

## Part II: Tolling Deals

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# Introduction

- Basics of Tolling Deals
- Power Market Mechanics
- Valuing Tolls—A Monthly Example
- Hedging Frictions—Block Size
- Daily Tolls
- Hedging Frictions—Strips, Vega and Spurious Risks
- The Vol-Lookup Heuristic
- Modeling Alternatives
- Conclusion

# Basics of Tolling Deals

## Deal Structure

- Tolling deal is a derivative rendition of a power generator.
  - Typically the fuel is natural gas.
- The Basic Structure:

$$\tilde{E} \left[ \sum_t d(0, t) \max(F_P(t, t) - H_* F_G(t, t) - V, 0) \right]$$

where:

- $t$  denotes delivery day (this is discrete time).
- $F_P$  denotes the forward (or spot) price of power for a particular delivery bucket (e.g. 5x16) and  $F_G$  denotes the price of natural gas; both are typically at liquid pricing hubs.
- $H_*$  is the heatrate (conversion rate between gas and power).
- $V$  is VOM (variable operation and maintenance).

# Basics of Tolling Deals

## Deal Structure

- The primary purpose of a toll is to annuitize the value of either a soon to be purchased asset or a soon to be built asset in order to facilitate borrowing.
- The typical structure is:
  - Daily day-ahead manual exercise into a standard power buckets.
  - Monthly "capacity payments" (as opposed to upfront premium).
  - Monthly settlement.

so that the valuation is really:

$$V = \tilde{E} \left[ \sum_m d(0, T_m) Q_m \sum_{d \in B(m)} \max(F_P(d, d) - H_* F_G(d, d) - V, 0) \right]$$

- $B(m)$  denotes the days in month  $m$  with delivery in the relevant power bucket  $B$ .

# Power Market Mechanics

## Linear Instruments

- Fixed price swaps settle on the monthly average realized spot price for a prescribed bucket.
- Eastern US:
  - Peak bucket is 5x16 (M-F 7AM to 11PM).
  - Offpeak (the "offpeak wrap") is the complement.
  - Often circumstances require trading (or at least viewing) the offpeak wrap as 2x16 and 7x8. These are highly illiquid swaps.
  - Standard contract size: 50MW.
- Western US:
  - Peak bucket is 6x16 (M-Sat 7AM to 11PM).
  - Offpeak (the "offpeak wrap") is the complement.
  - Standard contract size: 25MW.
- Texas (ERCOT):
  - Peak bucket is 5x16 (M-F 6AM to 10PM).
  - Offpeak (the "offpeak wrap") is the complement.
  - Standard contract size: 50MW.

# Power Market Mechanics

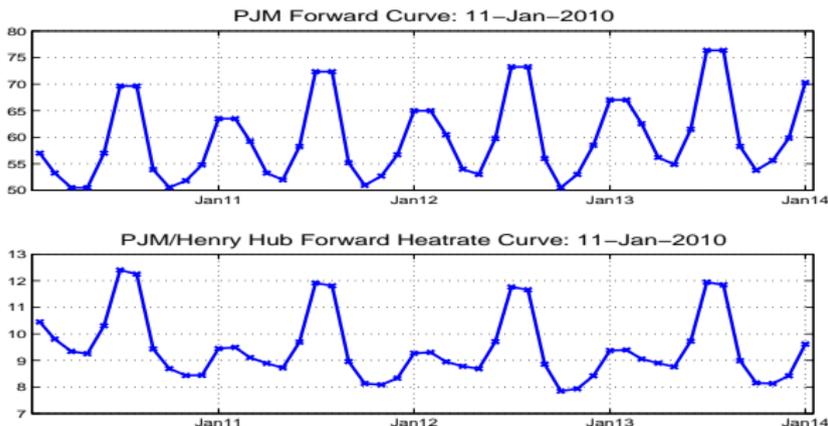
## Linear Instruments: Heatrates

- The term "heatrate" refers to a ratio of power price to a natural gas price.
  - The ratio can pertain to market prices, either spot or forward ("market heatrates").
  - It can also refer (as we'll see shortly) to engineering specs of a generator.
- Power swaps often trade as heat-rates:
  - A power buy/sell is associated with a sell/buy of a specified volume of natural gas, both over the same delivery period.
  - The trade will be quoted in heatrate units:  $\frac{F_P(t,T)}{F_G(t,T)}$ , where  $P$  and  $G$  denote power and gas respectively.

# Power Market Mechanics

## Linear Instruments: Heatrates

- The following figure shows PJM forward prices and PJM/Henry Hub forward heatrates.
  - The seasonality in both arises from (well-founded) expectations that loads will be higher in summer and to a lesser extent winter months.
  - This forces expected clearing prices higher up the stack into more expensive units.



# Power Market Mechanics

## Options

- Annual Swaptions
  - Same structure as natural gas in mechanics/valuation.
- Monthly options:
  - Same structure as natural gas.
  - Standard expiry: '-2b'
- Daily Fixed Strike
  - Financially settling and usually manually exercised day-ahead ('-1b')
  - Example: Cash settled value of an auto-exercised call:

$$\sum_{d \in m} \max [F(d, d) - K, 0]$$

- Example: Cash settled value of standard exercise:

$$\sum_{d \in m} 1_{\{E_d\}} [F(d, d) - K]$$

where  $E_d$  denotes exercise events.

- Dominant vol exposure: daily (spot).

# Power Market Mechanics

## Options

- Monthly Options:

- Exercises at time ( $T_e$ ) before the beginning of the delivery month into either:
  - A physical forward with delivery during the contract month at a price that is the strike  $K$ ;
  - Cash settlement based on the value  $F_m(T_e) - K$ .
- For example, the value of a call (in either case) is:  
 $d(0, T)\tilde{E}(\max[F_m(T_e) - K, 0])$ .

- Daily Options:

- A set of daily options usually exercising one business day before delivery.
  - These are usually financial settling on the spread between spot price and the strike:  $F(t, t) - K$  where  $t$  indexes the delivery day.
- For example, the value of a call is:  $d(0, T)\tilde{E}(\sum_{t \in m} \max[F(t, t) - K, 0])$ .
- The notation  $t \in m$  denotes the active delivery days in the option during month  $m$ . For peak (5x16) power options the sum would span the (roughly 20-22) business days in the particular month.

# Valuing Tolls—A Monthly Example

## Working Problem

- Consider a tolling deal with monthly exercise with the following terms:
  - Pricing date: 11Jan2010
  - Underlyings are PJM Western Hub 5x16 and Henry Hub natural gas.
  - Heatrate  $H_* = 11.0$
  - Delivery monthly Jul10
  - Exercise is standard penultimate settlement of NYMEX NG contract.
    - Note: for simplicity we will assume that PJM monthly options also expire '-4b').
  - Notional: 400 MW

# Valuing Tolls—A Monthly Example

## Relevant Data

- Remark on Notional:
  - The number of NERC business days in the Jul10 is 21.
  - So the total notional of this toll is  $21 \cdot 16 \cdot 400 = 134,400$  MWh.
- The relevant forward prices are:
  - $X_0 \equiv F_P(0, T) = 69.650$
  - $Y_0 \equiv H_* F_G(0, T) = 11.0 \cdot 5.603 = 61.633$
- The discount factor is 0.999 .
- Note: The market heatrate is:  $H = \frac{69.650}{5.603} = 12.431$ .
  - This is higher than the deal heatrate  $H_* = 11.0$
  - The option is in-the-money.

## Vol Backwardation:

- We do not have a vol backwardation issue as the respective legs are expiring (by assumption) at their vanilla expiry.

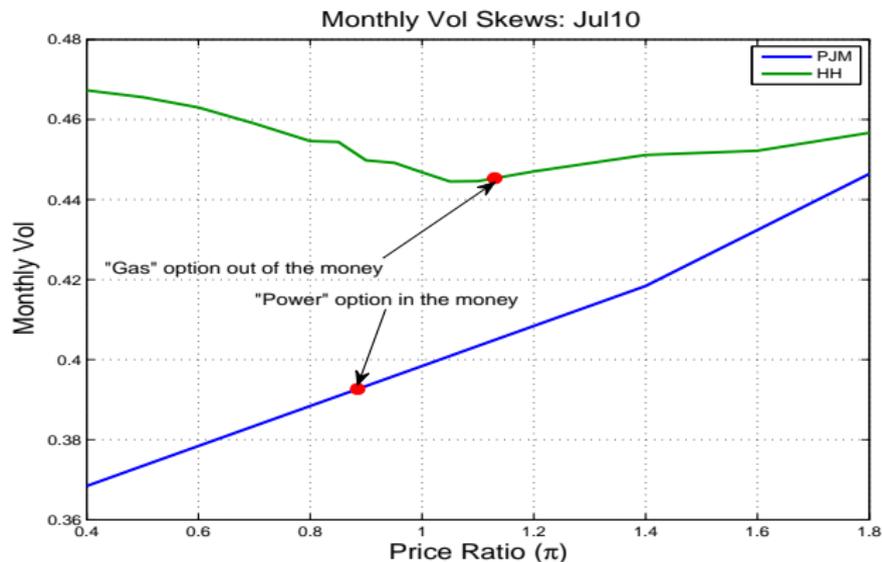
# Valuing Tolls—A Monthly Example

Skew: What vols do we pick?

- There is ambiguity as the vol skews for each underlying are defined in terms of fixed strike options.
- We have floating strikes in the sense that the "other" leg is itself a commodity price.
- A common approach is to use the underlying price of the opposing leg to define moneyness.
- For an option on  $F_1 - F_2 - K$  view:
  - $F_1$  in reference to  $F_2 + K$ :  $\pi_1 \equiv \frac{F(0, T_2) + K}{F(0, T_1)}$ .
  - $F_2$  in reference to  $F_1 - K$ :  $\pi_2 \equiv \frac{F(0, T_1) - K}{F(0, T_2)}$ .
- For this problem:
  - $\pi_X \equiv \frac{H_* F_G(0, T)}{F_P(0, T)}$  and  $\pi_Y \equiv \frac{F_P(0, T)}{H_* F_G(0, T)}$ .
  - In our working problem  $\pi_X = 0.885$  and  $\pi_Y = 1.130$ .
- The results of this vol lookup are:  $\sigma_X = 0.393$  and  $\sigma_Y = 0.445$ .

