The Portfolio Diversification Value of Nuclear Power in Liberalized Electricity Markets

By

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Malcolm Bean

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Abstract

The key difference between a regulated and a liberalized electricity market is the establishment of a competitive generation marketplace via spot markets, day-ahead auctions, and over-the-counter trading activity. In a liberalized market, power plants are no longer guaranteed a fixed return on capital investments or the ability to pass on increases in fuel prices to customers directly. Therefore, power generators have had to modify their capital allocation and marketing strategies to resemble that of a typical competitive market participant more closely, balancing expected returns with portfolio risk.

Advanced Combined Cycle Gas Turbine (CCGT) power plants are currently viewed as the most attractive generation investment option, offering low capital costs, short construction lead-times and financial option-like qualities. In contrast, a nuclear power plant's levelized cost is dominated by large fixed costs and capital expenditures. Even the perception of nuclear power as being a hedge against volatile natural gas markets has been called into question by power market Monte Carlo simulations. These simulations indicate that CCGT power plants are actually the generation option with the least exposure to natural gas and electricity price uncertainty because of the intrinsic hedge created by the historically high correlation of natural gas and electricity prices[1, 2].

Nevertheless our simulations, heavily focused on modeling the non-linearity of the power supply curve, indicate that the portfolio diversification value of nuclear power is dependent on the generation composition of the power market. In markets primarily composed of natural gas fired capacity, an investment in nuclear power offers no portfolio diversification value, with all three baseload generation types are effectively long positions in natural gas.

Conversely, in markets with a large amount of coal capacity there is a competition for market share between major marginal fuel types, coal and natural gas, which creates less favorable market dynamics for the CCGT. While we still observe a high natural gas-electricity correlation, the intrinsic hedge no longer stabilizes the CCGT profits. Our simulations indicate that in a bi-marginal fuel market a CCGT power plant is short natural gas, with cheaper natural gas helping to boost capacity factors, reduce operational heat rates, and displace coal power plants. Similarly, as currently observed in Northeastern power markets, cheap natural gas has not only shrunk coal power profit margins but also negatively impacted plant capacity factors. Therefore, the portfolio diversification value of nuclear comes from it being insulated from fossil fuel price uncertainty, but not because this attribute equates to a more stable levelized cost. Rather, nuclear power's low cost and low volatility fuel insures that an unfavorable shift in fossil fuel prices will not result in a large decrease in capacity factor and subsequent increase in profit volatility.

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1 Motivation

Historically, the most important components of an electricity generation investment analysis were the long-term electricity price forecast and projected levelized cost of generation[3, 4]. However, as recent events have proven in both the power generation and financial sectors, strategies to mitigate the impact of fundamental market shifts and volatility have become increasingly important and arguably on par with portfolio expected returns. Financial transaction oriented hedges, such as power purchase agreements and fuel options, can make a generation investment effectively risk-less but have limited time horizons and in most instances have a negative expected return. Alternatively, the ownership of various generation asset types, the focus of this analysis, is a long-term solution for reducing portfolio risk without directly sacrificing portfolio returns[5].

In an attempt to better capture the dynamics of electricity markets and investor risk aversion, academic analyses have begun to incorporate portfolio selection models and other power market characteristics such as the historical correlations of electricity and fuel used to generate electricity [2, 6, 7]. The high correlation of electricity and natural gas prices exhibited in many power markets has further cemented the advanced CCGT as the generation option of choice. While the high volatility of natural gas adds uncertainty to the levelized cost of natural gas-based generation, the electricity-natural gas correlation creates an intrinsic hedge for natural gas fired power plants, therefore making capital intensive investments such as nuclear, large coal and hydroelectric power plants the generation options with the greatest exposure to natural gas and electricity price volatility.

We agree that a Monte Carlo Simulation, which models fuel and electricity prices as correlated random variables, can provide an accurate assessment of a power market with a single primary marginal fuel type, such as NYISO and ISO-NE, on large time scales. However, such an approach cannot capture the supply curve dynamics of a power market with two competing marginal fuel types (i.e., PJM, MISO and SPP). These bi-marginal power markets also exhibit a high electricity-natural gas correlation and have comparable average market heat rates, but CCGTs have not enjoyed the same intrinsic hedge protection observed in NYISO and ISO-NE, with historical capacity factors $1/2$ to $1/4$ of the commonly assumed 85% before the recent decline in natural gas capacity factors to decade lows (Table 2 & Figure 3). While we find that even in bi-marginal markets advanced CCGTs are critical to the construction of an optimal generation portfolio, the variability of CCGT capacity factors exemplifies the importance of thorough and detailed characterizations of power markets when undertaking a generation investment analysis.

2 Capacity Factor & Heat Rate Risk

In our analysis of historical data we find there exists two types of risk that clearly affect natural gas and coal generation, but that tend to be overlooked in power generation investment analyses. Hereinafter, we will refer to these risks as *Capacity Factor Risk* and *Heat Rate Risk*. It will be shown that these risk factors do not greatly change the expected returns of a generation asset; however they do reveal other shortcomings that are commonly associated with generation investment analysis, namely static capacity factors and heat rates, and underestimation of the potential impact of market heat rate uncertainty. Also note that unless otherwise denoted, all data used to generate tables and figures are from the Ventyx Velocity Suite[8].

- *Capacity Factor Risk*: A capacity factor of 85% to 90% is commonly assumed for all base load generation options. However, based on historical data, we find that the capacity factors of natural gas and coal power plants are dependent upon fuel prices. This is particularly true of midwestern power markets, where coal fired power plants account for large portions of generation capacity. Additionally, based on the zonal price of electricity, a power plant may have a positive spark spread,

$$Spark\ Spread = Price\ of\ Electricity - (Cost\ of\ Gas)(Plant\ Heat\ Rate) \tag{1}$$

  but only a fraction of a power plant's full capacity clears the market due to transmission constraints and locational marginal price (LMP) minimization. Even in a levelized cost analysis, a dynamic capacity factor that can be significantly below 85% would add uncertainty to and increase the fixed O&M and capital cost components.

- *Heat Rate Risk*: In addition to sub-optimal operating heat rates during start up, shut down and partial output, we also consider uncertainty in the distribution of market clearing heat rates as a type of *Heat Rate Risk* with substantial financial implications for fossil fuel power plants. While the market heat rate tends to be less volatile than the other component of electricity prices, fuel prices, an explicit simulation of the market heat rate is particularly important for determining the risk profile of natural gas fired power plants. In the interest of simplicity, we assume that *EP*, the price of electricity, is the product of *NG*, the price of natural gas, and *MHR*, the market clearing heat rate,

$$EP = (NG)(MHR) \tag{2}$$

  and in turn, the operating profits, *OP*, of a nuclear plant can be written as,

$$OP = (NG)(MHR) - MC \tag{3}$$

  where *MC* is the plant's marginal cost of power. Assuming that the variance of *MC* and covariance of the market heat rate and the price of natural gas are negligible, the variance of a nuclear plant's operating profit, *Var(P)*, can be written as

$$Var(OP) \approx Var(EP) = [E(NG)]^2 Var(MHR) + [E(MHR)]^2 Var(NG) + Var(NG)Var(HR) \quad (4)$$

where *E(NG)* and *Var(NG)* are the expected value and variance of natural gas prices, and *E(MHR)* and *Var(MHR)* are the expected value and variance of *MHR.* Alternatively, the operating profits of an advanced CCGT, *OP'*, can be rewritten as,

$$OP' \approx (NG)(\Delta HR) \quad (5)$$

where,

$$\triangle HR \approx \max(MHR - Plant\ Heat\ Rate, 0) \quad (6)$$

The variance of an advanced CCGT's operating profits, *Var(OP')* can be written as,

$$Var(OP') \approx [E(NG)]^2 Var(\Delta HR) + [E(\triangle HR)]^2 Var(NG) + Var(NG)Var(\Delta HR) \quad (7)$$

where *E(ΔHR)* and *Var(ΔHR)* are the expected value and variance of ΔHR. Also by definition

$$E(\triangle HR) < E(MHR) \quad (8)$$

$$Var(\Delta HR) \leq Var(MHR) \quad (9)$$

Therefore,

$$Var(OP') \leq Var(OP) \quad (10)$$

Equation 10 is an alternative explanation as to why CCGTs have an intrinsic hedge against volatile natural gas prices. However on a normalized basis,

$$\frac{Var(\triangle HR)}{E(\triangle HR)} \geq \frac{Var(MHR)}{E(MHR)} \quad (11)$$

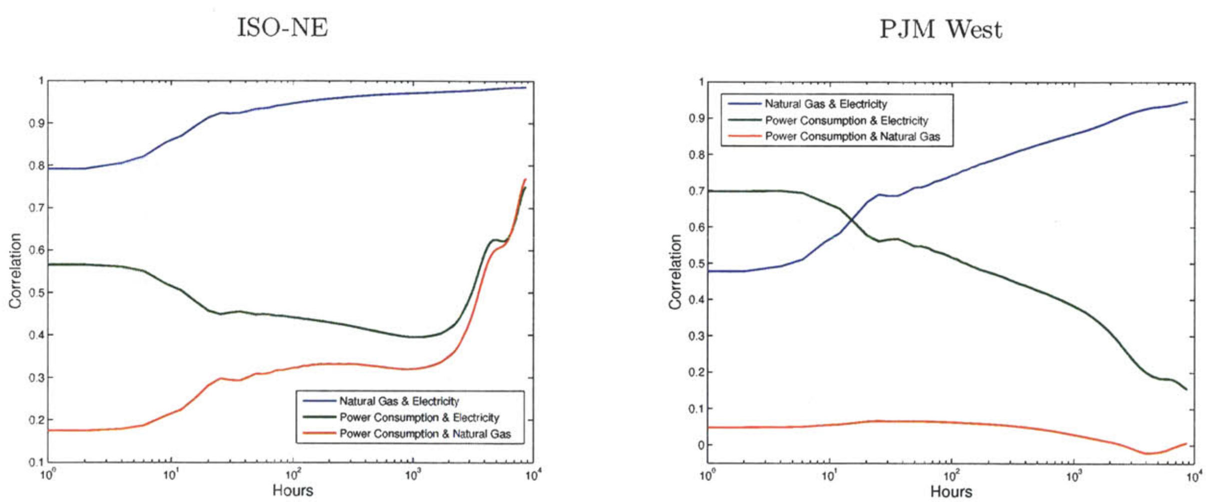
Consequently *OP'* is more sensitive to market heat rate volatility than *OP,* and thus the need to explicitly simulate market heat rate volatility.

- There are several scenarios that can be categorized as both a *Heat Rate Risk* and *Capacity Factor Risk.* As a rule of thumb we use the criteria below to distinguish between the two.

  - *Heat Rate Risk* is primarily concerned with uncertainty in spark spread margins. For example, a large solar installation potentially lowering the average on-peak heat rate from 12,000 Btu/kWh to 11,000 Btu/kWh on sunny summer days.
  - *Capacity Factor Risk* is primarily concerned with uncertainty in the power supply curve, which can be caused by large baseload generation installation and retirements, and shifts in fuel prices that rearrange the optimal dispatch ordering.

Figure 1 illustrates the correlations of power consumption, electricity prices and natural gas prices for two RTO hubs. As aforementioned, ISO-NE is a primarily natural gas powered market, and PJM is a bi-marginal market. As expected, natural gas and electricity prices have a fairly high correlation, especially as the time scale increases. However, notice the correlation of power consumption on the hourly scale in the bi-marginal PJM power market. While they have a non-linear relationship, power consumption essentially dictates the market heat rate on an hourly time scale, underscoring the importance of recognizing market heat rate as key piece of power market simulations. To insure that power consumption's high correlation to electricity prices is not spurious we also consider the correlation of natural gas and power consumption. This correlation appears only to be relevant on a yearly time scale ($\sim 10^4$ hours) in ISO-NE, perhaps linked to the large macroeconomic swings observed over the past several years. With that being said, the development of hydraulic fracturing and increase in proven natural gas reserves may weaken this correlation in the future.

Figure 1: The Correlations of Power Consumption, Electricity Prices and Natural Gas Prices



2.1 Capacity Factor & Heat Rate Risk - Yearly Time Scale

To properly frame and assess the impact of these two risks, we analyze competitive Regional Transmission Organizations' (RTO) market data from 2004 through 2011. First, we consider the yearly capacity factors, regional fuel prices and market generation capacity by fuel type.

Table 1: Natural Gas Capacity Factors [1]

	2004	2005	2006	2007	2008	2009	2010	2011
California ISO	55.1%	54.9%	57.1%	65.7%	67.3%	60.6%	56.8%	56.8%
ERCOT ISO	42.5%	46.3%	51.2%	52.7%	51.0%	49.5%	45.3%	45.3%
Midwest ISO	6.9%	20.6%	16.7%	21.1%	14.9%	14.4%	19.9%	19.9%
New England ISO	49.3%	54.5%	58.3%	56.4%	55.9%	56.7%	61.2%	61.2%
New York ISO	21.1%	25.1%	38.0%	48.3%	41.3%	54.0%	60.3%	60.3%
PJM ISO	14.9%	14.0%	15.5%	24.1%	24.3%	35.0%	41.3%	41.3%
SPP	15.6%	19.1%	23.9%	24.6%	28.3%	32.1%	34.4%	34.4%

Table 1's data is somewhat misleading in that some power plants may be purposefully operating at intermediate load generation, perhaps in an attempt to minimize major overhaul O&M costs or to maximize the longevity of plant components. Therefore, based on plant capacity factors, we filter to identify "baseload oriented" natural gas power plants (Table 2). We recognize this grouping of plants is likely skewed towards units in load pockets with favorable LMPs. However, being located near metropolitan areas is a clear advantage for natural gas power plants. Filtering for "Baseload Oriented" power plants has the greatest effect on NYISO and PJM, both of which have large and dense metropolitan areas. This is particularly true for Northeastern New Jersey, New York City and Long Island areas, where local generation is primarily composed of natural gas and petroleum based power and power demand is highest. We also observe that the operational heat rates of natural gas plants decreases as capacity factors increase (Table 3).

