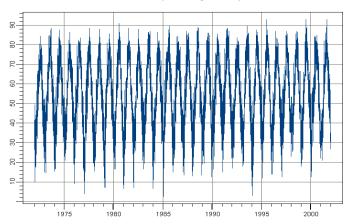
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 - No secondary market (Except on Enron-on-Line!!!)
- Mark-to-Market (or Model)
 - Essentially never changes
 - At least, Not Until Meteorology kicks in (10-15 days before maturity)
 - Then Mark-to-Market (or Model) changes every day
 - Contracts change hands
 - That's when major losses occur and money is made
- This hot period is not considered in academic studies
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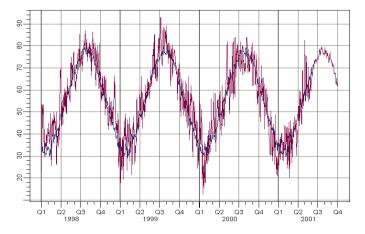
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La Guardia Daily Average Temperature

Daily Average Temperature at La Guardia.



Prediction on 6/1/2001 of Summer La Guardia Average Temperature

Prediction on 6/1/2001 of daily temperature over the next four months.

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Social function of the weather market

• Existence of a Market of Professionals (for weather risk transfer)

Under attack from

- (Re-)Insurance industry (but high freuency / low cost)
- Utilities (trying to pass weather risk to end-customer)
 - EDF program in France
 - Weather Normalization Agreements in US

Cross Commodity Products

- Gas & Power contracts with weather triggers/contingencies
- New (major) players: Hedge Funds provide liquidity

World Bank

• Use weather derivatives instead of insurance contracts

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The Weather Market Today

- Insurance Companies: Swiss Re, XL, Munich Re, Ren Re
- Financial Houses: Goldman Sachs, Deutsche Bank, Merrill Lynch, SocGen, ABN AMRO
- Hedge funds: D. E. Shaw, Tudor, Susquehanna, Centaurus, Wolverine

Where is Trading Taking Place?

- Exchange: **CME** (Chicago Mercantile Exchange) 29 cites globally traded, monthly / seasonal contracts
- OTC
- Strong end-user demand within the energy sector

Incomplete Market Model & Indifference Pricing

- Temperature Options: Actuarial/Statistical Approach
- Temperature Options: Diffusion Models (Danilova)
- Precipitation Options: Markov Models (Diko)
 - Problem: Pricing in an Incomplete Market
 - Solution: Indifference Pricing à la Davis

$$d\theta_t = p(t,\theta)dt + q(t,\theta)dW_t^{(\theta)} + r(t,\theta)dQ_t^{(\theta)}$$

$$dS_t = S_t[\mu(t,\theta)dt + \sigma(t,\theta)dW_t^{(S)}]$$

- θ_t non-tradable
- S_t tradable

Mathematical Models for Temperature Options

Example: Exponential Utility Function

$$\tilde{\boldsymbol{\rho}}_t = \frac{\mathbb{E}\{\tilde{\phi}(\boldsymbol{Y}_T)\boldsymbol{e}^{-\int_t^T V(s,Y_s)ds}\}}{\mathbb{E}\{\boldsymbol{e}^{-\int_t^T V(s,Y_s)ds}\}}$$

where

•
$$\tilde{\phi} = e^{-\gamma(1-\rho^2)f}$$

where $f(\theta_T)$ is the pay-off function of the European call on the temperature

•
$$\tilde{p}_t = e^{-\gamma(1-\rho^2)p_t}$$

where p_t is price of the option at time t

• Y_t is the diffusion:

$$dY_t = [g(t, Y_t) - \frac{\mu(t, Y_t) - r}{\sigma(t, Y_t)}h(t, Y_t)]dt + h(t, Y_t)d\tilde{W}_t$$

starting from $Y_0 = y$

• *V* is the time dependent potential function:

$$V(t,y) = -\frac{1-\rho^2}{2} \frac{(\mu(t,y)-r)^2}{\sigma(t,y)^2}$$





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