# Valuing Tolls—A Monthly Example

Skew: What vols do we pick?



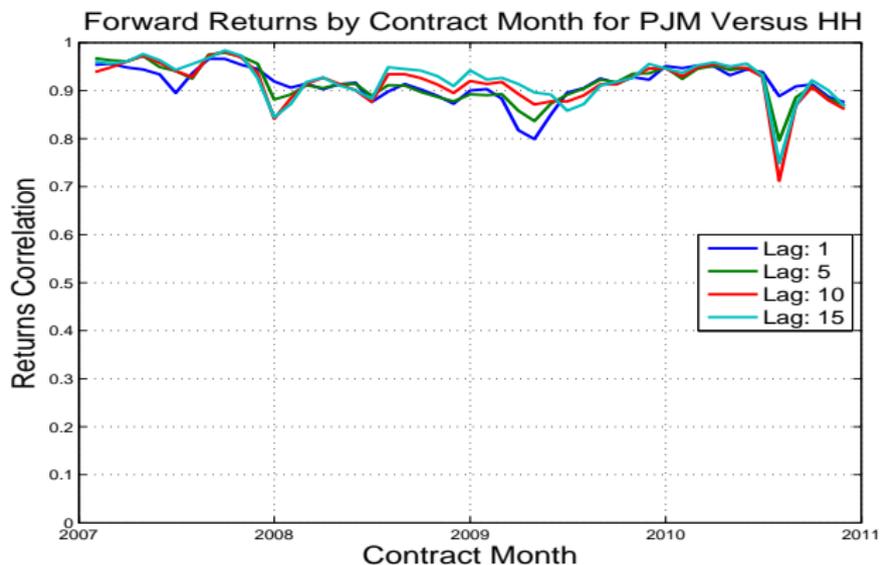
# Valuing Tolls—A Monthly Example

## Correlation

- What correlation should we use?
  - Monthly tolling deals are uncommon and there is no broker market from which to calibrate this parameter.
  - The following figure shows the returns correlation by contract month estimated over a 1Y trailing window using several time-scales (lags) for returns:
    - Specifically returns on lag  $L$  are defined as  $\log \left[ \frac{F(d, T)}{F(d-L, T)} \right]$ .
    - The purpose of considering returns for  $L > 1$  is to both view returns on time scales on which actual hedging activity may occur as well as to smooth out possible anomalies in historical marks.

# Valuing Tolls—A Monthly Example

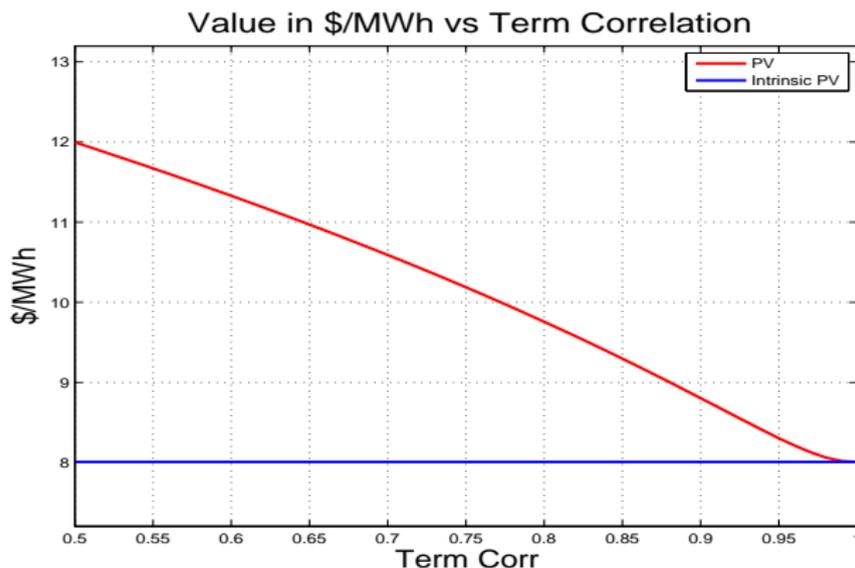
## Correlation



# Valuing Tolls—A Monthly Example

## Correlation

- The results for this working problem are shown in the figure below for a range of correlations.



# Valuing Tolls—A Monthly Example

## Delta and Gamma

- Deltas—recall:

$$\frac{\partial V}{\partial X} = N(d_1) \qquad \frac{\partial V}{\partial Y} = -N(d_2)$$

- Converting to our forward tolling setting yields:

$$\frac{\partial V}{\partial F} = d(\tau)QN(d_1) \qquad \frac{\partial V}{\partial G} = -d(\tau)QH_*N(d_2)$$

- Gamma—similarly:

$$\Gamma = d(\tau)Q \frac{N'(d_1)}{\hat{\sigma}} \begin{pmatrix} \frac{1}{F(0, T)} & -\frac{1}{G(0, T)} \\ -\frac{1}{G(0, T)} & \frac{F(0, T)}{G^2(0, T)} \end{pmatrix}$$

- $\Gamma$  is positive-definite because:

$$\bar{\alpha}^t \Gamma \bar{\alpha} = d(\tau)Q \frac{N'(d_1)}{\hat{\sigma} F(0, T)} \left[ \alpha_1 - \frac{F(0, T)}{G(0, T)} \alpha_2 \right]^2$$

- When  $\Delta$ -hedged, all directions point up.

# Valuing Tolls—A Monthly Example

## Delta and Gamma

- It is useful to diagonalize the matrix to see where the convexity is:
  - The eigenvalues are:

$$\lambda_1 = 0$$

$$\lambda_2 = d(\tau)Q \frac{N'(d_1)}{\hat{\sigma}} \left[ \frac{1}{F(0, T)} + \frac{F(0, T)}{G(0, T)^2} \right]$$

- The eigenvector corresponding to  $\lambda_1 = 0$  is:

$$\vec{v}_1 = \begin{bmatrix} \frac{F(0, T)}{G(0, T)} \\ 1 \end{bmatrix} \quad (1)$$

- There is no convexity when market heat rate  $H(t, T)$  is constant.
- The second eigenvector is:

$$\vec{v}_2 = \begin{bmatrix} 1 \\ -\frac{F(0, T)}{G(0, T)} \end{bmatrix} \quad (2)$$

- Convexity is maximal for price changes in which  $\Delta G = -H\Delta F$ .
- This direction is not particularly relevant to empirical natural gas and power dynamics.
- In this direction, a \$1 increase in *forward* power prices is associated with a roughly \$12 drop in natural gas prices; hardly an expected event.

# Valuing Tolls—A Monthly Example

## Vega

- The valuation above is identical to a call option on  $X$  struck at  $Y_0$  with the modification that the term volatility is given by the modified form:

$$\hat{\sigma}^2 = T [\sigma_X^2 + \sigma_Y^2 - 2\rho\sigma_X\sigma_Y]$$

- As with a call option,  $\frac{\partial V}{\partial \hat{\sigma}}$  is positive:

$$\frac{\partial V}{\partial \hat{\sigma}} = XN'(d_1)\frac{\partial d_1}{\partial \hat{\sigma}} - YN'(d_2)\frac{\partial d_2}{\partial \hat{\sigma}} = XN'(d_1)$$

- The chain rule clearly yields:

$$\frac{\partial V}{\partial \sigma_X} = \frac{\partial V}{\partial \hat{\sigma}} \frac{\partial \hat{\sigma}}{\partial \sigma_X}$$

- This means that:

$$\text{sign} \left[ \frac{\partial V}{\partial \sigma_X} \right] = \text{sign} \left[ \frac{\partial \hat{\sigma}}{\partial \sigma_X} \right] = \text{sign} [\sigma_X - \rho\sigma_Y]$$

# Valuing Tolls—A Monthly Example

## Vega

- By symmetry:

$$\text{sign} \left[ \frac{\partial V}{\partial \sigma_Y} \right] = \text{sign} [\sigma_Y - \rho \sigma_X]$$

- The implication is that vega with respect to one of the underlyings will be negative if:  $\min \left[ \frac{\sigma_X}{\sigma_Y}, \frac{\sigma_Y}{\sigma_X} \right] < \rho$ .
- As we know from our working example, this situation is not uncommon as  $\sigma_X$  and  $\sigma_Y$  are often of comparable magnitude and  $\rho$  is often very close to unity.
- The intuition is simple: if the correlation of the two assets is high and if  $\sigma_X > \sigma_Y$  then any increase in  $\sigma_Y$  "chews into" the volatility of the spread  $\hat{\sigma}$ .

# Valuing Tolls—A Monthly Example

## Vega

- By implicit differentiation:

$$\frac{\partial \hat{\sigma}}{\partial \sigma_X} = \frac{T^{\frac{1}{2}} (\sigma_X - \rho \sigma_Y)}{(\sigma_X^2 + \sigma_Y^2 - 2\rho \sigma_X \sigma_Y)^{\frac{1}{2}}}$$

with a symmetric result for  $\frac{\partial \hat{\sigma}}{\partial \sigma_Y}$ .