Table 2: "Baseload Oriented" Natural Gas Capacity Factors [2]

	2004	2005	2006	2007	2008	2009	2010	2011
California ISO	66.1%	66.9%	63.7%	71.3%	74.5%	71.4%	67.8%	47.1%
ERCOT ISO	49.1%	55.2%	56.3%	61.3%	61.8%	60.8%	58.3%	63.7%
Midwest ISO	7.9%	22.6%	16.8%	23.1%	15.1%	16.9%	22.6%	25.8%
New England ISO	47.4%	53.7%	59.2%	58.6%	58.1%	57.5%	62.0%	69.5%
New York ISO	67.0%	68.1%	64.1%	76.5%	65.4%	71.8%	74.6%	72.4%
PJM ISO	20.4%	17.5%	19.9%	29.6%	31.8%	45.4%	51.5%	61.5%
SPP	24.6%	39.1%	34.7%	41.8%	44.3%	47.1%	44.2%	47.4%

[1] Plant Heat Rates < 7,500Btu/kWh & Generation Capacities > 300MW

[2] Based on cumulative capacity factors, in each RTO we designate "Baseload Oriented" natural gas power plants as those power plants in the top two quartiles of natural gas plant capacity factors.

Table 3: Nameplate vs. Operating Heat Rates of "Baseload Oriented" Natural Gas Plants [3, 4]

	Nameplate	2004	2005	2006	2007	2008	2009	2010	2011
California ISO	7.00	8.28	7.47	7.61	7.37	7.20	7.14	7.02	7.53
ERCOT ISO	7.13	8.61	8.02	7.81	7.59	7.64	7.49	7.46	7.31
Midwest ISO	7.10	11.62	8.43	11.00	8.03	8.70	8.32	8.04	7.82
New England ISO	7.00	8.12	7.79	7.59	7.44	7.60	7.63	7.76	7.52
New York ISO	7.16	8.51	8.67	8.13	7.47	7.17	7.19	7.10	7.08
PJM ISO	7.12	8.18	7.81	7.89	7.87	7.85	7.64	7.60	7.51
SPP	7.23	8.94	7.76	7.75	7.72	7.86	7.57	7.84	7.62

Table 4: Coal Power Capacity Factors[5]

ISO Name	2004	2005	2006	2007	2008	2009	2010	2011
California ISO	82.7%	86.7%	89.8%	78.1%	78.8%	86.3%	73.2%	75.8%
ERCOT ISO	84.0%	88.6%	89.5%	84.5%	82.0%	83.0%	77.4%	76.8%
Midwest ISO	69.2%	68.8%	68.0%	70.1%	68.3%	63.8%	66.6%	63.0%
New England ISO	72.8%	83.8%	75.4%	87.4%	79.3%	71.6%	64.9%	35.9%
New York ISO	87.8%	85.6%	87.5%	89.9%	79.7%	55.7%	72.7%	57.2%
PJM	71.1%	73.6%	73.3%	72.6%	70.4%	63.0%	65.9%	62.2%
SPP	78.8%	75.5%	75.9%	77.8%	76.5%	75.6%	74.3%	73.6%

Unlike natural gas power plants, heat rates are not the primary economic differentiator for coal power plants. Rather, coal power plant economics are dependent upon the type of coal required and the distance from the coal supply. For example, a coal power plant may have sulfur dioxide emissions credits or Flue-Gas Desulfurization (FGD) technology that enables it to use high sulfur coal, a relatively cheaper alternative to standard coal on a \$/MMBtu basis. The impact of distance from coal mines is illustrated in Figure 2, with midwestern coal plants paying significantly less than their Mid-Atlantic and New England counterparts. In contrast, natural gas prices have a much lower geographical variance (Figure 3).

[3]Heat Rates in Units of MMBtu/MWh

[4]RTO Heat Rates based on Generation Capacity Weighted Averages

[5]Plant Heat Rates < 10,000Btu/kWh & Generation Capacities > 500MW

Table 5: Nuclear Power Capacity Factors

ISO Name	2004	2005	2006	2007	2008	2009	2010	2011
California ISO	83.4%	88.2%	89.5%	92.4%	81.8%	82.1%	95.9%	92.1%
ERCOT ISO	94.2%	86.5%	96.5%	92.2%	93.7%	93.8%	93.8%	91.0%
Midwest ISO	87.3%	86.2%	92.9%	89.3%	92.3%	89.2%	88.3%	89.0%
New England ISO	92.0%	90.0%	97.6%	86.8%	92.1%	96.3%	91.5%	88.1%
New York ISO	92.4%	93.6%	94.9%	90.8%	94.9%	94.0%	94.6%	92.4%
PJM	92.4%	92.8%	92.8%	93.2%	94.6%	92.7%	94.1%	90.8%
SPP	94.3%	87.5%	87.3%	98.8%	89.4%	85.6%	100.2%	84.9%

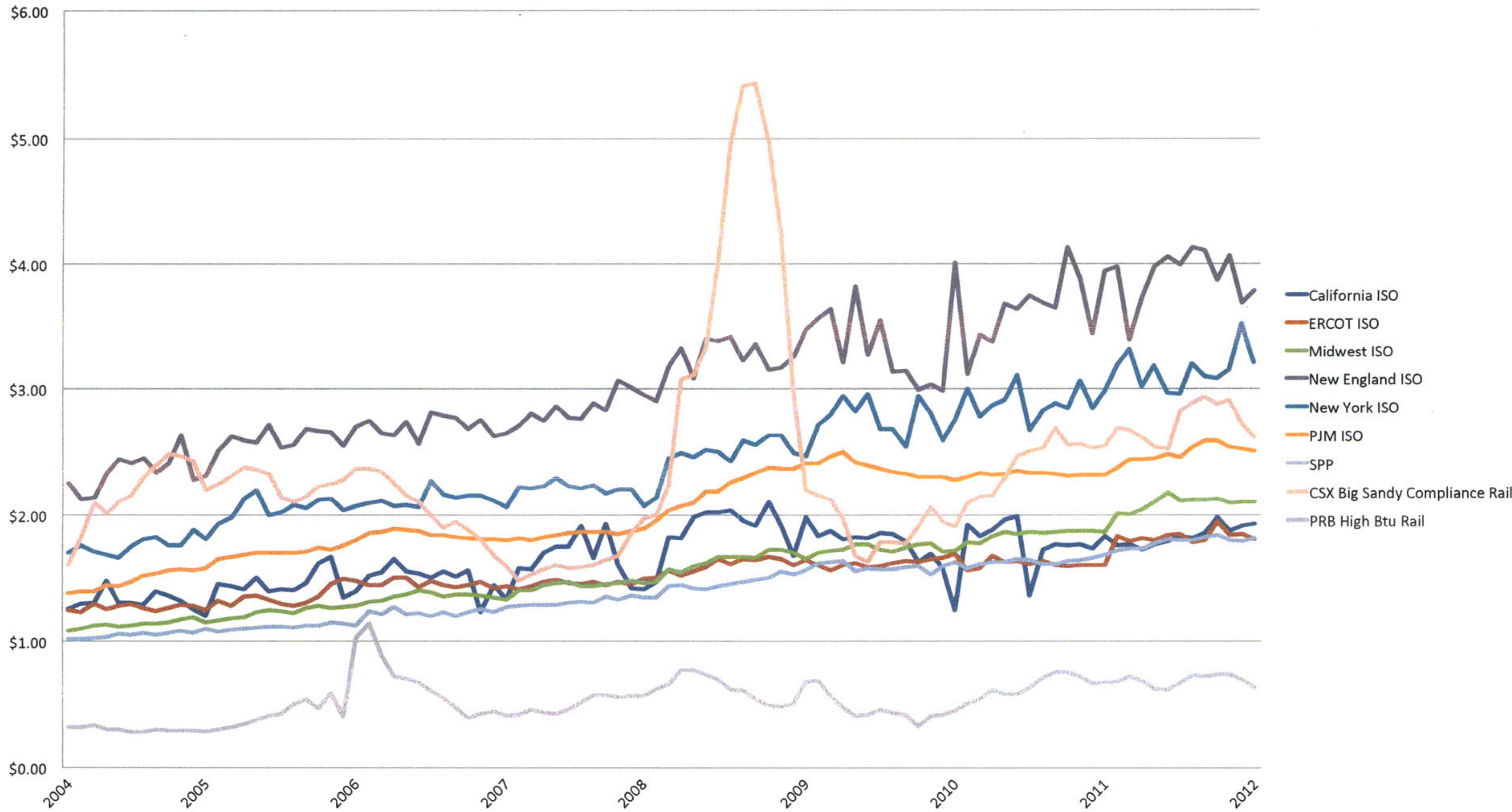
We can clearly see that fossil power plant capacity factors are influenced by fuel prices and power market generation capacity composition (Table 6). In all regions, the recent decline in the price of natural gas has resulted in increased CCGT capacity factors. Cheaper natural gas is also viewed as the sole driver of lower coal capacity factors. However, the relatively high and steadily increasing coal prices (7% to 8% increases year-over-year) in the New England and the Mid-Atlantic regions have also negatively impacted coal capacities in NYISO, ISO-NE and PJM. Contrastingly, in the Western (CAISO) and Midwestern markets where coal has remained below \$2.00/MMBtu, we see essentially no change in baseload coal capacity factors. Additionally, in markets that are predominately coal fired by capacity with access to cheap coal, there appears to be an upper bound on CCGT capacity factors. This phenomenon would likely be observed on a zonal market level in western PJM, which has direct access to Western Pennsylvania and West Virginia's coal mines. In these regions, assuming coal is \$2/MMBtu, a CCGT power plant would require natural gas to drop below \$2.75/MMBtu to have a marginal cost that is comparable to that of a baseload coal power plant.

Table 6: ISO Generation Capacity by Fuel Type

	Coal	Gas[6]	Nuclear	Renew	Hydro
California ISO	3.0%	57.8%	11.7%	11.4%	16.0%
ERCOT ISO	20.2%	65.3%	3.9%	9.9%	0.5%
Midwest ISO	49.4%	32.4%	6.1%	8.4%	3.6%
New England ISO	6.6%	64.5%	13.1%	6.2%	9.5%
New York ISO	6.1%	62.6%	13.2%	4.5%	13.6%
PJM ISO	40.2%	35.5%	16.9%	3.6%	3.6%
SPP	36.2%	50.4%	2.8%	7.2%	3.3%

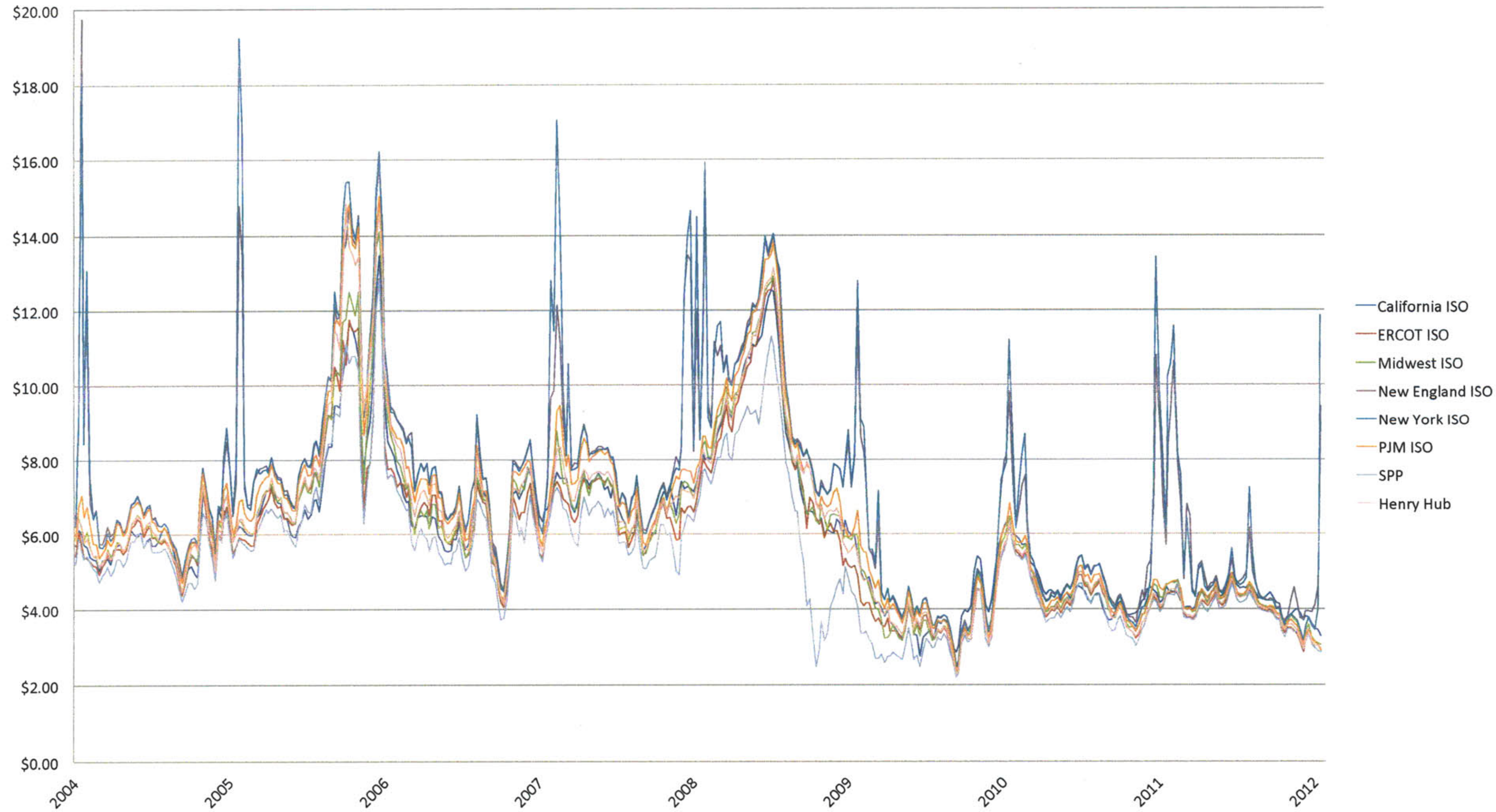
[6] Petroleum capacity in ISO-NE, NYISO and PJM has been included as natural gas capacity because the majority of these units are co-fired and can operate on natural gas or petroleum. In the other RTOs capacity specified as etroleum-fired make up less than 1% of capacity.