- Therefore:

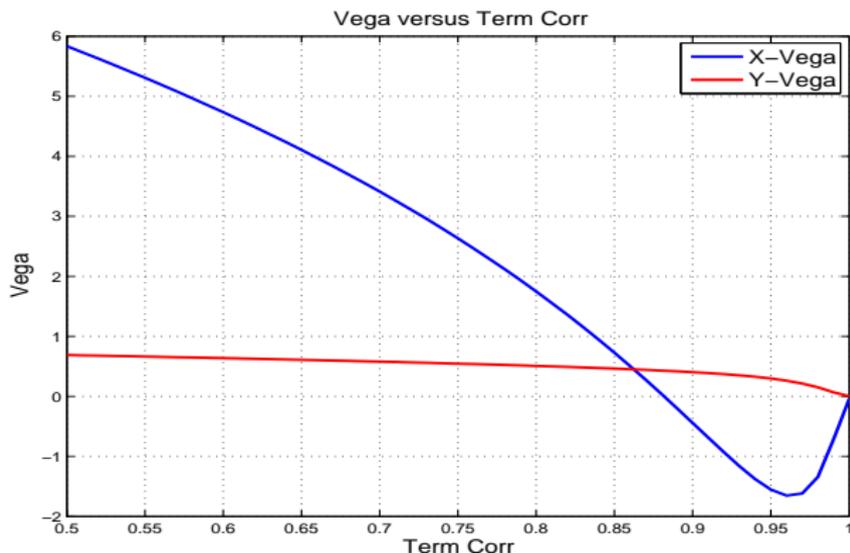
$$\frac{\partial V}{\partial \sigma_X} = XN'(d_1) \frac{T^{\frac{1}{2}} (\sigma_X - \rho \sigma_Y)}{(\sigma_X^2 + \sigma_Y^2 - 2\rho \sigma_X \sigma_Y)^{\frac{1}{2}}}$$

which scales as  $T^{\frac{1}{2}}$ .

# Valuing Tolls—A Monthly Example

## Vega

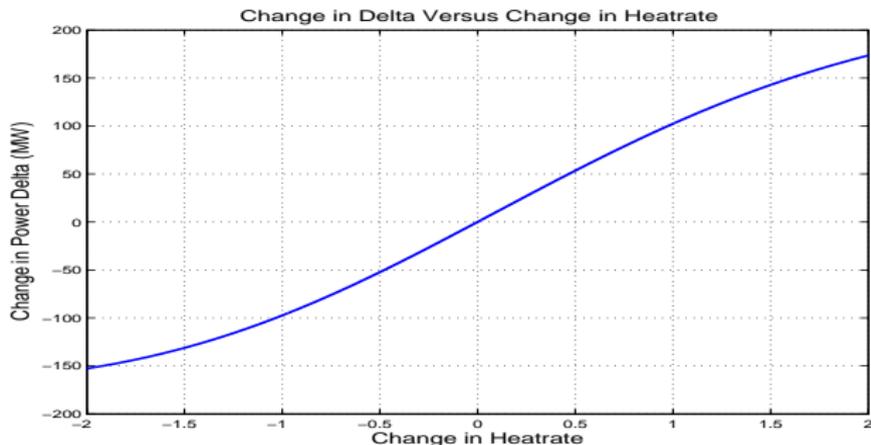
- In our working problem the correlation threshold for negative vega is  $\frac{\sigma_X}{\sigma_Y} = 0.882$ .
- We expect X-vega to be negative.
- The following plot shows both vegas as a function of correlation.



# Hedging Frictions

## Block-Size Impact on Hedging

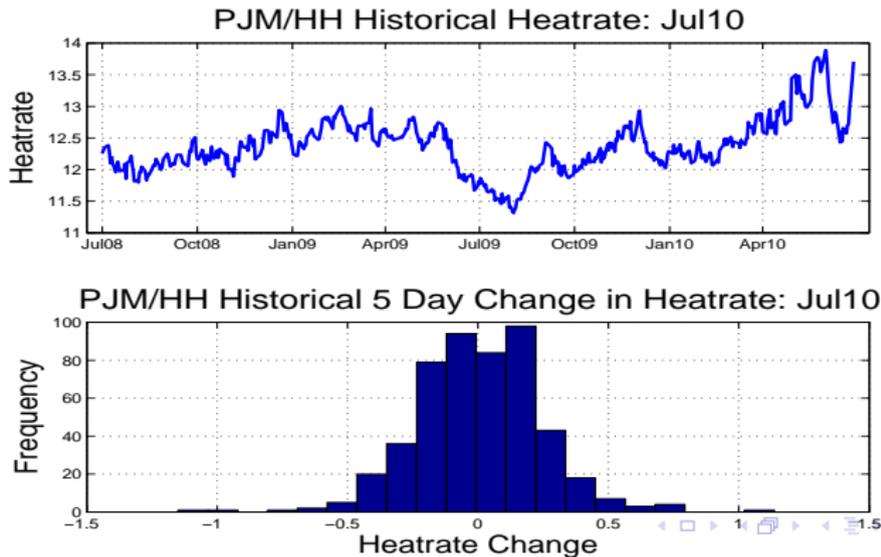
- This has implications for hedging.
  - The fact that you can only trade 50MW limits your ability to capture the modeled extrinsic value.
  - This limitation is an issue in all markets, but particularly so for power and natural gas.
  - The following plot shows the change in delta (converted to MW) as a function of a change in heatrate on the trade date.



# Hedging Frictions

## Block-Size Impact on Hedging

- How much do heatrates actually move?
  - The following plot shows heatrate history for the Jul10 contract as well as the distribution of 5 day heatrate changes.
  - The conclusion is that delta hedging a 400 MW toll is not going to be a very fruitful enterprise.



# Daily Tolls

## Working Problem

- Most tolls trade for tenors of 5-7 years.
  - This is well outside the liquidity window at which individual contract months trade.
  - The impact on hedge performance can be non-trivial—but has yet to be estimated rigorously.
- In what follows we will switch to the following toll:
  - Pricing date: 11Jan2010
  - Underlyings are PJM Western Hub 5x16 and Henry Hub natural gas.
  - Heatrate: 8.0
  - Delivery period: 01Jan11 to 31Dec11
  - Standard exercise: '-1b'.
  - Notional: 400 .
- Note: A 2-factor Gaussian exponential framework was used for each with correlations specified to be roughly consistent with implied correlations.

# Daily Tolls

## Multi-Factor Approach

- In the absence of quoted markets for heatrate options, one might consider using estimated correlations as a benchmark.
- In the two-factor framework:

$$\frac{dF_k(t, T)}{F_k(t, T)} = \sum_{j=1}^2 \left[ \int_0^t \sigma_j^{(k)}(T) e^{-\beta_j(T-t)} dB_j^{(k)}(s) \right]$$

where

- $k = 1$  corresponds to power.
  - $k = 2$  corresponds to natural gas.
- Factor correlations:
    - $\text{corr} \left[ dB_1^{(1)}, dB_1^{(2)} \right] = \rho_{\text{long}}$ .
    - $\text{corr} \left[ dB_2^{(1)}, dB_2^{(2)} \right] = \rho_{\text{short}}(t)$ .

# Daily Tolls

## Multi-Factor Approach

- The terms "monthly vol" ( $\bar{\sigma}_M$ ) and "daily vol" ( $\bar{\sigma}_D$ ) will always refer to implied vols pertaining to the fixed strike options.
- Market dichotomy:
  - Power: Monthly and daily fixed strike options are the vanilla options.
  - Natural Gas: Monthly and the forward starter are the vanilla options.
- Calibration of the model above for each commodity involves setting  $\{\sigma_j^{(k)}(T)\}_{j=1}^2$  to be consistent with  $\bar{\sigma}_M^{(k)}$  and  $\bar{\sigma}_D^{(k)}$  by contract month.

# Daily Tolls

## Spot Volatility

- Recall the caricature of spot (daily) prices processes with returns for the daily spot prices i.i.d. normal:

$$F(t, t) = F_m(T_m)e^{\zeta Z_t - \frac{1}{2}\zeta^2}$$

where

- $F_m$  denotes the contract month containing day  $t$
- $Z_t$  is standard normal.
- $\zeta$  is the spot volatility.

# Daily Tolls

## Valuation

- In this modeling framework each of the two underlying commodities is log-normally distributed:
  - Valuation eventually leads to Margrabe/quadrature.
  - The term correlation can be explicitly calculated analytically directly from the two-factor diffusions.
- In the caricature model:
  - Each underlying has a log-normal distribution with volatilities  $\bar{\sigma}_{D,k}$  which satisfies:

$$\bar{\sigma}_{D,k}^2 T_D = \bar{\sigma}_{M,k}^2 T_M + \zeta_k^2$$

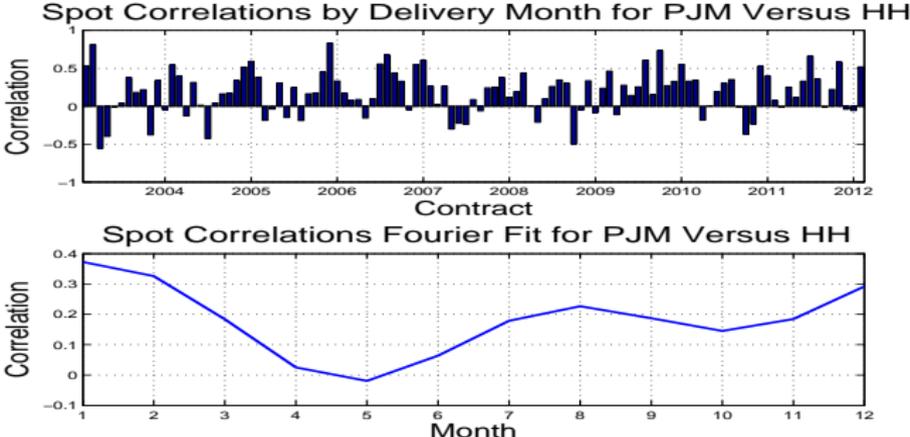
- The term-correlation is given by:

$$\rho_{\text{term}}(T_D) = \frac{\bar{\sigma}_{M,1}\bar{\sigma}_{M,2}T_{MPL} + \zeta_1\zeta_2\rho_S}{\bar{\sigma}_{D,1}\bar{\sigma}_{D,2}T_D}$$