Figure 2: Historical Coal Prices ($/MMBtu)



It should be noted that the vast majority of coal is bought through structured forward contracts. Therefore, spot coal exchange indexes, such as CSX Big Sandy Compliance or PRB High Btu Rail, are not indicative of actual power plant fuel costs. Also, notice the geographical dependence of coal. This is a result of transportation costs accounting for a large portion (25% to 50%) of the total coal price.

Figure 3: Historical Natural Gas ($/MMBtu)



From our understanding natural gas spot market prices are an accurate approximation of the fuel prices paid by natural gas power plants. However it is difficult to know exactly how a power plants procures natural gas because of the natural gas market's high liquidity and purely financial hedges options. Natural gas prices are slightly dependent upon geography exact for the northeastern "bottleneck" that occasional has basis spikes relative to Henry Hub prices.

Figure 4: Monthly Spot Uranium Prices ($/lbs of U_3O_8)

While Ventyx Velocity Suite does not provide the data, it is very likely that the nuclear power plants have longer-term fuel agreements with suppliers. Therefore, similar to coal spot prices, the volatility of uranium spot prices is not indicative of actual fuel price uncertainty. Additionally, raw uranium only accounts for approximately 2% to 5% of the levelized cost of nuclear power. As a percentage of levelized costs, this is significantly lower than fossil fuel power plants, whose fuel costs account for upwards of 40% of levelized costs.

2.2 Capacity Factor & Heat Rate Risk - Hourly Time Scale

While our analysis of yearly capacity factors has given insight into the type of systematic errors that can be embedded in a generation investment analysis, data must be analyzed on the hourly time scale in order to fully assess all aspects of capacity factor and heat rate risks. If a power plant is truly "base-loaded" (i.e., the unit is always generating power, excluding O&M outages), then the power plant's ramp rate and transmission constraints have essentially no financial impact. However, our yearly capacity factors indicate that this can only be legitimately assumed for nuclear power plants for all RTOs.

The nameplate heat rate of a power plant is its optimal conversion rate of fuel to electricity, commonly measured in fuel units of British Thermal Units (BTU) or Millions of British Thermal Units (MMBtu) and power units of kilowatt-hours (kWh) or megawatt-hours (MWh). The nameplate heat rate is typically achieved when the plant is operating at its maximum capacity. However, when not operating at full capacity, the heat rate of a power plant can be approximated with equation 12[8],

$$EHR = \frac{Ax^2 + Bx + C}{x} \tag{12}$$

where EHR is the effective heat rate, x is the plant generation in megawatts, and A, B and C are parameters specific to the power plant. This approach, calculated by the Ventyx Velocity Suite, is a common approach to modeling a power plant's efficiency. Equation 13 attempts to account for the physical constraints of a power plant's ramp rate and other instances in which a power plant generates only a portion of its maximum output. For example, a power plant may choose to temporarily tolerate a negative spark spread in order to be fully operational for on-peak prices or only have a fraction of its output clear the market due to LMP price minimization.

$$CF = \begin{cases} D\tanh(Es+F) & \tanh(Es+F) \geq X \\ 0 & \tanh(Es+F) < X \end{cases} \tag{13}$$

where CF is the plant capacity factor, s is the heat rate spread (i.e market clearing heat rate - plant's nameplate heat rate), X is the minimum capacity factor of a power plant, and D, E and F are free parameters. In our simulations we assume a minimum capacity factor of 20%, which is the approximate minimum generation load of a CCGT. These parameters are estimated based on plant level capacity factors from fossil power plants in PJM, NYISO and ISO-NE. Also note that the our usage of hyperbolic tangent is purely based on what we believed was the best analytic function to model capacity factor as function of spark spread; a piecewise linear function that has the approximate shape of a collar option would also be appropriate. Nuclear power plant dispatch is based on a schedule rather than the hourly price of electricity and spark spreads, therefore we assume that the hourly revenue for a nuclear power plant's is the product of the electricity price, the plant capacity and 92.1%, the average national nuclear capacity factor.

2.2.1 Sample Calculation of *EHR* and *CF* Parameters

For this sample calculation, we use the 2007 through 2011 generation data of Mystic Station Power Plant located in Charlestown, Massachusetts. The power station has two high efficiency turbines with generation capacities of 872.2MW and nameplate heat rates of 7,172 Btu/kWh (CC9) and 7,125 Btu/kWh (CC8). Figure 5 is a graphical verification of Ventyx Velocity Suite's heat rate regression and observed hourly operational heat rates. To estimate the parameters of CF, we plot the capacity factor versus the heat rate spread. Next, to generate a non-linear fitted curve, we sort the capacity factor and spark spreads in ascending order and fit the sorted data with a hyperbolic tangent function(Figure 6).

Table 7: Mystic Station Power Plant Heat Rate Parameters

	A	B	C
CC8	1591.6	4.8	5.0E-05
CC9	1730.0	4.7	5.0E-05

Figure 5: Curve-Fitted vs. Actual Heat Rates

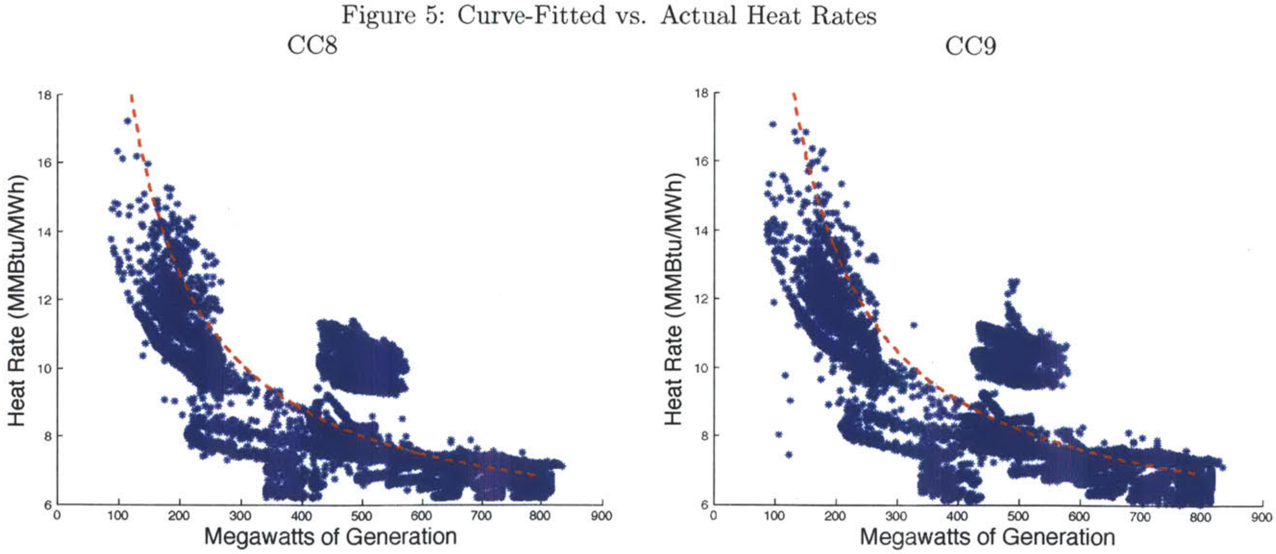
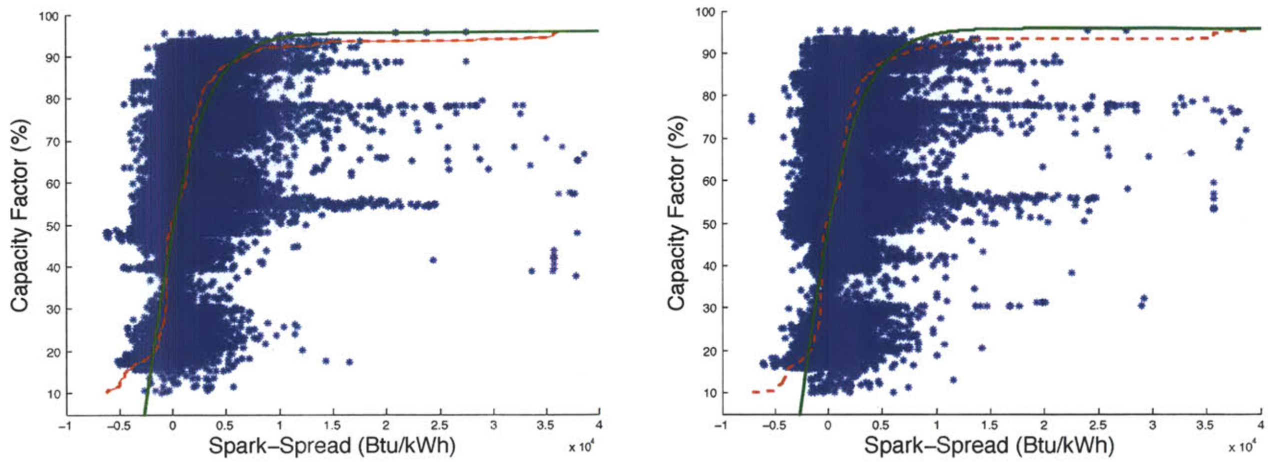


Figure 6: Capacity Factor Curve Fitting

CC8 CC9



$CF = 95.6 \tanh(0.0001896s + 0.5689)$ $CF = 96 \tanh(0.0001899s + 0.5677)$

*Note that the red dashed line is the non-linear fitted curve and the solid green line is the fitted hyperbolic tangent function

3 Electricity Price Forecaster

The most complex and critical component of a generation investment analysis is the simulation of electricity prices. Strategies range from supply curves based on the plant marginal costs in a load zone, to grid level linear programming simulation and non-linear fuzzy-logic models based on empirical data. The latter will be the basis of our simulation. Historically, generation investment analyses simulate electricity and fuels used to generate electricity as correlated random variables, with correlations and volatility based on historical data and mean energy prices based on forecasts such as EIA's Annual Energy Outlook. However, this approach views the non-linearity of a power market's supply curve and uncertainty in power consumption as a simple covariance between electricity and the fuels used to generate electricity.

Therefore, in order to capture the potential impact of system load volatility and the non-linearity of the power supply curve, we focus on market heat rates and the relative prices of natural gas and coal. To quantify the relative prices of natural gas and coal, we use a "price parity" (PP) metric,

$$PP = 7.5(NG) - 11(Coal) \tag{14}$$

where *NG* is the price of natural gas and *Coal* is the price of coal on a \$/MMBtu basis. Theoretically, we justify using this approach because the shape of an RTO's power supply curve is dependent on the relative price of fuel. It should be stressed that the the multiplicative constants in equation 13 are *arbitrary* and based on "typical" heat rates of baseload natural gas and coal fired power plants, with *PP* effectively being the \$/MWh between the two generic power plant types. With system load and *PP* as independent variables and market heat rate as the dependent value, we generate non-linear regression models using MATLAB's neural network toolbox. The models are used to simulate RTO power supply curves based on power plant heat rates, which can be used to calculate capacity factors and operating heat rates. Then when combined with fuel prices the models indicate electricity prices and power plant revenues.

The key difference between the two market types, bi-marginal and predominately natural gas, is how the heat rate curves shift with respect to *PP*(see Figures 7 & 8). As *PP* varies in the ISO-NE, the heat rate curve primarily shifts laterally. This is the expected consequence of base load generation capacity being installed or removed from the RTO. While the coal capacity has remained relatively constant in ISO-NE, as the price of natural gas declines, high marginal cost coal plants are more likely to be mothballed for off peak months and baseload coal plants become selective about when they generate power to minimize start-up costs and component wear-&-tear. In contrast, as *PP* varies in PJM, we observe large longitudinal shifts in the elastic region of the heat rate curve and convergence in the inelastic region. This indicates that while the overall amount of capacity participating in the market is relatively constant, the price-minimizing power plant supply stack ordering is heavily influenced by fuel prices.

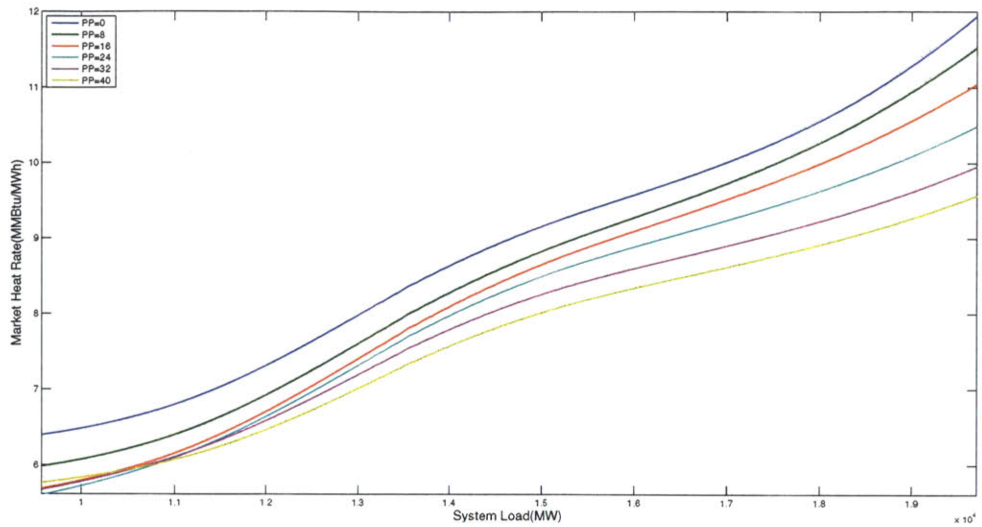
In essence, the difference between the two market types is the ability of their supply curves to "counteract" a natural gas price increase. Notice that when $PP=0$ in both RTOs the heat rate curve begins at approximately 6.5 MMBtu/MWh, but as PP approaches 40, the base of the ISO-NE curve only drops to 5.5 MMBtu/MWh, while the PJM curve has dropped to 2.5 MMBtu/MWh. Obviously no power plant has a heat rate of 2.5 MMBtu/MWh (2,500 Btu/kWh). However based on a power plant's marginal cost relative to the price of natural gas, an *effective heat rate* of 2,500 Btu/kWh is appropriate when determining its place in the power supply curve dispatch order. For example, if the price of coal is \$2.00/MMBtu and natural gas is \$8.00/MMBtu the effective heat rate for a 10,000 Btu/kWh coal plant would be 2,500 Btu/kWh, ($^{10{,}000Btu/kWh}/_{4}$). This phenomena explains why PJM's market heat rate curve moves dramatically with changes in PP.

Table 8: Historical Price Parity in ISO-NE, NYISO and PJM[7]

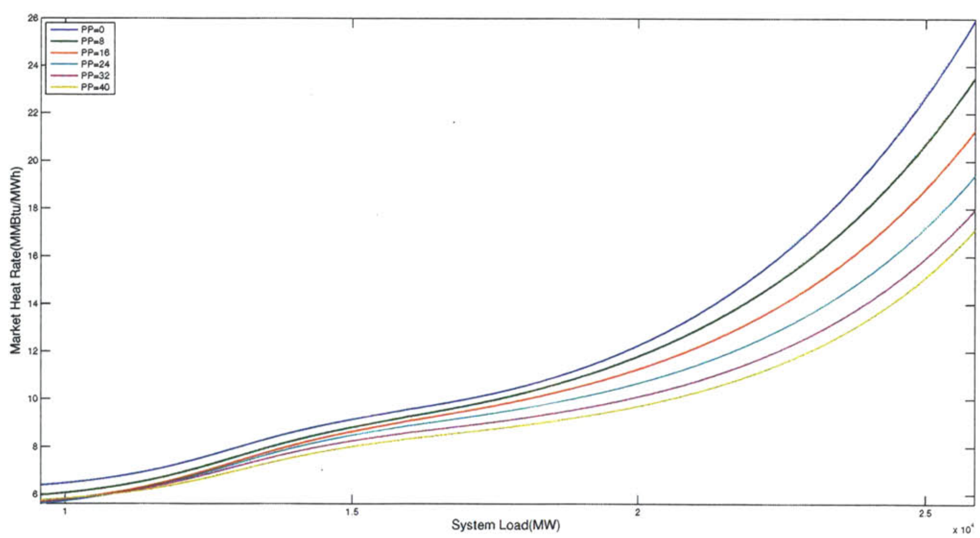
	Natural Gas Hub	1st Quintiles	2nd Quintiles	3rd Quintiles	4th Quintiles	Minimum/ Maximum
ISO-NE	Algonquin Citygate	-8.67	4.01	24.36	35.79	-26.60/ 149.19
PJM-West	Dominion South	3.69	10.86	29.82	40.42	-12.87/ 101.45

[7]Data from 2005 through 2011

Figure 7: ISO-NE Market Heat Rates Curves at various PP Values

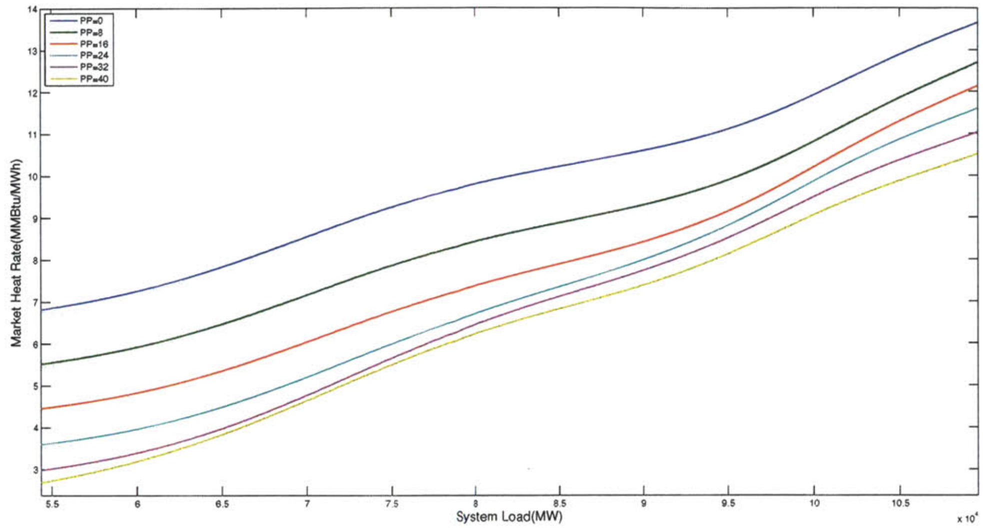


*X-Axis is 1st to 95th percentiles of System Load

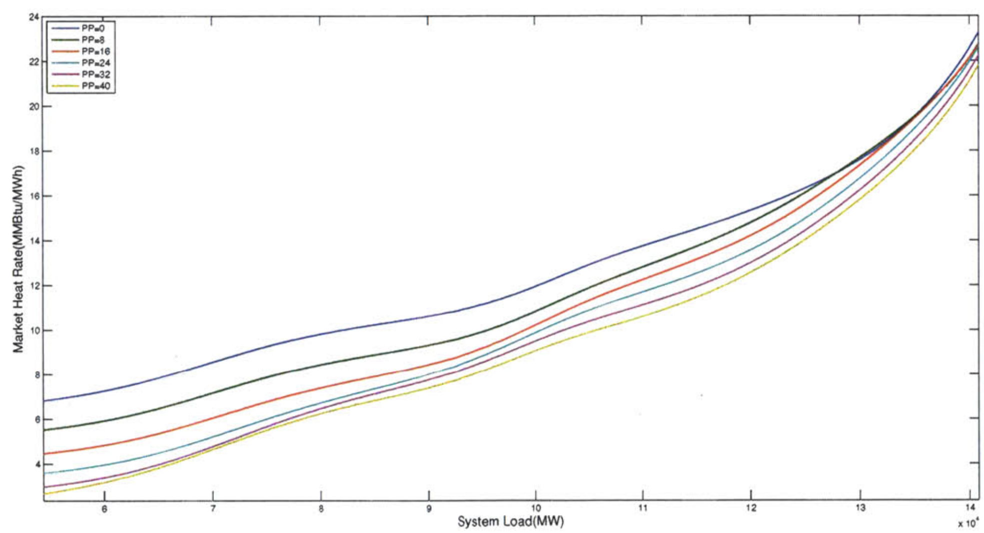


*X-Axis is 1st to 99.9th percentiles of System Load

Figure 8: PJM Market Heat Rates Curve at various PP Values



*X-Axis is 1st to 95th percentiles of System Load

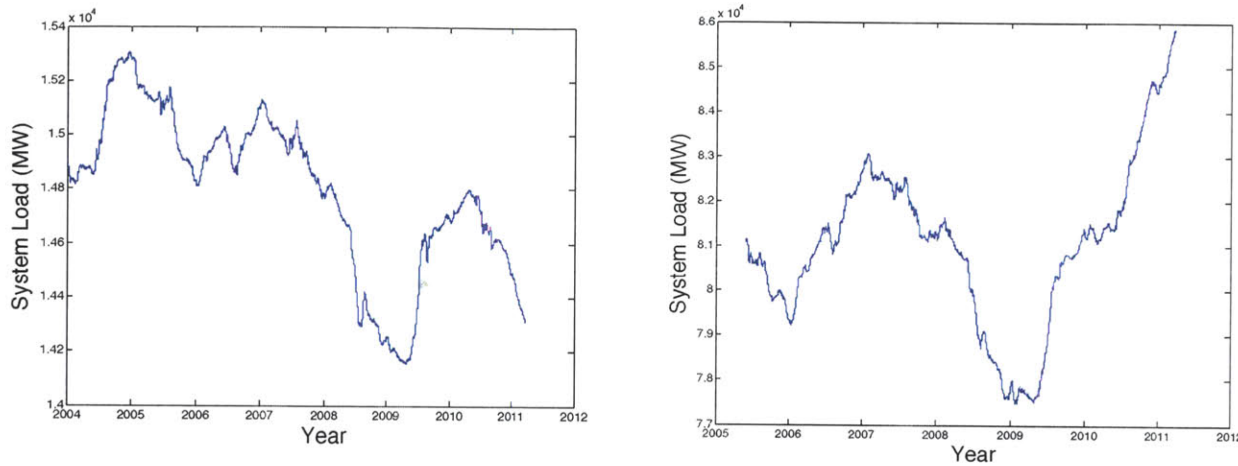


*X-Axis is 1st to 99.9th percentiles of System Load

Figure 10 depicts the yearly system load moving averages for ISO-NE and PJM. Notice the distinct drop in system loads across the three RTOs from 2008 through 2009. This phenomenon is most likely associated with the height of the subprime mortgage crisis.

Figure 9: RTO Yearly System Load Moving Averages

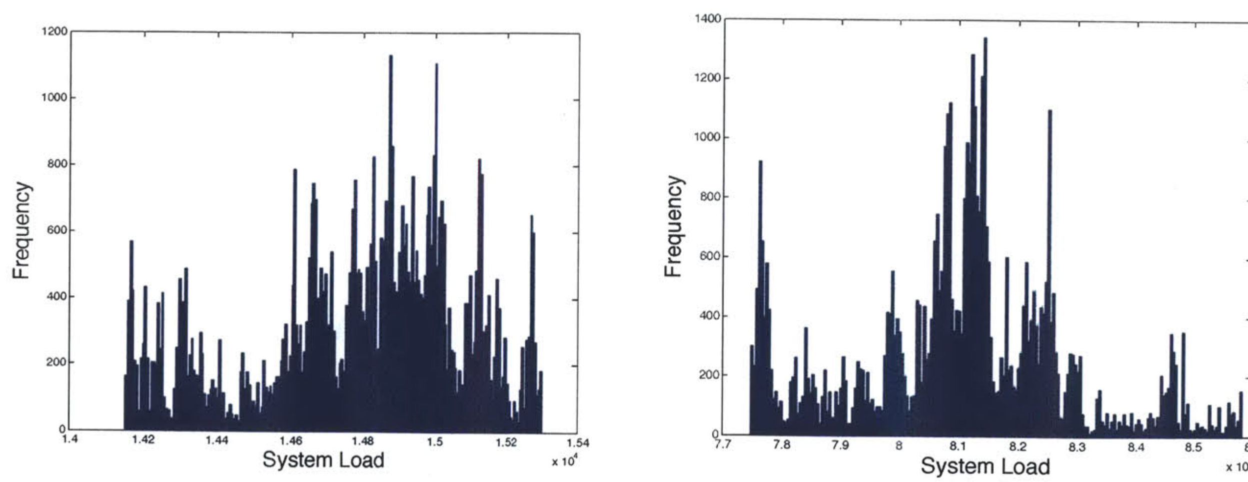
ISO-NE PJM



On the yearly scale, RTO system loads are well approximated as log-normal distributions. However, the yearly moving average of power consumption does not resemble any standard distribution. Therefore, we utilize historical yearly load distributions from 2005 to 2011 as our sample space. Figure 11 depicts the histograms of RTO yearly moving averages.

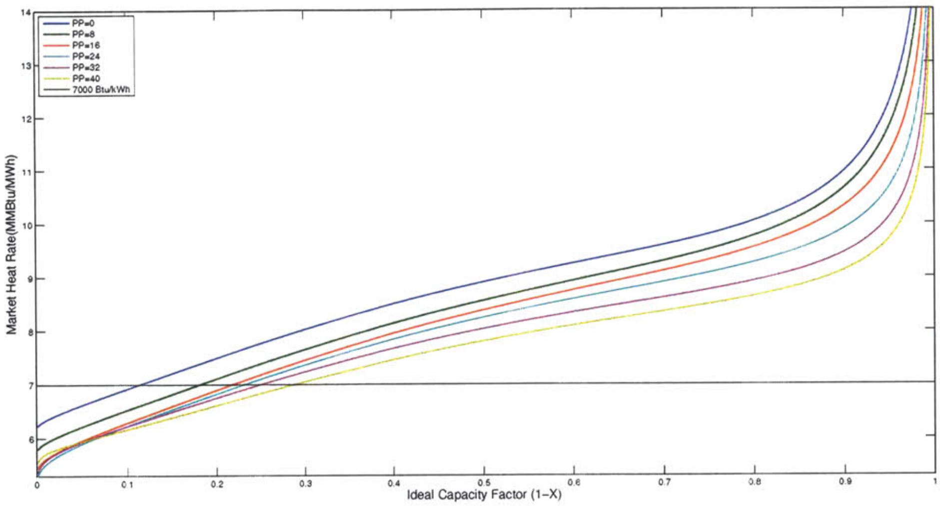
Figure 10: Histograms of RTO Yearly System Load Moving Averages

ISO-NE PJM

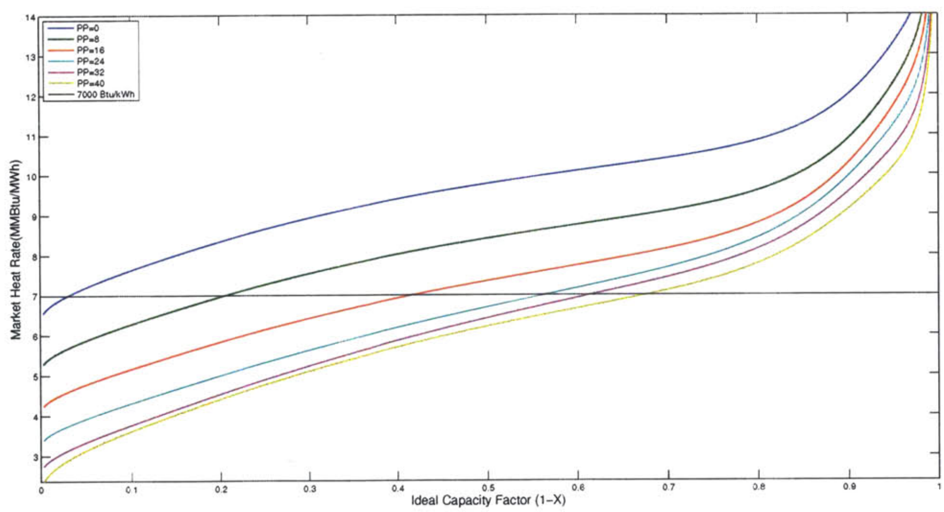


Lastly, by multiplying the heat rate supply curves by the median distribution of system load, we can generate an approximate CDF of heat rates (Figure 11). This curve depicts optimal capacity factors, which better illustrate the differences among the RTOs. In both RTOs considered, when natural gas is cheap relative to coal (PP$\approx$0), CCGT power plants have highly idealized capacity factors (90% to 100%). As PP increases, we observe the impact of RTO generation capacity composition. In the predominantly natural gas based RTOs, CCGT capacity factors are minimally impacted if natural gas becomes relatively expensive. Alternatively, in PJM, which is approximately 40% coal and 35% natural gas by capacity, we see a steep decline in idealized CCGT capacity factors.