# Daily Tolls

## Valuation

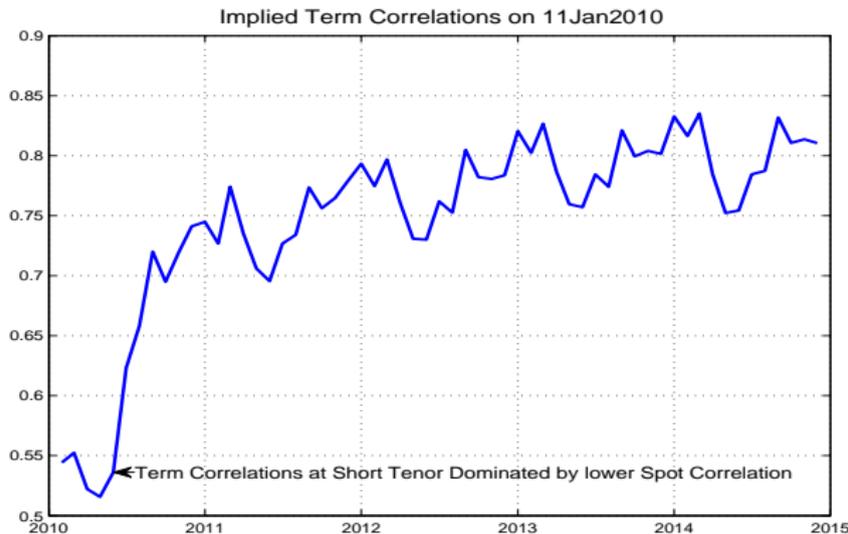
- Note the seasonality:
  - Higher correlation in winter months due to gas price spikes being the driver of power prices.
  - Weather drives summer price dynamics, independently of fuel prices.



# Daily Tolls

## Valuation

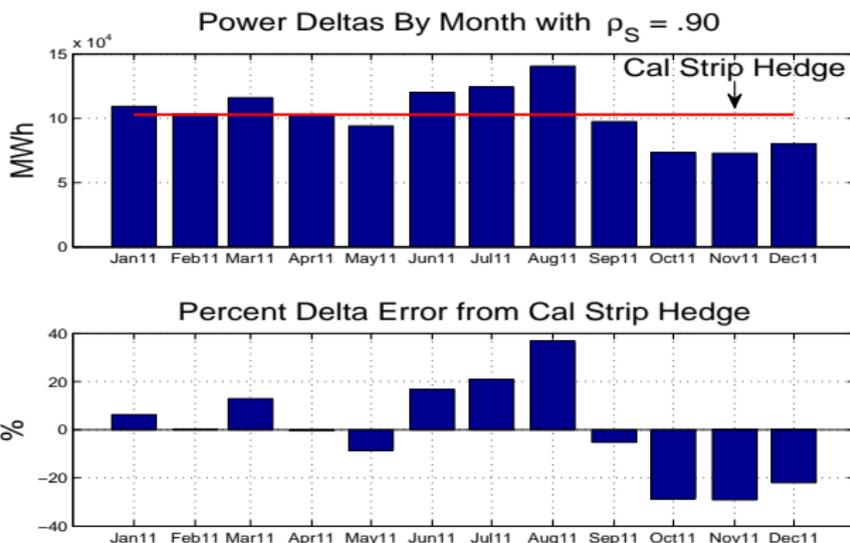
- Using  $\rho_S$  from statistical estimate yields the following term structure of correlation.
- Trading activity suggests implied values of  $\rho_S$  that are *much* higher than these.
- Why?



# Hedging Frictions

## Impact of Strips

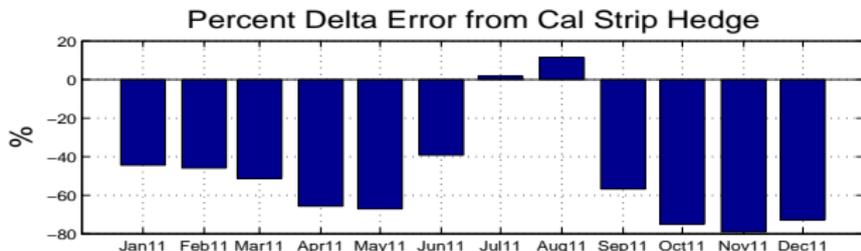
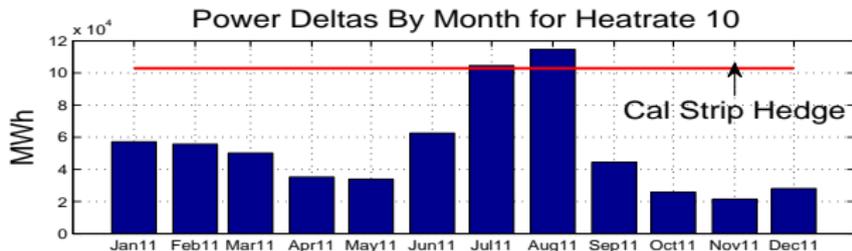
- The following figure shows deltas by month as well as the total cal strip delta, both in absolute terms as well as a percentage difference for our toll.
- Note the nontrivial variation from the cal strip quantity.



# Hedging Frictions

## Impact of Strips

- The problem is exacerbated at higher heatrates, which "pushes" the delta into fewer months making the cal strip instrument an even more blunt instrument.
- The following figure shows the same results for an  $H_* = 10$  heatrate.



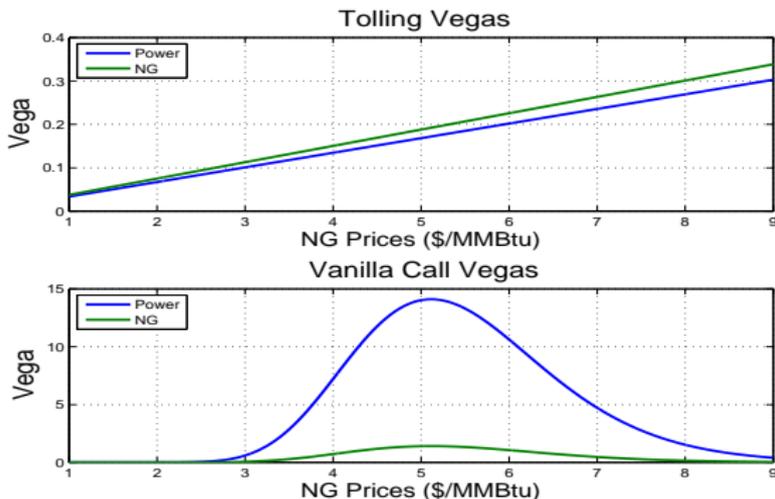
# Hedging Frictions

## Mismatch in Greek Behavior

- Hedging gamma and vega exposure for tolls is nontrivial:
  - Since vanilla options have a single expiration convention, with expiry near delivery, you have to choose between vega and gamma hedging.
  - Typically you choose to control gamma at shorter tenors and vega and longer tenors.
- The behavior of vega arising from tolling structures is different than that of the vanilla products.
  - The following figures show vega for a sample 8HR toll with tenor 1Y.
  - The underlying prices were \$50/MWh and \$5/MMBtu.
  - The vols were .50 for each leg and correlation was set at .90.

# Hedging Frictions

## Mismatch in Greek Behavior



- The top figure shows the power and gas vegas for the toll across a range of gas prices assuming that the power price remains at the market heatrate (10).
- The lower figure shows the same for ATM vanilla calls.
- Note the meaningfully different behavior both in slope and in magnitude.
- Costly rebalancings of vega hedges would be required to maintain neutrality.

# Hedging Frictions

## Spurious Risks

- Use of this approach results in exposures to volatility and correlations that can be large and unmanageable.
- Are these induced by the choice of model?
- Rephrased:
  - Under this modeling paradigm are changes in volatilities and correlations (if liquidity permitted observation and calibration) off-setting?
  - Value is very dependent on the spot volatility which is driven by the spread between  $\bar{\sigma}_D$  and  $\bar{\sigma}_M$ . Is this real?
  - The absence of implied correlation data of a quality analogous to implied vols renders this unanswerable.
- The hedging program that follows is highly questionable.

# Hedging Frictions

## Spurious Risks

- Vega exposure is not confined to  $\bar{\sigma}_D$  for the two commodities.
- The resulting vegas with respect to  $\bar{\sigma}_M$  and  $\bar{\sigma}_D$  for each of the commodities is largely driven by the implicit correlation effect.

$$\frac{\partial V}{\partial \bar{\sigma}_D} = \frac{\partial V}{\partial \bar{\sigma}_D} \Big|_{\rho} + \frac{\partial V}{\partial \rho} \Big|_{\bar{\sigma}_D} \frac{\partial \rho}{\partial \bar{\sigma}_D}$$

- The term correlation effect for vega hedging results in substantial positions:
  - Long/short or (short/long) positions in monthly/daily vega depending on relative values of the various component volatilities.