Figure 11: CDF of Market Heat Rates
ISO-NE



PJM-West



3.1 Capacity Payments

A RTO's capacity payment is essentially a guaranteed revenue stream for existing power plants, which is critical to the economics of peaking and intermediate load power plants. In exchange, it is understood that peaking plants will bid into the market based solely on their marginal cost. To insure this the major capacity paying RTOs implement price caps of \$1000/MWh[9], which is rarely met. Conversely, the Electric Reliability Council of Texas (ERCOT) is a competitive market that does not have a capacity payment. In ERCOT, it is not uncommon to have daily peak prices of 1,000 to 3,000 \$/MWh, the current RTO price cap[10], as peaking plants attempt to recoup large overhead fixed costs. Table 9 and 10 list the historical capacity payments for ISO-NE and PJM, the two RTOs of interest in our simulations and assessment of nuclear power's portfolio value. ISO-NE has one capacity payment for the entire RTO. PJM has a tiered system, with MAAC, EMAAC and SWMAAC being more populated load regions, where location generation tends to be higher heat rate natural gas and petroleum plants. We assume a constant capacity payment based on historical means in our power market simulations.

Table 9: ISONE Capacity Payments

Units($/MW-Hour)	10/11	11/12	12/13	13/14	14/15	15/16	Mean
ISO-NE	6.16	4.90	4.04	4.04	4.39	4.70	4.71

ISO-NE's capacity auction is collared at 60% and 200% of CONE (cost of new entrant), which is determined by the ISO. For the 6 capacity payment periods listed, the lower bound of 60% of CONE was reached.
ISO-NE's capacity payments are determined approximately 4 years in advance.

Table 10: PJM Capacity Payments

Units($/MW-Hour)		07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	Mean
PJM	RTO	1.70	4.66	4.25	7.26	4.58	0.69	1.16	5.25	3.69
	MAAC	1.70	4.66	7.97	7.26	4.58	5.56	9.42	5.69	5.86
	EMAAC	8.24	6.20	7.97	7.26	4.58	5.81	10.21	5.69	6.99
	SWMAAC	7.86	8.75	9.89	7.26	4.58	5.56	9.42	5.69	7.38

PJM's capacity payments are determined approximately 3 years in advance.

4 Power Market Simulations

To assess the portfolio diversification effect of nuclear power, we simulate ISO-NE and PJM under various fuel price and system load assumptions. ISO-NE represents predominantly natural gas powered markets where nuclear power has minimal portfolio diversification value. PJM (West Hub) represents the bi-marginal market in which nuclear power has significant portfolio diversification value. Our analysis uses a capacity-scaled earnings before interest, taxes, depreciation and amortization (EBITDA) (i.e. EBITDA/MWh of capacity) as its economic metric. This metric is specifically scaled to the magnitude of the $/MWh prices observed in RTOs and represents the average hourly operating profit per megawatt of capacity. With this metric, we can observe and quantify the relationships that dictate portfolio diversification value without specifying capital investment costs or discount rates, both of which vary greatly from project to project and can overwhelm or dictate analysis results; consider that a power plant's overnight capital cost may not be representative of the price paid for a late-stage equity transaction or lease payments. With natural gas fired power plants currently being viewed as the highest return and lowest risk investment among the baseload options, developers and early equity investors may demand a premium for a post-operational equity stake or from a lease agreement counterparty.

Table 11: Power Plant Operating Parameters

Parameter	Units	Nuclear	Coal	Natural Gas Units	
Heat Rate	Btu/kWh	10,000	9,000	7000	11,000
Approx. Fuel Range[5]	\$/MMBtu	0.55 - 0.86 (0.71[6])	1.00 - 6.00	2.00 - 16.00	
Variable O&M	\$/MWh	2.25[7]	1.55	0.47	1.39
Fixed O&M	\$/MWe-Hour Capacity	7.23	3.25	0.83	1.82
Capacity Payment	ISO-NE	ISO-NE	ISO-NE	ISO-NE	ISO-NE
	PJM	RTO	RTO	(Mean)[8]	SWMAAC

We begin by simulating the effect that variations in the price of natural gas and coal have on power plant EBITDA in PJM and ISO-NE (see Figure 12 & 13). As expected, nuclear and coal power plants are essentially long positions in natural gas, with an increase in coal prices being unfavorable for coal plants and slightly favorable for nuclear power plants. We also observe non-linear market dynamics with the scaled EBITDA of the natural gas plants. For the most part the advanced CCGT or "Natural Gas (7000 Btu/kWh)" is a long position in natural gas, with higher fuel prices boosting spark spreads and, subsequently, plant EBITDA. However, for each price level of coal, there is an inflection point in profitability. This is the result of lower capacity factors and higher realized heat rates as the marginal cost of the advanced CCGT becomes greater than even the most inefficient coal fired plants. Note that the legend corresponds to the various coal price levels.

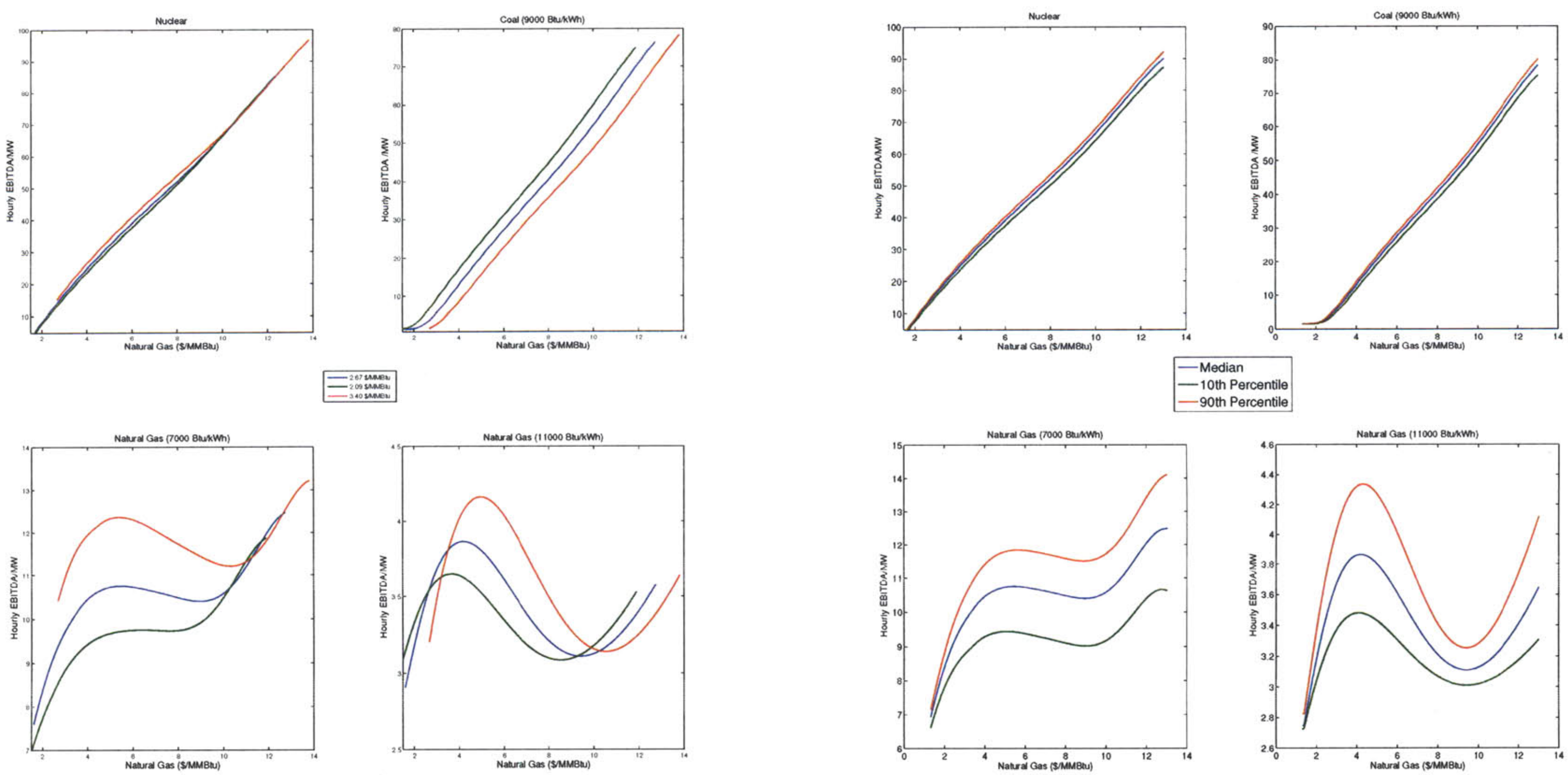
For the load following or peaking power plant, "Natural Gas (11000 Btu/kWh)", market heat rate is the driver of revenue; notice how its EBITDAs are maximal when natural gas is relatively cheap (\$4/MMBtu). With natural gas in this price range high marginal cost coal plants are more likely to be mothballed for off peak months and baseload coal plants are more selective about when they generate power to minimize start-up costs. While the price of natural gas still effectively dictates the average price of electricity, the incremental removal of coal capacity causes a favorable shift in the distribution of market heat rates. This changes the role of the 11000 Btu/kWh natural gas fired plant from a true peaking power plant for hot summer days to a load following plant that provides power for weekly peaks. Also notice that the profits of the natural gas based power plants are more sensitive to system load uncertainty, a type of *Heat Rate Risk*, as we had predicted in the beginning of section 2.

Figure 13 is the equivalent of Figure 12 for PJM. The critical difference between ISO-NE and PJM is the EBITDA profile of the Natural Gas (7000 Btu/kWh) power plant, which is caused by the increased the

Figure 12: Power Plant EBITDAs in ISO-NE

Coal Price Uncertainty

System Load Uncertainty

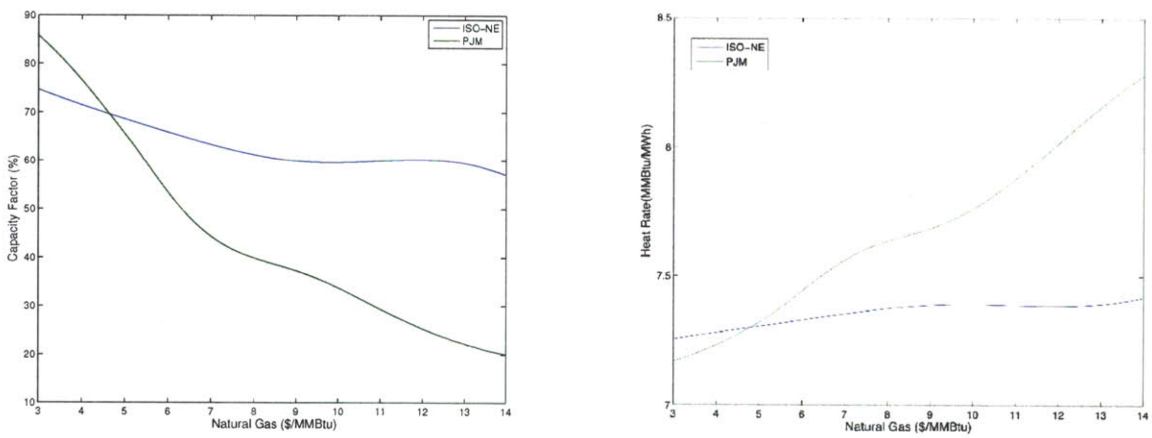


*The crossing curves observed in the Coal Price Uncertainty-Natural Gas (11000 Btu/kWh) is a nonsensical artifact of the simulation method.

amount of coal capacity in the RTO. Because there is such a large amount of coal generation capacity, even a low heat rate CCGT is quickly relegated to a load following generation role as natural gas becomes increasingly expensive. Nevertheless, after being displaced above all coal power in the supply curve CCGT profits plateau. Lastly, Figure 14 depicts the forecasted capacity factors and operating heat rates of the Natural Gas (7000 Btu/kWh) plant in PJM and ISO-NE.