# Hedging Frictions

## Spurious Risks

- Note that the spread vol that enters Margrabe is:

$$\hat{\sigma}^2 = [\bar{\sigma}_{M,1}^2 + \bar{\sigma}_{M,2}^2 - 2\rho_L \bar{\sigma}_{M,1} \bar{\sigma}_{M,2}] T_M + [\zeta_1^2 + \zeta_2^2 - 2\rho_S \zeta_1 \zeta_2]$$

from which we see that:

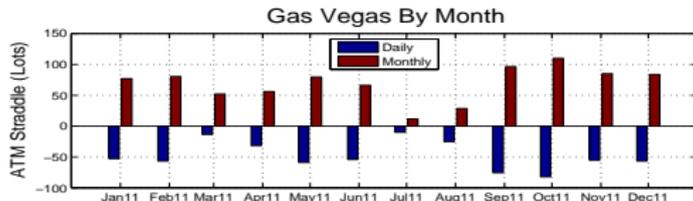
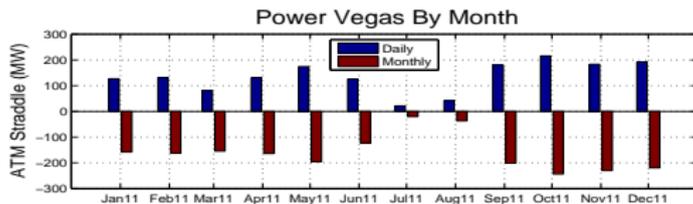
$$\frac{1}{2} \hat{\sigma} \frac{\partial \hat{\sigma}}{\partial \bar{\sigma}_{M,1}} = [\bar{\sigma}_{M,1} - \rho_L \bar{\sigma}_{M,2}] T_M + \frac{\partial \zeta_1}{\partial \bar{\sigma}_{M,1}} [\zeta_1 - \zeta_2 \rho_S]$$

- The sign of the first term on the RHS is exactly like the monthly vega terms in the previous monthly example.
- We know that  $\frac{\partial \zeta_1}{\partial \bar{\sigma}_{M,1}} < 0$  and  $\frac{\partial \zeta_1}{\partial \bar{\sigma}_{D,1}} > 0$  and similarly for all other permutations of vols and commodity leg.

# Hedging Frictions

## Spurious Risks

- The figure below shows initial vega exposures in our example.
  - Implied vol hedging strategy involves substantial volume in monthly and daily options in both commodities.
  - Moreover, these hedges would also have to be unwound  $t \uparrow T$ .



# Vol-Lookup Approximation

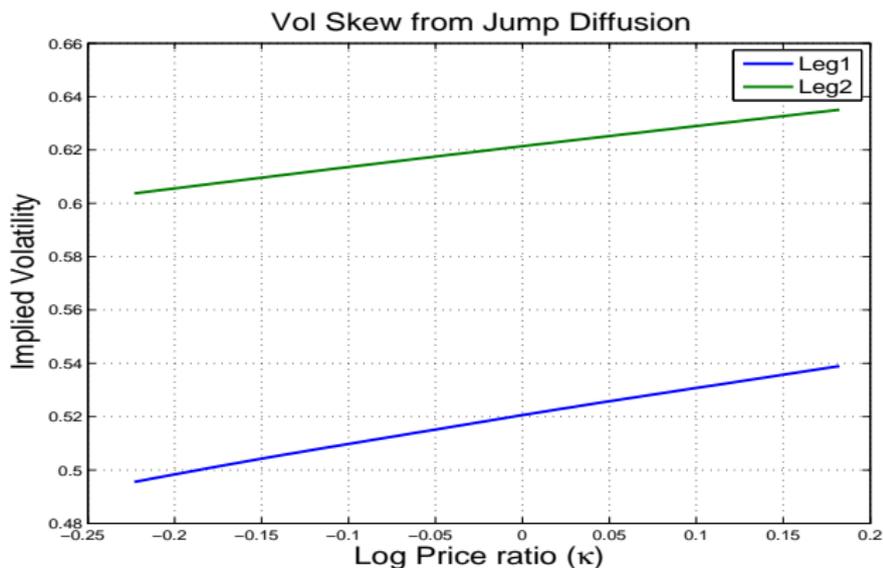
## Simple Experiment

- How much error is sustained in the vol-lookup approximation.
- The following analysis considers a reasonable setup:
  - A spread option with tenor of  $\frac{1}{4}$  of a year.
  - Power and gas forwards of \$100 and \$10 respectively
  - Heatrates  $H_*$  are varied on the interval  $[8, 12]$ .
- The procedure:
  - $N=100,000$  standard i.i.d normal deviates  $\bar{Z}_n$  where each  $\bar{Z}_n \in \mathbb{R}^2$
  - Poisson jumps with arrival rate 8/year and size 2 were added to  $Z_{n,1}$ .
  - The  $\{\bar{Z}_n\}_{n=1}^N$  were normalized to unit standard deviation and transformed to yield  $\bar{X}_n$  with correlation .90.
  - These were normalized to have a standard deviation corresponding to implied vols of .50 and .60 respectively.

# Vol-Lookup Approximation

## Simple Experiment

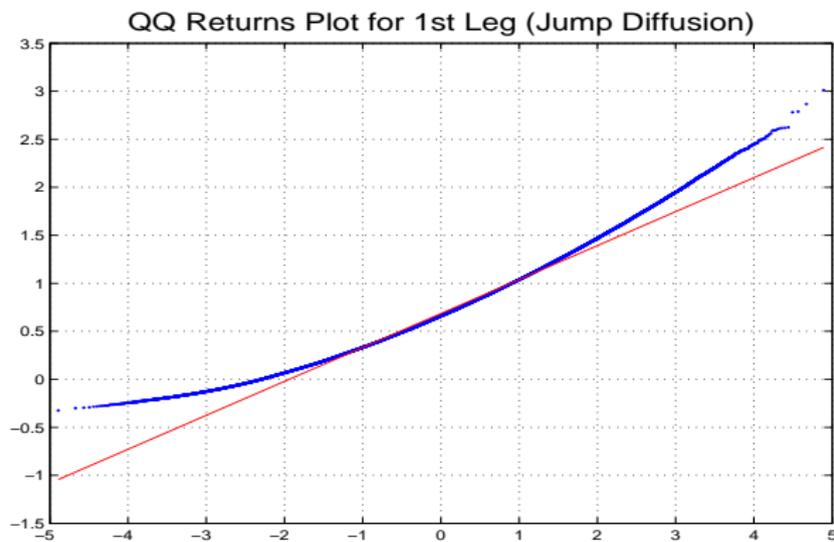
- The following plot shows the skew for the two legs.



# Vol-Lookup Approximation

## Simple Experiment

- The qq-plot of the returns is shown below.



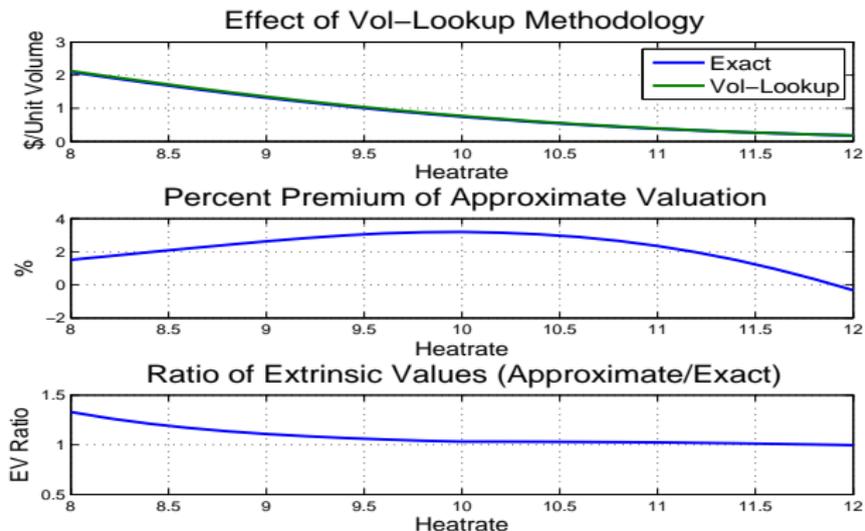
# Vol-Lookup Approximation

## Simple Experiment

- The following plot shows the results comparing exact (simulation) valuation to the vol-lookup methods as a function of the deal heatrate.
  - The Monte-Carlo error is typically well under \$0.10.
  - The vol-lookup approximation is roughly 2% higher at low strikes.
  - The third plot shows the ratios of extrinsic values which is more ominous, with low heatrates seeing ratios above 1.5.

# Vol-Lookup Approximation

## Simple Experiment

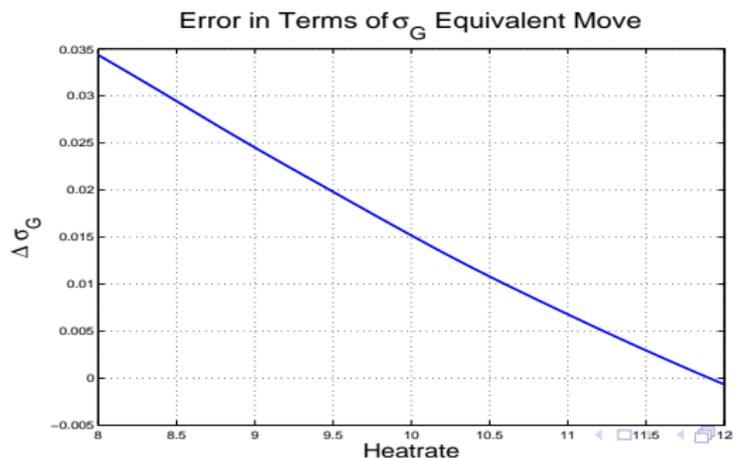


# Vol-Lookup Approximation

## Simple Experiment

- Vol Perspective:

- Converting this difference in extrinsic value into a  $\sigma_G$  equivalent move by dividing the difference by the  $G$ -vega yields the following.
- The errors can be meaningfully outside of the volatility bid-offer.
- This has been a subject of some investigation (see C. Alexander and A Venkatraman 2011).
- However, a rigorous and efficient methods for bounding this error remain undeveloped.



# Modeling Alternatives

## Movitations

- The substantial difficulties in hedging heat rate options calls into question the entire modeling framework—arguably even the relevance of risk-neutral pricing methodologies.
- It is typical to proceed with methodologies similar to those discussed above, simply cranking the correlation up to levels which either:
  - Are consistent with what trading activity is observed.
  - Result in realized payoffs that dominate theta bleed.
- Is this a reasonable thing to do?