Figure 14: Capacity Factors and Operating Heat Rates of Natural Gas (7000 Btu/kWh)

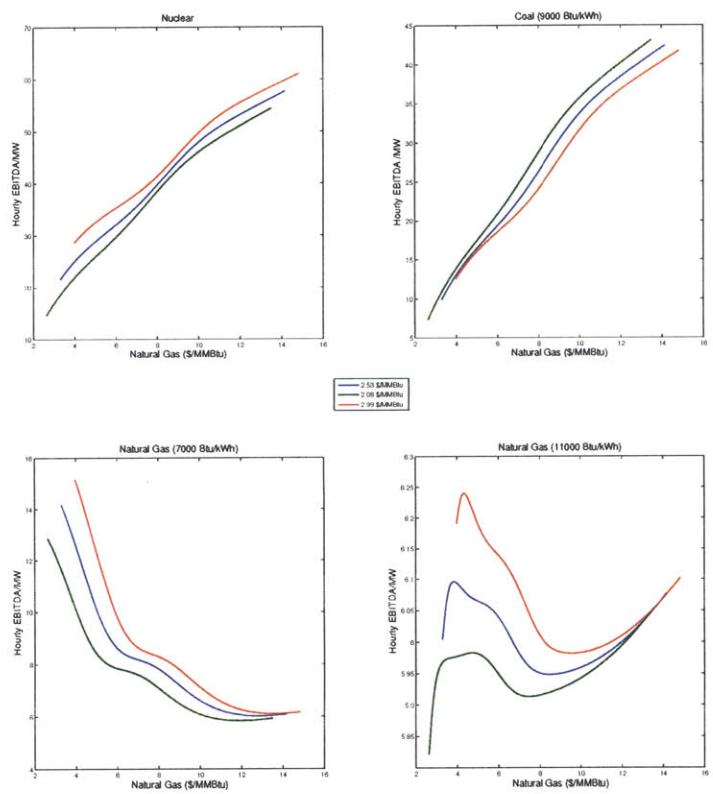
Capacity Factors | Operating Heat Rates



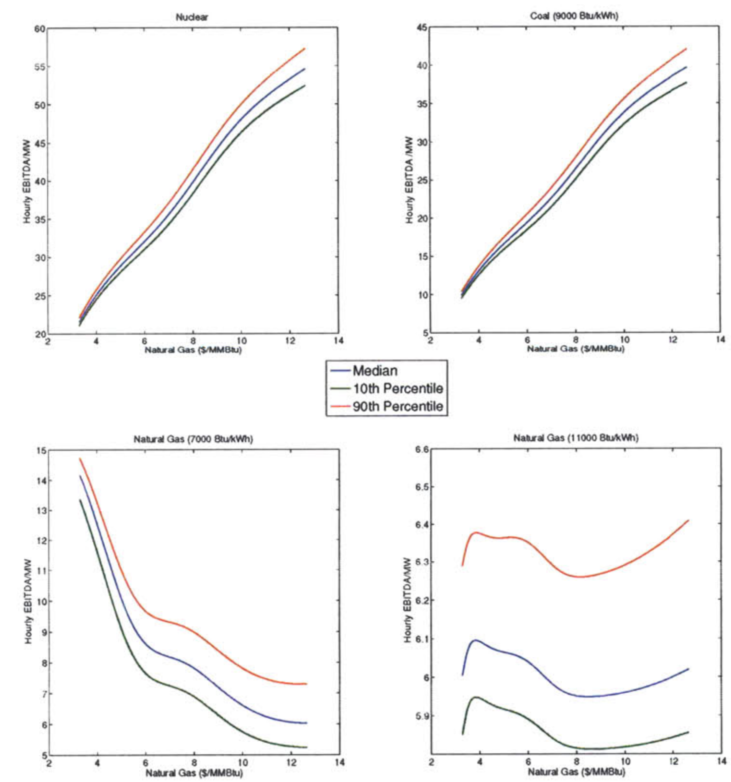
Coal = $2.67/MMBtu for both ISO-NE and PJM

Figure 13: Power Plant EBITDAs in PJM

Coal Price Uncertainty



System Load Uncertainty



5 Portfolio Diversification Value of Nuclear

The utility, U, of an investor can be symbolically represented by the following equation,

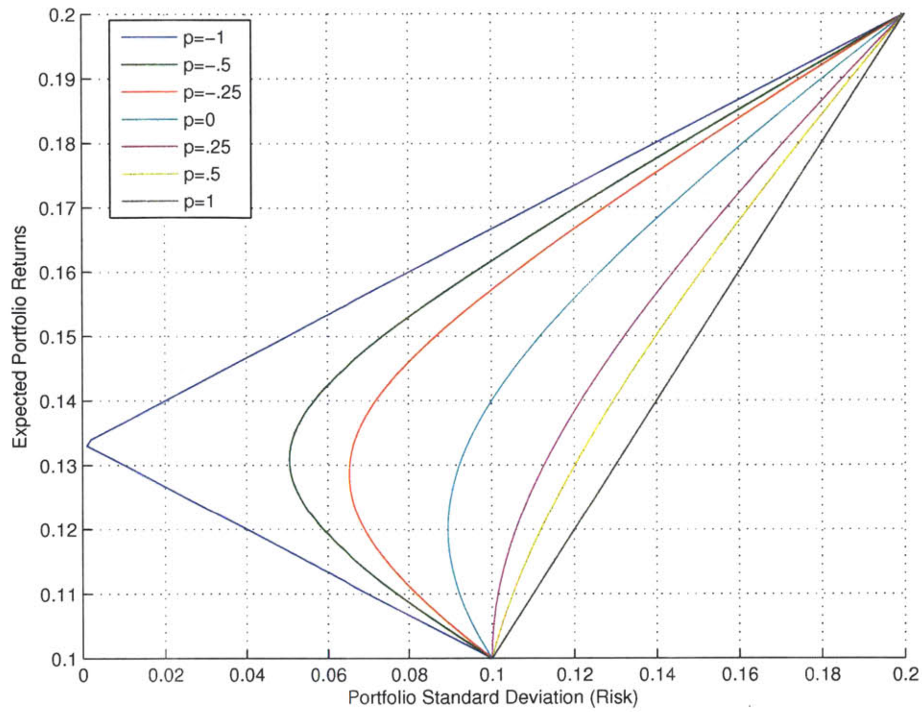
$$U = Returns - \lambda(Risk) \tag{15}$$

where λ is an arbitrary parameter which is positive for risk adverse and negative for risk seeking. Given equation 15, there are two ways to increase utility. First, an asset can proportionally increase returns more than risk. Second, an asset can decrease risk with a proportionally smaller decrease in portfolio returns. However it tends to be easier to achieve the latter than the former. In finance, diversification means reducing risk by investing in a variety of assets. If the returns from a portfolio's assets are not perfectly correlated, then theoretically, the diversified portfolio will have less risk than the weighted average risk of its constituent assets. As such, we define the portfolio diversification value of an asset as its ability to increase investor utility via the aforementioned second mechanism.

Sections 5.1 and 5.2 outline the standard formulations for the portfolio selection metrics commonly used to assess portfolio diversification value. Portfolio risk is calculated using summation in the minimization constraints of the standard formulations. Both of these formulations are based on the Taylor expansion of a logarithmic utility function, *log(1 + x)*. In our simulations, we found that the higher moment correlation matrices (coskewness and cokurtosis) made no material difference to our results. Therefore, we only use the mean variance model to assess portfolio diversification value. The Four-Moment Capital Asset Pricing Model would become more relevant if our simulation used heavy-tail, polynomial decaying distributions rather than exponentially decaying distributions. We also make reference to the efficient frontier in our analysis. The efficient frontier represents the set of optimal portfolios that offers the lowest risk for a given level of expected return.

Figure 15 shows the efficient frontiers of a two asset portfolio with varying levels of correlation(ρ); this figure also illustrates the potential impact of portfolio diversification. While negatively correlated assets are ideal for maximizing portfolio diversification value, uncorrelated and weakly correlated can still significantly reduce portfolio risk.

Figure 15: Two Asset Efficient Frontier with various Correlations



The two assets have expected returns and standard deviations of 0.2 and 0.1 respectively

5.1 Mean Variance Model

In a standard formulation of the Mean-Variance model we have the following quadratic programming problem, for a given expected return ρ:

$$
\begin{aligned}
\min \quad & \sum_{j=1}^{n}\sum_{i=1}^{n}\sigma_{ij}x_i x_j \\
s.t. \quad & \sum_{j=1}^{n} x_j E(R_j) > \rho \\
& \sum_{j=1}^{n} x_j = 1 \\
& l_j \le x_j \le u_j \qquad j = 1...n
\end{aligned}
$$

- x_j is the percentage of total capital invested in the j^{th} asset

- $E(R_j)$ is the expected return on investment of the j^{th} asset
- σ_{ij} is the covariance between the returns of i^{th} andj^{th} assets
- l_j, u_j represent the maximum and minimum amounts of capital which can be invested in the j^{th} asset

5.2 Four-Moment Capital Asset Pricing Model

In a standard formulation of the Four-Moment Capital Asset Pricing model we have the following quadratic programming problem, for a given expected return ρ:

$$
\begin{aligned}
\min \quad & \sum_{j=1}^{n}\sum_{i=1}^{n} \alpha\sigma_{ij}x_i x_j - \beta\tau_{ij}x_i x_j + \gamma\upsilon_{ij}x_i x_j \\
s.t. \quad & \sum_{j=1}^{n} x_j E(R_j) > \rho \\
& \sum_{j=1}^{n} x_j = 1 \\
& l_j \leq x_j \leq u_j \qquad\qquad j = 1 \ldots n
\end{aligned}
$$

- x_j is the percentage of total capital invested in the j^{th} asset
- $E(R_j)$ is the expected return on investment of the j^{th} asset
- σ_{ij}, τ_{ij}, υ_{ij}, represent the covariance, coskewness and cokurtosis between the returns of i^{th} andj^{th} assets
- α, β, γ, are arbitrary constants that weight covariance, coskewness and cokurtosis based on a given risk profile
- l_j, u_j represent the maximum and minimum amounts of capital which can be invested in the j^{th} asset

5.3 Simulation

While we have specifically avoided assigning capital costs to each generation option we must assign a relative measure of cost, which we refer to as the Relative Principal Investment, to properly scale the covariance matrix. Figures 16 and 17 display the relative principal investment as a function of natural gas prices. The graphs' data are in line with the results of levelized cost analyses. With nuclear power's overnight capital costs being in the range of 4000 to 5000 \$/kW and advanced CCGTs being on the order of 1000 \$/kW, ISO-NE natural gas must be at least \$6/MMBtu in order for nuclear power to have comparable returns. Similarly, coal fired power plants, with an overnight cost of 2500 to 3000 \$/kW, have a slight edge on nuclear power if natural gas remains above \$5/MMBtu[3]. However, as currently observed in ISO-NE where natural gas is cheaper than coal, coal power plants can quickly become uneconomic as they are mothballed or forced to cycle as load following power plants.

In PJM we see a slightly steeper Nuclear vs. Natural Gas (7000 Btu/kWh) curve, with higher natural gas price negatively impacting CCGT profitability. Nevertheless, nuclear power still needs natural gas to remain above \$7/MMBtu in order to be competitive. While this may seem inconsistent, recall that we assumed that the CCGT is receiving a higher capacity payment. Additionally, electricity is generally cheaper in PJM because of cheaper coal and significantly more coal capacity in comparison to ISO-NE. We also observe a coal-favorable shift in the relative investment curve in comparison to ISO-NE, which is a consequence of the cheaper coal in PJM.

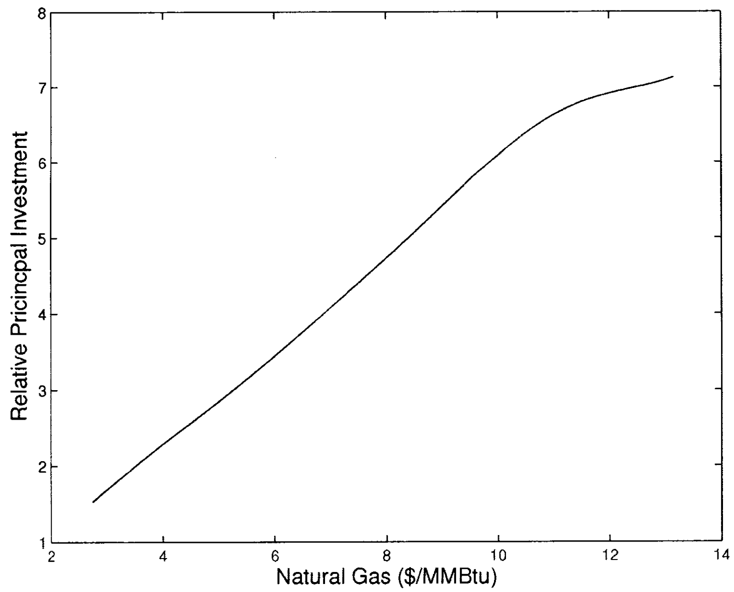
For our simulation, we consider three types of uncertainty; natural gas, coal and system load uncertainty. Natural gas is currently at decade lows. However, EIA's 2012 Energy Outlook estimates the real price of natural gas will rise to nearly \$7/MMBtu by 2035, with an average price of \$5.23/MMBtu from 2012 to 2035. Perhaps more difficult to estimate is the future variance of natural gas. From 2005 through 2011, natural gas had a region-dependent standard deviation between 2.50 and 3.00 \$/MMBtu. However, the ability to hydraulically fracture shale gas deposits has greatly increased proven reserves in the United States. Therefore, it is unlikely that natural gas will ever again reach historically observed levels of volatility. Thus, we assume that natural gas prices are log normally distributed with a mean of $\mu = 1.65$ (mean = 5.23) and two levels of natural gas price volatility, $\sigma = 0.386$ and $\sigma = 0.193$, with 0.386 being the historical observed volatility.

Unlike natural gas, whose uncertainty entails month-to-month and year-to-year price swings, coal price uncertainty is more centered around the 5 to 10 year trajectory of coal prices. The key question is whether or not coal prices will plateau or continue to steadily rise. Thus, we assume two coal price scenarios. The first scenario has constant coal prices of \$3.53/MMBtu and \$2.65/MMBtu[8], in ISO-NE and PJM, respectively. The second scenario has coal prices that are triangularly distributed with the constant coal prices as their mean values.

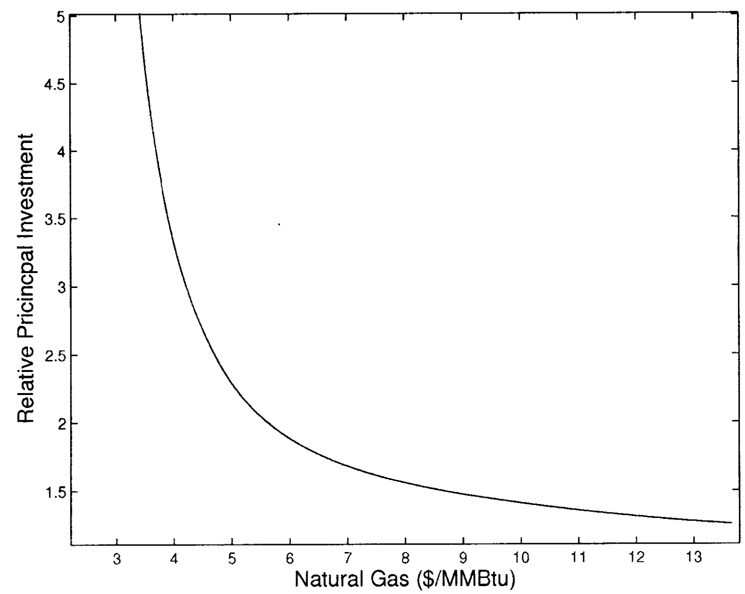
[8]Data from 2005 through 2011

Figure 16: Relative Principal Investment in ISO-NE

Nuclear vs. Natural Gas (7000 Btu/kWh)



Nuclear vs. Coal (9000 Btu/kWh)

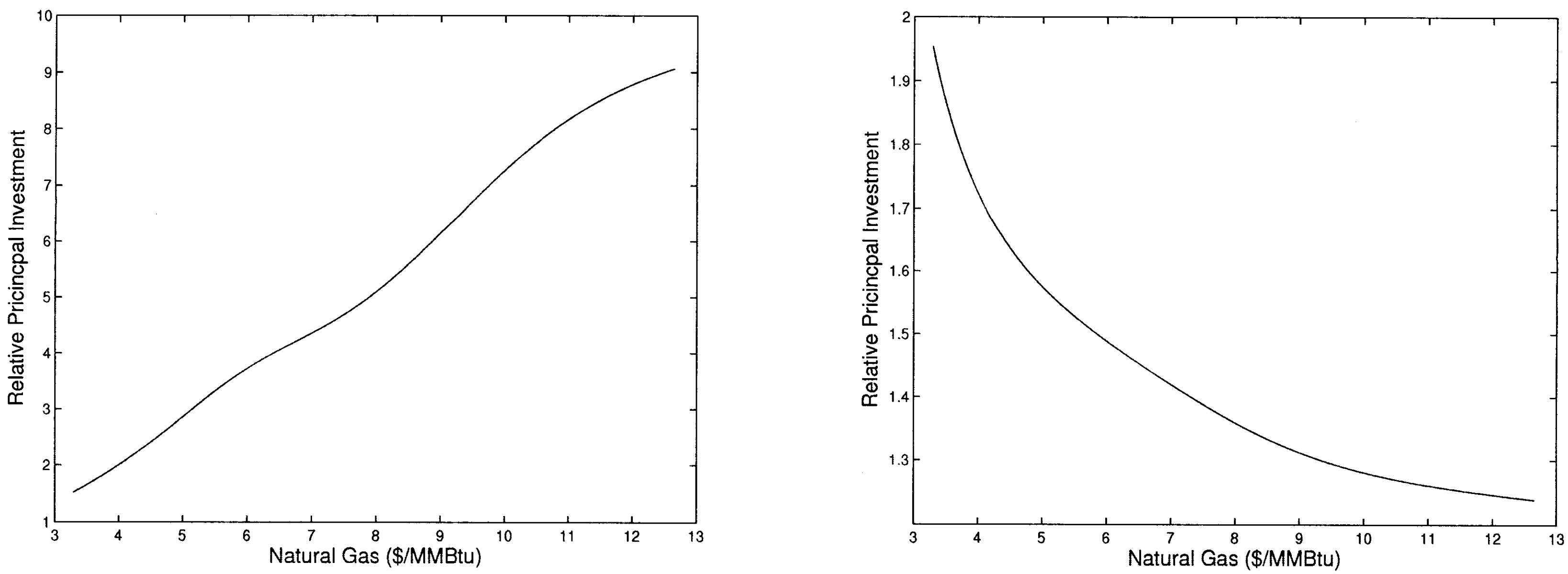


Coal=$3.50/MMBtu

Figure 17: Relative Principal Investment in PJM

Nuclear vs. Natural Gas (7000 Btu/kWh)

Nuclear vs. Coal (9000 Btu/kWh)



Coal=$2.50/MMBtu

Lastly, to quantify the impact of system load uncertainty, we sample between the 5th and 95th percentiles of historical system load distributions. The covariance matrices are scaled assuming an expected return of 15% for each base load generation option and 10% for the 11000 Btu/kWh natural gas plant.

5.3.1 ISO-NE

With the price of natural gas being the only source of uncertainty, natural gas based generation options are clearly the lowest risk investments in ISO-NE. We also observe a portfolio diversification value opportunity, which is created by the covariance of the 7000 Btu/kWh and 11000 Btu/kWh being lower than the individual variances. The bundling of various heat rate natural gas plants is a common portfolio diversification strategy. While the 11000 Btu/kWh offers lower returns, the returns are less volatile and essentially uncorrelated to natural gas prices unlike the other generation options. A decrease in natural gas volatility reduces the profit risk for all three base load generation options. However, the 7000 Btu/kWh is still the optimal choice with a profit variance an order of magnitude less than nuclear or coal power.

Next, we assume that coal prices are triangularly distributed with a minimum, mode, mean and maximum of 2.56, 3.28, 3.53 and 4.74, respectively. With this added uncertainty, the most notable change is the increased portfolio weight of the 11000 Btu/kWh plant. The introduction of coal price uncertainty disproportionately increases the volatility of the 7000 Btu/kWh profits. Nevertheless, system load uncertainty essentially neutralizes the effect of coal price uncertainty in terms of suggested portfolio weights. Thus, we have confirmed that nuclear and coal power effectively have no portfolio diversification value in a primarily natural gas based power market. To gain any significant weight in the set of efficient frontier portfolios requires that the non-natural gas based power options have expected returns that are vastly superior to that of a 7000 Btu/kWh natural gas plant.

Table 12: Uncertainty Assumptions for ISO-NE Simulations

	Natural Gas	Coal	System Load
Simulation 1	$\mu = 1.65$, $\sigma = 0.386$	3.53	2nd Quartile
Simulation 2	$\mu = 1.65$, $\sigma = 0.193$	3.53	2nd Quartile
Simulation 3	$\mu = 1.65$, $\sigma = 0.386$	a=2.56, b=3.28, c=4.74	2nd Quartile
Simulation 4	$\mu = 1.65$, $\sigma = 0.386$	a=2.56, b=3.28, c=4.74	5th - 95th Percentile

Table 13: ISO-NE Covariance Matrices

Simulation 1

	7000 Btu/kWh	11000 Btu/kWh	Coal	Nuclear
7000 Btu/kWh	1.84E-04	6.72E-05	1.90E-03	7.28E-04
11000 Btu/kWh	6.72E-05	2.04E-04	-5.75E-04	-1.29E-04
Coal	1.90E-03	-5.75E-04	3.09E-02	1.11E-02
Nuclear	7.28E-04	-1.29E-04	1.11E-02	4.07E-03

Simulation 2

	7000 Btu/kWh	11000 Btu/kWh	Coal	Nuclear
7000 Btu/kWh	1.57E-05	5.91E-06	2.01E-04	9.14E-05
11000 Btu/kWh	5.91E-06	3.66E-05	-1.64E-04	-6.59E-05
Coal	2.01E-04	-1.64E-04	4.28E-03	1.88E-03
Nuclear	9.14E-05	-6.59E-05	1.88E-03	8.32E-04

Simulation 3

	7000 Btu/kWh	11000 Btu/kWh	Coal	Nuclear
7000 Btu/kWh	3.10E-04	1.18E-04	1.56E-03	7.82E-04
11000 Btu/kWh	1.18E-04	2.44E-04	-7.58E-04	-1.21E-04
Coal	1.56E-03	-7.58E-04	3.17E-02	1.10E-02
Nuclear	7.82E-04	-1.21E-04	1.10E-02	4.10E-03

Simulation 4

	7000 Btu/kWh	11000 Btu/kWh	Coal	Nuclear
7000 Btu/kWh	3.74E-04	2.08E-04	1.69E-03	8.14E-04
11000 Btu/kWh	2.08E-04	3.64E-04	-4.93E-04	-3.08E-05
Coal	1.69E-03	-4.93E-04	3.11E-02	1.08E-02
Nuclear	8.14E-04	-3.08E-05	1.08E-02	4.02E-03

Table 14: ISO-NE Efficient Frontiers

Simulation 1

Expected Return	Standard Deviation (Risk)	Portfolio Weights			
		7000 Btu/kWh	11000 Btu/kWh	Coal	Nuclear
12.69%	1.14%	53.86%	46.14%	0.00%	0.00%
13.15%	1.15%	63.09%	36.91%	0.00%	0.00%
13.62%	1.18%	72.31%	27.69%	0.00%	0.00%
14.08%	1.22%	81.54%	18.46%	0.00%	0.00%
14.54%	1.28%	90.77%	9.23%	0.00%	0.00%
15.00%	1.36%	100.00%	0.00%	0.00%	0.00%

Simulation 2

Expected Return	Standard Deviation (Risk)	Portfolio Weights			
		7000 Btu/kWh	11000 Btu/kWh	Coal	Nuclear
13.77%	0.37%	75.32%	24.68%	0.00%	0.00%
14.01%	0.37%	80.26%	19.74%	0.00%	0.00%
14.26%	0.37%	85.19%	14.81%	0.00%	0.00%
14.51%	0.38%	90.13%	9.87%	0.00%	0.00%
14.75%	0.39%	95.06%	4.94%	0.00%	0.00%
15.00%	0.40%	100.00%	0.00%	0.00%	0.00%

Simulation 3

Expected Return	Standard Deviation (Risk)	Portfolio Weights			
		7000 Btu/kWh	11000 Btu/kWh	Coal	Nuclear
11.91%	1.39%	37.92%	61.86%	0.22%	0.00%
12.53%	1.41%	50.51%	49.49%	0.00%	0.00%
13.14%	1.45%	62.88%	37.12%	0.00%	0.00%
13.76%	1.53%	75.26%	24.74%	0.00%	0.00%
14.38%	1.64%	87.63%	12.37%	0.00%	0.00%
15.00%	1.76%	100.00%	0.00%	0.00%	0.00%

Simulation 4

Expected Return	Standard Deviation (Risk)	Portfolio Weights			
		7000 Btu/kWh	11000 Btu/kWh	Coal	Nuclear
12.42%	1.70%	48.36%	51.64%	0.00%	0.00%
12.93%	1.71%	58.69%	41.31%	0.00%	0.00%
13.45%	1.74%	69.01%	30.99%	0.00%	0.00%
13.97%	1.79%	79.34%	20.66%	0.00%	0.00%
14.48%	1.85%	89.67%	10.33%	0.00%	0.00%
15.00%	1.93%	100.00%	0.00%	0.00%	0.00%

5.3.2 PJM

The results of our PJM simulations are less decisive than our ISO-NE results. We find that a series of efficient frontier plots is the most effective method for analyzing simulation results. Table 15 summarizes the various assumptions that correspond to each efficient frontier plot. The first three frontier curves on each plot represent the efficient frontier without one of the three base load generation options. The fourth is the efficient frontier of a portfolio only composed of natural gas based power plants (Figure 19).

The best and worst performing frontiers indicate the generation option with the lowest and highest of portfolio diversification value, respectively. For example in the graph of Simulation 1's results, the "Without Coal" and "Without CCGT" are the best and worst performing curves. Therefore, coal power has the lowest portfolio diversification value and the advanced CCGT has the highest portfolio diversification value under the assumed market conditions. The "Only Natural Gas" curve is used to ensure that nuclear and coal power play a significant role in the "Without Coal" and "Without Nuclear" portfolios. This curve tends to be below the original three curves, therefore confirming that nuclear and coal power play a significant role when included in the construction of a given optimal portfolio.

Consider Simulations 2 and 4, which are the same as Simulations 1 and 3 with less volatile natural gas. From these graphs, we can deduce that less volatile natural gas is favorable for the natural base power plants, indicated by the favorable shift in the "Only Natural Gas" frontiers. Similarly, Simulations 3 and 4 are Simulations 1 and 2 with coal price uncertainty, respectively. The four simulations indicate that limited coal price uncertainty benefits coal power plants. This may seem counterintuitive, but the coal uncertainty increases the negative correlation of the coal and the natural gas power options and increases the individual volatility of the other three generation options. Simulation 5 models the impact of a \$20/ton carbon tax, which would effectively increase the cost of coal by \$2/MMBtu and natural gas by \$1/MMBtu. Under these market conditions, we see the risk of coal power greatly increase. This is somewhat representative of recent power market conditions with natural gas and coal being close in price on a MMBtu basis. Under these market conditions, even low heat rate coal plants are at risk of being displaced by high efficiency natural gas plants. Because of this increased risk, we observe an unfavorable shift of the "Without Nuclear" frontier. In Simulation 6, we assess the impact system load uncertainty, which yields unexpected results. Rather than disproportionately lowering the value of the "Only Natural Gas" portfolio, we find that system load uncertainty is most unfavorable for nuclear and coal power. System load uncertainty lowers the negative correlation of nuclear and coal power to the CCGT profits, which is for the portfolio diversification value of nuclear and coal power.