# Modeling Alternatives

## Heatrate Distributions

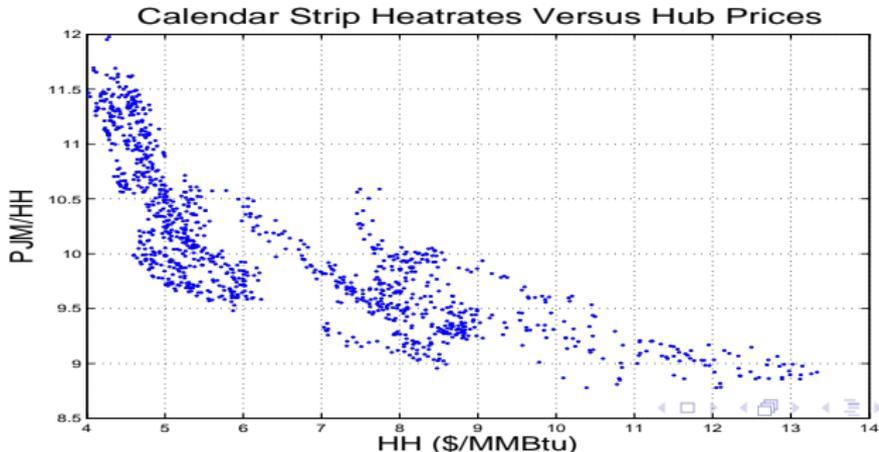
- Rolling calendar strip heatrates versus natural gas prices.
- Note the systematic decrease in heatrates as NG prices increase.
  - Bidding behavior of NG power generation:

$$p_{\text{bid}} = H_* G(t, t) + K$$

which would suggest:

$$H(t, T) = H_* + K/G(t, T)$$

- Switching:  $G(t, T) \uparrow$  means cheaper sources of generation on the margin.
- It also explains why monthly power vols are lower than for natural gas.



# Modeling Alternatives

## Heatrate Distributions

- What are the implications of the two-factor modeling heatrate distributions?
- For any fixed time  $t$  let:

$$\begin{aligned}\tilde{\sigma}_F &= \sigma_F t^{\frac{1}{2}} \\ \tilde{\sigma}_G &= \sigma_G t^{\frac{1}{2}}\end{aligned}$$

where  $\sigma_F$  and  $\sigma_G$  are volatilities of the two underlying forward prices.

- We know that:

$$H(t, T) \equiv \frac{F(t, T)}{G(t, T)} = \frac{F(0, T)}{G(0, T)} e^{\tilde{\sigma}_F Z_F - \frac{1}{2} \tilde{\sigma}_F^2 - \tilde{\sigma}_G Z_G + \frac{1}{2} \tilde{\sigma}_G^2}$$

where:

- The normal deviates corresponding to the two underlyings at time  $t$  are  $Z_F$  and  $Z_G$  respectively.
- The correlation between the two deviates is  $\rho$ .
- For time-varying local volatility these are the implied volatilities for  $[0, t]$ .

# Modeling Alternatives

## Heatrate Distributions

- Writing:  $Z_F = \rho Z_G + \sqrt{1 - \rho^2} W$  where  $W$  is independent of  $Z$  we have:

$$H(t, T) = \frac{F(0, T)}{G(0, T)} \left[ e^{\tilde{\sigma}_F \sqrt{1 - \rho^2} W - \frac{1}{2}(1 - \rho^2) \tilde{\sigma}_F^2} \right] \left[ e^{(\rho \tilde{\sigma}_F - \tilde{\sigma}_G) Z_G - \frac{1}{2}(\rho^2 \tilde{\sigma}_F^2 - \tilde{\sigma}_G^2)} \right]$$

- The heatrate  $H(t, T)$  is not in general a martingale since the third term has an expected value:

$$\begin{aligned} \tilde{E} \left[ e^{(\rho \tilde{\sigma}_F - \tilde{\sigma}_G) Z_G - \frac{1}{2}(\rho^2 \tilde{\sigma}_F^2 - \tilde{\sigma}_G^2)} \right] &= e^{\frac{1}{2}[(\rho \tilde{\sigma}_F - \tilde{\sigma}_G)^2 - (\rho^2 \tilde{\sigma}_F^2 - \tilde{\sigma}_G^2)]} \\ &= e^{\tilde{\sigma}_G(\tilde{\sigma}_G - \rho \tilde{\sigma}_F)} \end{aligned}$$

- Using the fact that:

$$G(t, T) = G(0, T) e^{\tilde{\sigma}_G Z_G - \frac{1}{2} \tilde{\sigma}_G^2}$$

we have:

$$Z_G = \frac{1}{\tilde{\sigma}_G} \log \left[ \frac{G(t, T)}{G(0, T)} \right] + \frac{1}{2} \tilde{\sigma}_G$$

# Modeling Alternatives

## Heatrate Distributions

- Putting this all together we have:

$$\begin{aligned} H(t, T) &= \frac{F(0, T)}{G(0, T)} \left[ e^{\tilde{\sigma}_F \sqrt{1-\rho^2} W - \frac{1}{2}(1-\rho^2)\tilde{\sigma}_F^2} \right] \\ &\quad \left[ e^{(\rho\tilde{\sigma}_F - \tilde{\sigma}_G) \left( \frac{1}{\tilde{\sigma}_G} \log \left[ \frac{G(t, T)}{G(0, T)} \right] + \frac{1}{2}\tilde{\sigma}_G \right) - \frac{1}{2}(\rho^2\tilde{\sigma}_F^2 - \tilde{\sigma}_G^2)} \right] \\ &= \frac{F(0, T)}{G(0, T)} \left[ e^{\tilde{\sigma}_F \sqrt{1-\rho^2} W - \frac{1}{2}(1-\rho^2)\tilde{\sigma}_F^2} \right] e^{\frac{1}{2}\rho\tilde{\sigma}_F(\tilde{\sigma}_G - \rho\tilde{\sigma}_F)} \left[ \frac{G(t, T)}{G(0, T)} \right]^{\left(\rho\frac{\tilde{\sigma}_F}{\tilde{\sigma}_G} - 1\right)} \end{aligned}$$

- This establishes that under the Margrabe paradigm  $H(t, T)$  is related to  $G(t, T)$  functionally as:

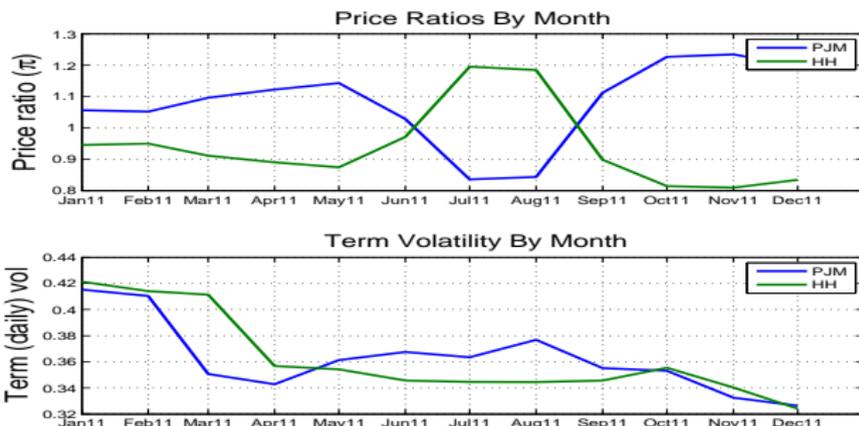
$$H(t, T) = cXG(t, T)^{\left(\rho\frac{\tilde{\sigma}_F}{\tilde{\sigma}_G} - 1\right)}$$

where  $c$  is a constant and  $X$  is a unit mean log-normal random variable and "returns" variance  $\tilde{\sigma}_F \sqrt{1-\rho^2}$ .

# Modeling Alternatives

## Heatrate Distributions

- For  $H(t, T)$  to be a decreasing function of  $G(t, T)$  requires that:  $\rho \frac{\sigma_F}{\sigma_G} < 1$ .
- Issues:
  - In many months  $\sigma_F > \sigma_G$ .
  - Increasing  $\rho$  to near unity causes a breakdown in "known" behavior.
- Note the potential problems with the  $H_* = 10$  toll.



# Modeling Alternatives

## Heatrate Distributions

- Key Points:
  - Simply cranking the term correlation up does not result in realistic distributions in many cases.
  - The liquidity in daily options for power is highly concentrated near-the-money.
  - For natural gas, liquidity in daily options is very limited in both strike and tenor.
  - Using "marked" vols is often little more than feeding "Curious George Draws a Vol Surface" into a multi-factor model.
- Some practitioners and researchers have gravitated to alternatives.

# Modeling Alternatives

## Econometric Models

- The goal is to generate a physical measure of all related prices and then either:
  - Construct hedges and calculate value directly.
  - Transform the distribution to be consistent with market tradables.
- Consider at regression form:

$$\log \left[ \frac{p(d)}{p_{\text{NG}}(d)} \right] = \alpha + \gamma p_{\text{NG}}(d) + \sum_{k=1}^K \theta(d)^k + \epsilon_d$$

where:

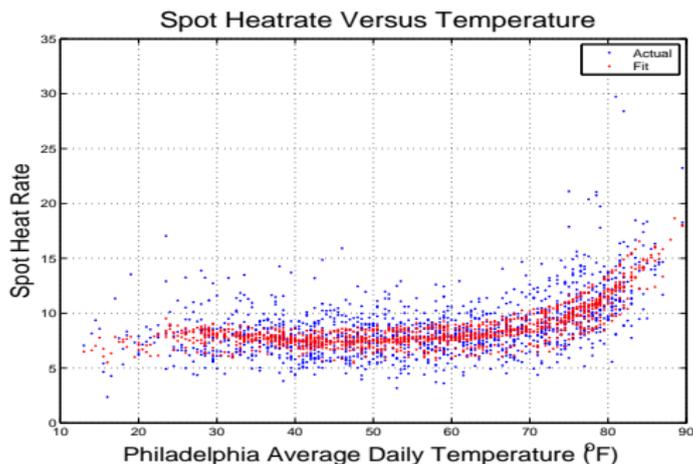
- The modified temperature is:  $\theta(t) = \frac{e^{\lambda(t)}}{1+e^{\lambda(t)}}$  with  $\lambda(t) \equiv \frac{\tau(t) - \tau_{\text{ref}}}{w}$ .
- Here  $\tau_{\text{ref}}$  and  $w$  selected to be characteristic mean and width of temperatures realized over the entire data set.
- The fact that  $\theta \in [0, 1]$  results in regular behavior beyond the range of historical data.

# Modeling Alternatives

## Econometric Models

- The result is shown below.
- Coupled with:
  - Temperature simulations (more on this later).
  - Simulations for  $p_{NG}$

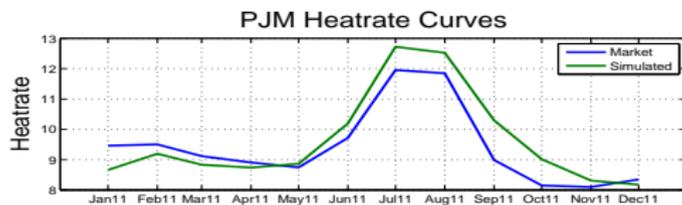
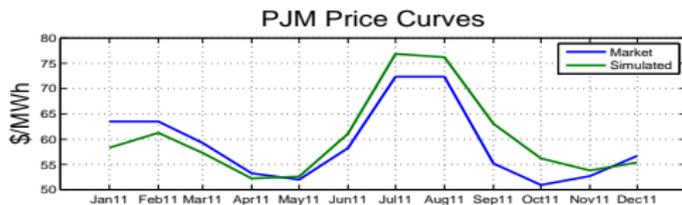
yields a joint distribution for:  $\vec{\pi} \equiv [\tau, p_{NG}, p]$ .



# Modeling Alternatives

## Econometric Models

- Expected values of simulated prices need not equal forward prices.
  - The simulations are physical measure.
  - The difference is an estimate of a risk premium.



# Modeling Alternatives

## Econometric Models

- Valuation process:

- Generate simulations for  $\vec{\zeta}(d) \equiv [\tau, p_{\text{NG}}, p](d)$ .
- Compute the simulated payoffs of:
  - The asset or trade in question:  $\Pi_A$ .
  - The set of potential hedges:  $\vec{X}$
- Compute an optimal static (initial) hedge—for example:

$$\vec{h}_* \equiv \underset{\vec{h}}{\operatorname{argmin}} \operatorname{var} [\Pi + \vec{h}^\dagger \vec{X}]$$

- The resulting hedge portfolio:  $\Pi_* \equiv \Pi + \vec{h}_*^\dagger \vec{X}$  usually has a non-trivial probability distribution.
- The mid-price of the structure  $\Pi$  is (arguably) the sum of the expected residual and the market prices of the hedges  $\vec{p}_X$ .

$$E(\Pi_*) + \vec{h}_*^\dagger \vec{p}_X$$

- Bid/offer can be constructed from the probability distribution (e.g. percentiles or standard deviations from the mean).

# Modeling Alternatives

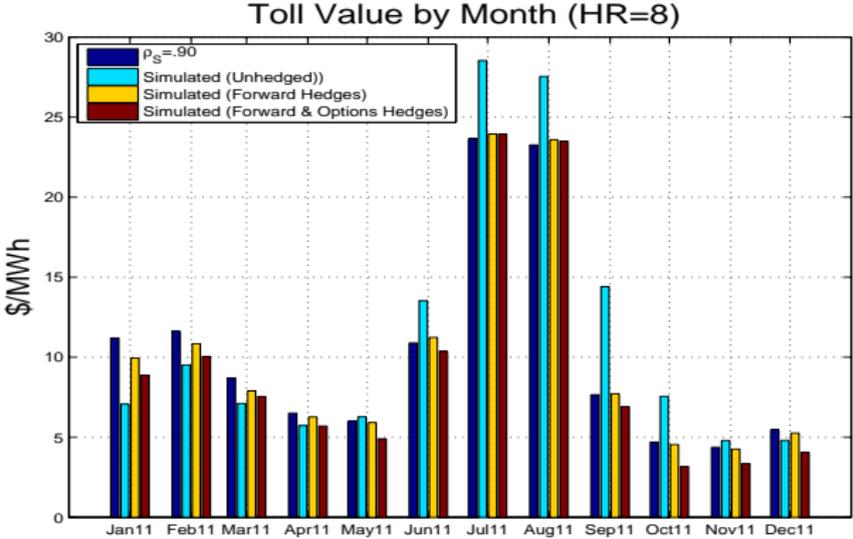
## Econometric Models

- Valuation process:
  - If the structure payoff  $\Pi$  is spanned by the hedges then the resulting value is the usual mark-to-market.
  - Example: Suppose  $\Pi$  is just the payoff of a power swap  $\Pi = Np(d)$ .
    - The optimal hedge is  $h_* = [0, 0, -N]$  (“sell  $N$  of the power swap”).
    - The resulting variance of  $\Pi_*$  is zero (this is a perfect hedge).
    - If the forward power price is  $F$  then the value of  $\Pi$  is  $N \cdot F$ .
    - This approach yields the proper mark-to-market value if  $\Pi$  can be constructed from available hedging instruments.

# Modeling Alternatives

## Econometric Models

- Valuation process:
  - Returning to our working problem, the following figure shows results using forwards and forwards+ATM options as hedges by month.



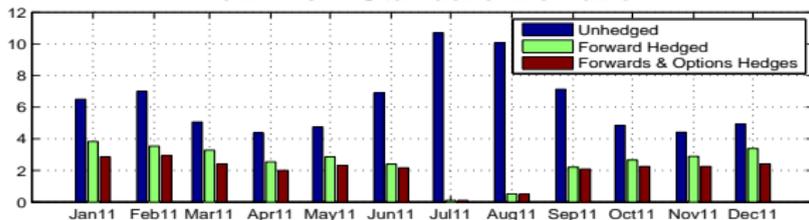
# Modeling Alternatives

## Econometric Models

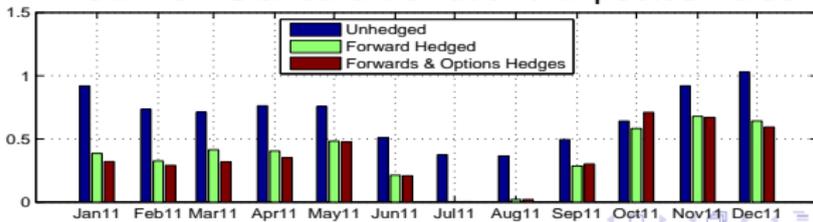
- Valuation process:

- The following figure shows the risk reduction in the various scenarios.
- The effect of options hedges on the residual risk was minimal.
- Fixed strike options are not particularly useful at hedging tolls.

P&L Risk: Standard Deviation



P&L Risk: Standard Deviation / Expected Value



# Modeling Alternatives

## Econometric Models

- Valuation process:

- The unit heatrate  $H_*$  is relevant—the higher the heatrate the less "swap-like" the toll.
- The results can differ meaningfully from "standard" methods.

Heat rate	Financial	Simulated Unhedged	Simulated Forwards	Simulated Forwards & Options
$H_* = 8$	10.37	11.28	10.01	9.27
$H_* = 10$	4.06	4.16	3.24	2.43

# Modeling Alternatives

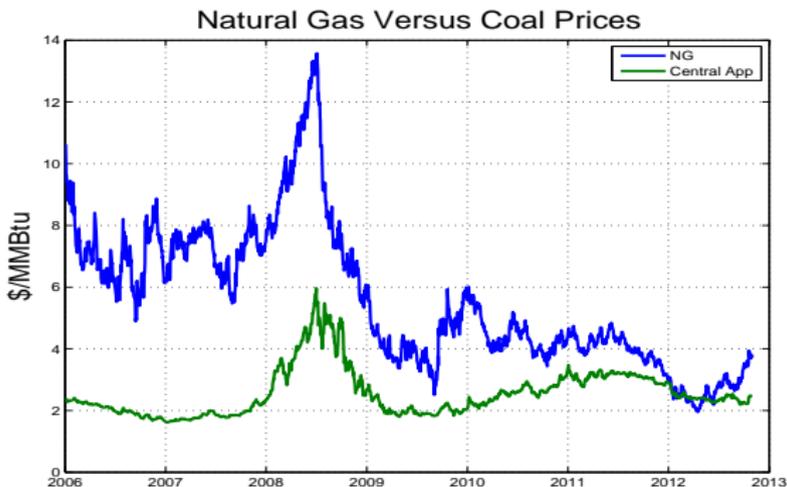
## Econometric Models

- Strengths:
  - Construction of (arguably) realistic price processes and effective static hedges.
  - The use of static hedges underestimates the value in theory, but given hedge frictions discussed previously this is more of a "feature" than a "bug."
  - The residual post-hedging risk can be quantified and used to construct bids and offers.
- Weaknesses:
  - Dynamic hedging reflected only implicitly if options structures are included in the hedge basket.
  - Vulnerable to systemic changes / nonstationarity; e.g. coal switching, regulatory changes).
- Structural (stack) models are an alternative.