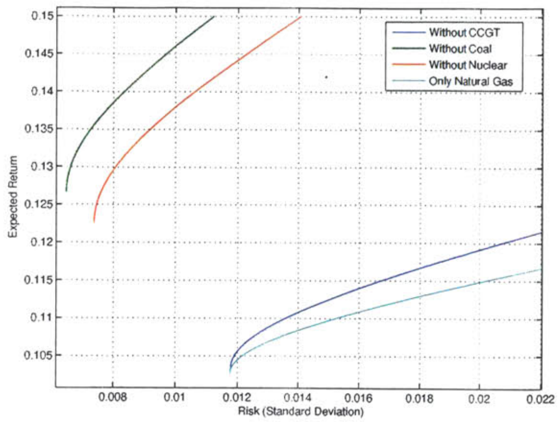
In Simulation 7, we identify the market conditions that maximize the portfolio value of nuclear power, which is when the distribution price parity has extreme values (i.e., PP<0 & PP>40). Under these market conditions, capacity factor risk is maximal for both fossil fuel types, which consequently makes nuclear power the lowest risk base load generation option (Figure 19). Our simulations also highlight the importance of natural gas assets in an optimal generation portfolio; the "Without CCGT" frontier is completely below the "Without Coal" and "Without Nuclear" frontiers in 5 out of the 7 simulation scenarios. Also, while not simulated in our analysis, uncertainty regarding the future composition of a power market (.i.e if a power market will remain bi-marginal or become predominately natural gas) would also increase the portfolio value of both natural gas power options, as both are critical to the optimal portfolios in both our ISO-NE and PJM simulations.

Table 15: Uncertainty Assumptions for PJM Efficient Frontier Curves

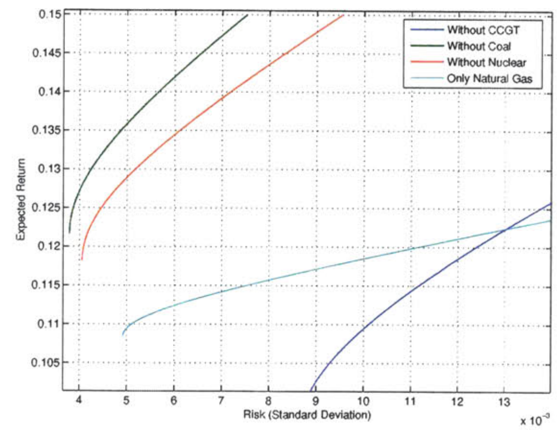
	Natural Gas	Coal	System Load
Simulation 1	$\mu = 1.65$, $\sigma = 0.386$	2.65	2nd Quartile
Simulation 2	$\mu = 1.65$, $\sigma = 0.193$	2.65	2nd Quartile
Simulation 3	$\mu = 1.65$, $\sigma = 0.386$	a=2.00, b=2.45, c=3.50	2nd Quartile
Simulation 4	$\mu = 1.65$, $\sigma = 0.193$	a=2.00, b=2.45, c=3.50	2nd Quartile
Simulation 5	$\mu = 1.83$, $\sigma = 0.386$	a=4.00, b=4.45 c=5.50	2nd Quartile
Simulation 6	$\mu = 1.65$, $\sigma = 0.386$	2.65	5th - 95th Percentile
Simulation 7	$\mu = 1.65$, $\sigma = 0.386$	a=2.50, b=3.50 c=6.00	2nd Quartile

Figure 18: PJM Efficient Frontier Curves

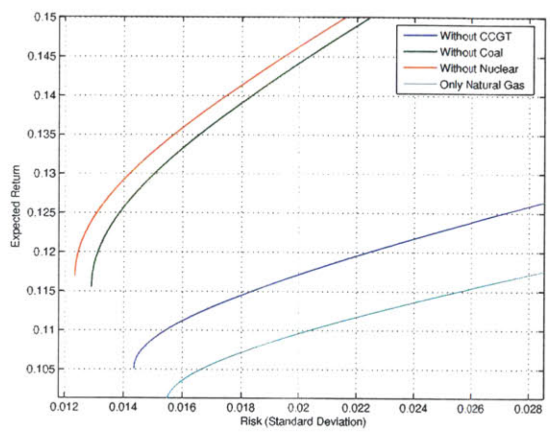
Simulation 1



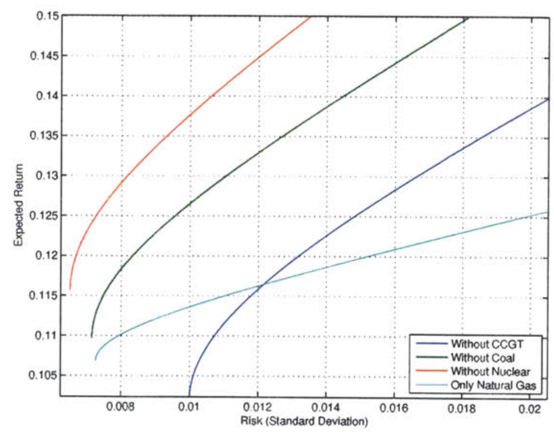
Simulation 2



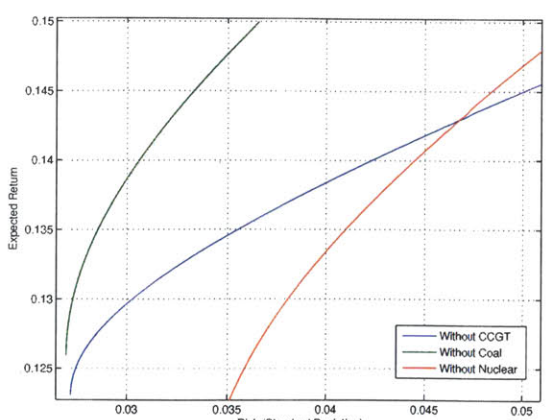
Simulation 3



Simulation 4



Simulation 5



Simulation 6

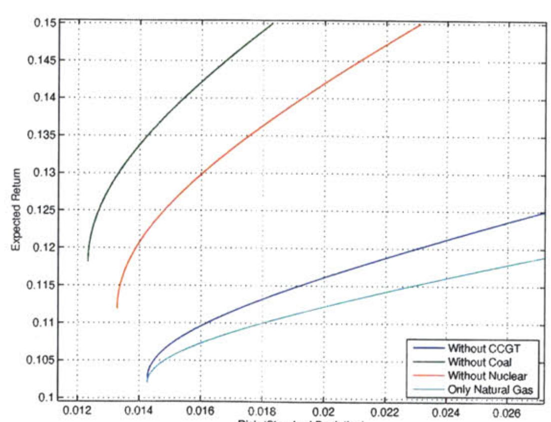
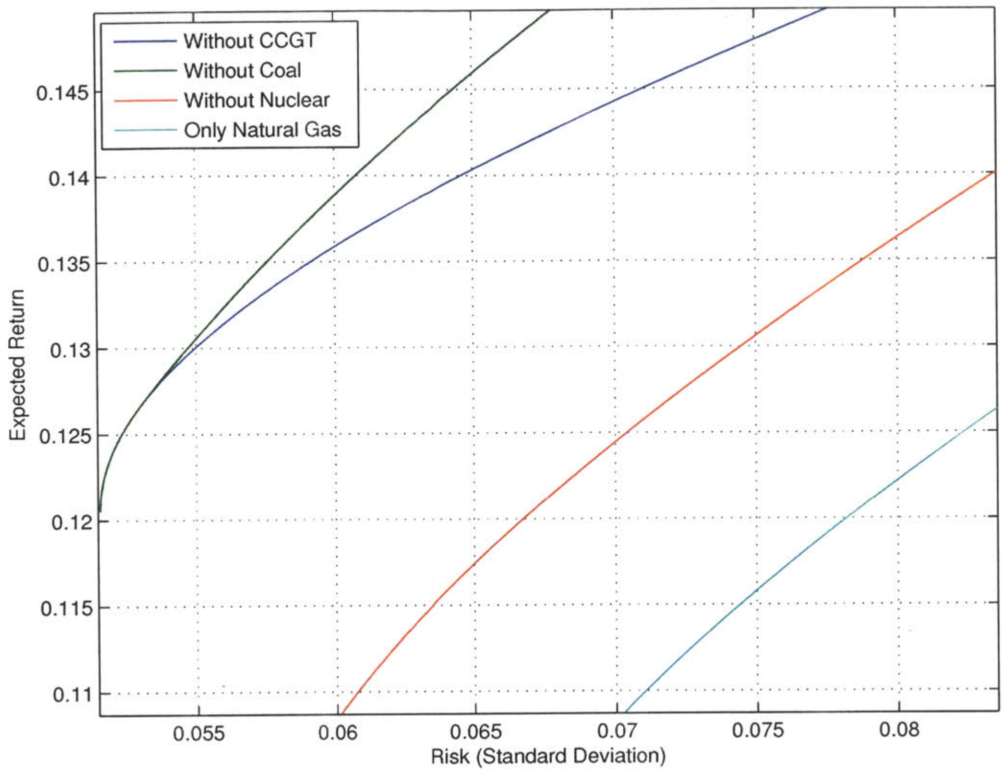


Figure 19: Simulation 7-Efficient Frontier Curves



6 Conclusion

While we have identified market conditions that make an investment in nuclear power attractive, this is a dated analysis in many ways. Cheap natural gas and proposed EPA regulations[9] nearly guarantee that today's bi-marginal markets will eventually become primarily natural gas fired markets. If this occurs, the only way for nuclear power to become an attractive investment is through its ability to deliver superior returns, which is directly linked to lower capital costs and higher natural gas prices. Looking forward, a more relevant question would be the impact of a significant renewable energy build out. Initially, more renewable energy will negatively impact intermediate and load following, as the intermittency of wind and solar power generation increases market heat rate uncertainty during on-peak hours. However, if renewable energy begins to account for a large fraction of power generation, this would be unfavorable for nuclear power. During off-peak hours and seasons, nuclear power will begin to have instances in which it is either

[9] Titled the Standards of Performance for Greenhouse Gas Emissions for New Stationary Sources: Electric Utility Generating Units; this purposed EPA regulation would require any fossil fuel-fired power plant greater than 25-megawatts must meet an output-based standard of 1,000 pounds of CO2 per megawatt-hour. This is specifically achievable for natural gas-fired combined cycle technology and not for new coal technology without carbon capture.

the marginal fuel type or forced to shut down.

Ultimately the attractiveness of a power generation investment is dependent upon the investor's risk tolerance, market expectations and existing portfolio assets. Some will likely find our assumptions of the three base load generation options having the same static expected returns a gross oversimplification. However, the aim of our analysis was first and foremost to offer a sophisticated alternative to modeling the price of electricity and its fuels as correlated random variables.

6.1 Future Research

Regarding future research we suggest analyses focus on two areas in particular:

1. Refinement and Validation of Simulation Methods: There are several ways in which the accuracy and sophistication of the electricity price and supply curve model can be improved. For instance, we assumed static distributions for fuel price and system load uncertainty. However given the evolution progression of fuel prices and system load are times series, stochastic process simulations would be a more appropriate simulation method. Another shortcoming in our model is only considering system load and fuel prices to determine the power supply curve shape and electricity prices, when it should also be a function of power from low marginal cost power sources, such as nuclear, hydroelectric and other renewables, and the availability factors of dispatchable fossil plower plants. With that being said, the empirical neural network model method ultimately should be replaced by a grid level linear programming model which can directly account for transmission constraints and changes to an RTO's generation composition.

2. Utility Function of Generating Companies (GenCos): While it is likely that entities owning or operating a power plant are risk averse, it is unlikely that a mean-variance framework is the best approximation of their objective/utility function. Ideally fuel hedges and power purchase contracts would also be intergrated into the simulation framework, as they play a critical role in the risk profile of GenCos.

References

[1] Roques, F et al., Nuclear Power: a Hedge against Uncertain Gas and Carbon Prices?, Judge Business School, University of Cambridge, England, 2006

[2] Roques, F et al., Fuel mix diversification incentives in liberalized electricity markets: a Mean-Variance Portfolio Theory Approach, International Energy Agency, Economic Analysis Division, 14 March 2006

[3] Lazard Ltd., Levelized Cost of Energy Analysis - Verison 3.0, February 2009

[4] Du, Y and J. Parsons., Update on the Cost of Nuclear Power, Center for Energy and Environmental Policy Research, Massachusetts Institute of Technology, May 2009

[5] Madlener, R et al., Optimization of E.ON's Power Generation with a Special Focus on Renewables, E.ON Energy Research Center Series Volume 2, Issue 2, Rwthaachen University

[6] Delarue, E et al., Applying portfolio theory to the electricity sector: Energy versus power, University of Leuven (K.U.Leuven) Energy Institute, Energy Economics 33 (2011) pg. 1223

[7] Arnesano, M. et al, Extension of portfolio theory application to energy planning problem – The Italian case, Energy, Volume 39, Issue 1, March 2012, Pages 112-124,

[8[Velocity Suite: Investment Grade Data & Analysis. (2012) Ventyx an ABB Company. Retrived from https://velocitysuite.globalenergy.com

[9] Chatterjee, B and K. Collin., CAISO Market Surveillance Committee Meeting, August 10, 2007

[10] Today in Energy- U.S. Energy Information Administration(EIA), Texas Heat Wave, August 2011: Nature and Effects of an Electricity Supply Shortage,

[11] Madlener, R et al., Efficient Investment Portfolios for the Swiss Electricity Supply Sector, Institute for Future Energy Consumer Needs and Behavior (FCN), Faculty of Business and Economics / E.ON Energy Research Center, Aachen, Germany August 2008

[12] Roques, F et al., Fuel mix diversification incentives in liberalized electricity markets: a Mean-Variance Portfolio Theory Approach, International Energy Agency, Economic Analysis Division, 14 March 2006.

[13] Roques, F., Technology choices for new entrants in liberalized markets: The value of operating flexibility and contractual arrangements, Utilities Policy, 16, issue 4, p. 245-253, 2008

[14] Madlener, R et al., Applying Mean-Variance Portfolio Analysis to E.ONs Power Generation Portfolio in the UK and Sweden, Faculty of Business and Economics / E.ON Energy Research Center (E.ON ERC), 2009