# Modeling Alternatives

## Stack Models: Motivations

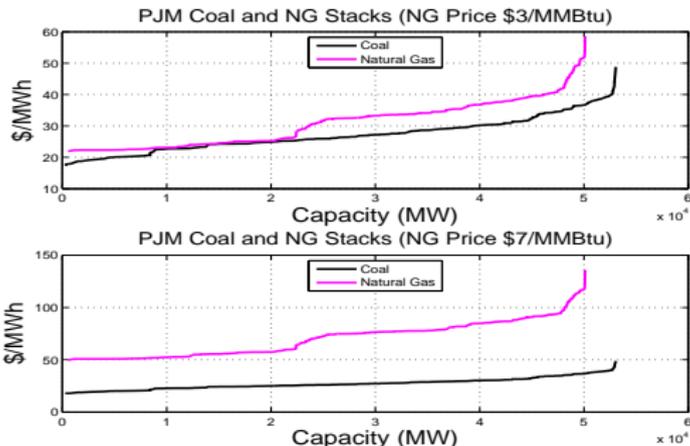
- Consider the following comparison of historical natural gas versus coal prices.
  - The structural drop in NG prices has put the traditionally more expensive combined cycle generators near parity with coal plants.
  - The traditional segregation of the two types of units, which are very different in attributes, is no longer a given.



# Modeling Alternatives

## Stack Models: Motivations

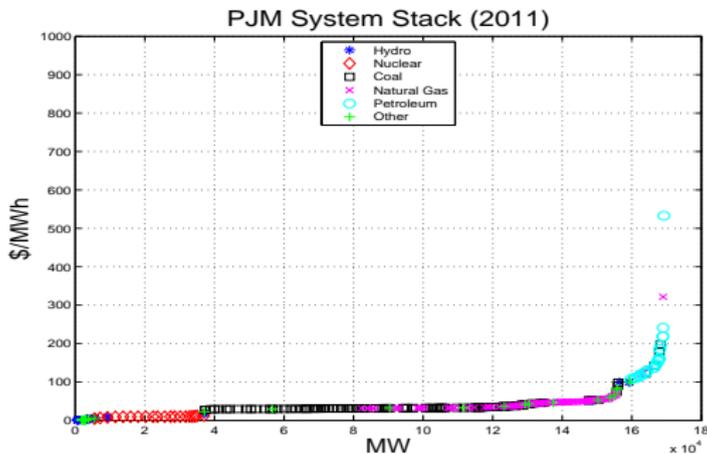
- The change in the "merit order" of the two sub-stacks for two price regimes is shown below.
  - The competition between the flexible natural gas units and the baseload coal units is likely to have a meaningful effect on heatrate behavior and correlation structure.
  - How can/should this be modeled?



# Modeling Alternatives

## Stack Models

- The Stack: Marginal cost of generation versus total capacity:
  - Capacities  $[C_1, \dots, C_N]$  sorted in increasing cost (\$/MWh)  $[p_1, \dots, p_N]$ , the stack is a plot of  $p_n$  vs  $\sum_{1 \leq k \leq n} C_k$ .
  - The result is  $p_{MC} \approx \Phi [C | \bar{F}_t]$ .
    - $p_{MC}$  is the marginal cost utilizing total capacity  $C$ .
    - We have explicitly identified fuel dependence.



# Modeling Alternatives

## Stack Models

- The Basic Modeling Tenant:

- Given a load (demand)  $L_t$  at time  $t$  and a version of the stack  $\Phi_t$  at time  $t$  the spot price is:

$$p_t = \Phi_t [L_t(1 + \delta_t) | \bar{F}_t] + \epsilon_t$$

- $\delta$  are random variables reflecting uncertain availability (outages).
  - $\epsilon$  are random variables reflecting randomness in bidding.
  - $\Phi_t$  is time dependent and is probably not  $\Phi$  (full availability).
- Issues:
    - Calibration without over parameterizing the problem.
    - The power system is a grid with high-dimensional optimization setting locational prices; stack models are "stylized representations" of such intending to capture the "essence" of spot price phenomena.
  - Perceived advantages:
    - The distribution of  $p_t$  depends upon fuel prices in a sensible way.
    - Changes to the stack (new builds or retirements) are sensibly extrapolated into changes in the the distribution of  $p_t$ .

# Modeling Alternatives

## Stack Models

- Create and maintain a detailed database of the "region" in question.
- Calibration:
  - Assume parametric forms for  $\delta$  and  $\epsilon$ .
  - Generate the historical stack on a daily basis using prevailing fuel prices.
  - Assume a functional form for the seasonal availability of generation; e.g;

$$C_i^{\text{actual}}(t) = C_i \Psi(t)$$

where

$$\Psi(t) = \sum_{k=1}^K [\gamma_k \sin(2\pi kt) + \delta_k \cos(2\pi kt)]$$

- Assumes all generation types sustain the same seasonal availability.
- The form is then:

$$\Phi_t [C | \bar{F}_t] = \Phi \left[ \frac{C}{\Psi_t} | \bar{F}_t \right]$$

- Set the free parameters via MLE.

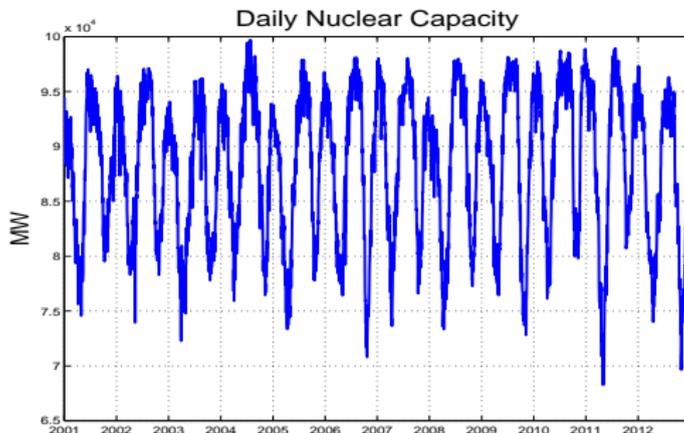
# Modeling Alternatives

## Stack Models

- You now have a model under "physical" measure for spot price dynamics:

$$p_t = \Phi \left[ \frac{L_t(1 + \delta_t)}{\Psi_t} \mid \bar{F}_t \right] + \epsilon_t$$

- Why incorporate  $\Psi(t)$ ?
  - The following figure shows available U.S. nuclear capacity.
  - Maintenance follows lower seasonal demand in "shoulder" months.



# Modeling Alternatives

## Stack Models

- Two approaches: (as with econometric models)
  - Risk neutral: Create a risk-neutral measure by adjusting parameters and/or the distribution of  $L_t$  to hit market forwards and options prices.
    - Pricing is via Monte Carlo and is believed (by some anyway) to yield realistic distributions.
    - This does not resolve the issue of limited ability to hedge (recall peaking options).
  - Physical: Use the physical measure to construct minimum-variance hedges using instruments that trade now ( $t = 0$ ).

# Modeling Alternatives

## Stack Models

- Simplified Stack Models:

- The approach above requires extensive data—arguably too much detail.
- An alternative: Each type of generation is its own "sub-stack" which can be represented analytically.
- Stack Arithmetic:
  - Suppose that we group each generation by input fuel and represent the "sub-stacks" by  $\Phi_j(C|F_j)$ . Then:

$$\Phi^{-1} [p] = \sum_j \Phi_j^{-1} \left[ \frac{p}{F_j} \right]$$

- To see this note that  $\Phi^{-1} [p]$  is the total capacity with cost  $\leq p$ .
- The above simply totals all generation with cost  $\leq p$ .
- Judicious choices of functional forms for  $\Phi_j$  (notably exponential) can yield analytical tractability and enhanced numerical efficiency.<sup>1</sup>

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<sup>1</sup>See, for example, Carmona, Coulon and Schwarz: "A Structural Model for Electricity Prices."

# Modeling Alternatives

## Stack Models

- Summary of Stack Model Implementation:

- Build a stack:
  - Unit by unit from a database.
  - Via parametric forms invoking:  $\Phi^{-1}[\rho] = \sum_j \Phi_j^{-1}\left[\frac{\rho}{F_j}\right]$
- Generate simulations:
  - Temperature  $\tau_d$ .
  - Hourly loads  $\bar{L}_d$  conditional on  $\tau_d$ .
  - Simulations for the input fuel prices  $\bar{F}(t, T)$ .
  - The resulting spot price distribution is obtained from:

$$\bar{p}_d = \Phi \left[ \frac{\bar{L}_d(1 + \delta_d)}{\Psi_t} | \bar{F}(d, d) \right] + \bar{\epsilon}_d$$

- This yields a joint distribution of  $[\tau, L, \bar{F}, \bar{p}]$ .
- Calibration:
  - Physical measure: Deploy the above historically adjusting free parameters to hit realized spot prices.
  - Risk neutral: Adjust free parameters to “hit” market data.
- Simulation: The joint distribution is used to to price and hedge.

# Modeling Alternatives

## Stack Models

- State-of-Affairs:
  - Building stack models from actual generation databases in a given region/ISO/zone yields models that:
    - Are difficult to calibrate.
    - Ignore the network nature of actual power systems.<sup>2</sup>
  - “Caricature” stack models have substantial advantages:
    - The relative tractability renders calibration potentially viable.
    - Arguably remains a “work in progress.”

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<sup>2</sup>The computational requirements for models that attempts to capture the entire system currently preclude calibration to historical weather, load and price data or forward market data. 

# Conclusions

- Multi-factor models applied to daily tolls in the risk-neutral setting have issues:
  - Spurious risk due to spot correlation effects.
  - Hedging programs that are difficult to affect.
  - Dependence on volatilities and correlations that are often not traded.
- This has spawned development alternatives:
  - Econometric models:
    - Calibrated to historical price behavior
    - Ostensibly more realistic price distributions.
    - Valuation can yield estimates of hedging slippage.
    - Difficult to embed anticipated systemic changes.
  - Structural models:
    - Intended to accommodate anticipated systemic changes.
    - Challenging to implement—still a work in progress.

## On Deck

- Variable Quantity Swaps
- Natural Gas Storage