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Valuing Assets Using Real Options: An Application to Deregulated Electricity Markets

by Gregory P. Swinand, London Economics and Indecon, Carlos Rufin, Babson College, and Chetan Sharma, Cinergy Corporation*

The burgeoning literature on real options¹ has brought to the fore an idea that in the past may have only been grasped subconsciously at best—the significant contribution to value creation within a business enterprise by assets that can be adapted to differing circumstances. However, the implementation of this perspective in the form of practical valuation tools has confounded potential users and limited the practical application of the real options framework as a decision-making tool. The arcane mathematics involved in both the original Black-Scholes option pricing model and its adaptation to processes beyond the context of financial markets have kept real options in the realm of “rocket science” for many valuation practitioners and executives.² In this paper, we seek to bridge concept and practice by demonstrating the use of real options analysis to value a commercial contract in the context of deregulated electricity markets. The techniques presented below were originally developed as part of a consulting project that resulted in a successful bid by an energy company to enter into a tolling contract with a manufacturing facility.

Our choice of an intangible asset rather than, say, a piece of equipment is deliberate. We believe that such an example widens the scope of applicability of the real options framework beyond its current uses, and as such illustrates the adaptability of the framework to a wide range of situations confronted by managers. Most presentations of real options techniques draw examples from tangible assets such as oil wells or ships, but the valuation potential of these techniques can be extended to many other types of productive resources.

The context of our example is that of emerging deregulated electricity markets, which, as the recent experience in California shows, are not only important for investors and managers of firms in this industry, but also for “old” and “new” economy consumers of energy alike.³ As in many

other sectors of the economy, over the last decade the supply of electricity has been significantly deregulated in a growing number of countries around the world. In general, deregulation has turned the purchase and sale of electric power into a highly competitive activity, where prices fluctuate hourly or even on a real-time basis. In these markets, flexibility is extremely important because of the random nature of supply and demand in the very short term, and the need to balance supply and demand at every instant due to the difficulty of storing electrical energy, which together can make electricity prices extremely volatile. The importance of electricity as an economic input and the importance of flexibility within electricity markets thus add to the interest of our example.

In the effort to develop practical tools to place a value on flexibility, several factors have come together to make this possible: options valuation techniques derived from the by now well-known Black-Scholes formula; the development of new technologies, like combined-cycle plants in the case of electricity, that make flexible production a concrete possibility; advances in contract design to take advantage of such flexibility, such as “tolling” contracts that allow the buyer to “rent” equipment to transform the thermal energy of natural gas into electrical energy; and, not least, rapid growth in computing power, which allows desktop handling of large numbers of calculations and of ever-larger quantities of data.

Over the last decade, the economic valuation tools for financial assets have been extended to non-financial assets, since real investment decisions are frequently quite analogous to financial options (although the validity of continuous trading and the ability to hedge real options runs counter to the assumptions of financial options valuation techniques). For instance, access to a flexible thermal plant selling electricity into a competitive market can be regarded as equivalent to the ownership of a series of

* We are very thankful to Professor Stephen Allen of Babson College for his comments and suggestions. Naturally, all errors and omissions remain our own.

1. See, for example, Lenos Trigeorgis, *Real Options in Capital Investment: Models, Strategies, and Applications* (Westport, CT: Praeger, 1995); and Avinash Dixit and Robert S. Pindyck, *Investment Under Uncertainty* (Princeton, New Jersey: Princeton University Press, 1994).

2. A survey found that 46% of North American firms that experimented with something called “real options analysis” gave up, perhaps because it is too rarefied a concept (it exploits highbrow financial techniques that are used to price share options in order

to assess the value of business investments). See “Fading Fads,” *The Economist* (April 20, 2000).

3. According to the California Independent System Operator (CAISO) Summer 2001 reliability statements, net capacity investment over the 1990s in California was in fact negative, after accounting for capacity degradation of plant over time. California relies heavily on hydro-based electricity imports to meet summer peak demand. The effect of a surge in demand in 2000 and 2001 and hot and dry weather caused a major energy crisis in California that led to the state’s largest utility, PG&E, filing for Chapter 11 protection and a demise of the state’s day-ahead power pool, the CalPX.

European call options on supplies of electricity.⁴ Flexibility adds value because the plant can shut down if prices go too low. In the case of a buyer of electricity (i.e., having a long position in a forward contract for delivery), the flexibility to temporarily reduce electricity use is seen as a European put option; the user can always sell electricity in the market if the price is high (as the cost of the electricity is limited to the production cost), or use it internally (for heating, air conditioning, or actual manufacturing processes) if the market price is low.

The main lessons from research into the application of options valuation techniques to real investment decisions point to the various ways in which flexibility can be valuable and thus drive the option value of an asset:

1. Option value increases with volatility in prices of outputs and inputs. High volatility means that the price of the products obtained from a given asset, or the cost of the inputs needed to obtain those products, can change very quickly and unpredictably, *up* or *down*. An asset's option value—the value of its *flexibility*—can only increase with higher volatility. Flexibility means that production can be stopped when product prices plunge or costs spike, so greater volatility cannot decrease the benefits of flexibility. But with greater volatility, the profits earned when product prices spike or costs drop will surely increase. Greater upside without greater downside—that's what greater volatility does to an asset's option value.

2. Option value decreases with the tendency of input and output prices to move together. Obviously, the ability to realize value from flexibility depends on the existence of a positive margin between revenue and cost when prices suddenly rise, so that production can be stepped up and the margin realized on the greatest possible volume of sales. However, if input and output prices move more closely together, the margin is in effect “locked in,” so there is very little value to flexibility; the asset operates so long as the product price is greater than zero. By contrast, when costs and revenues can move in opposite or unpredictable ways, the flexibility to stop or crank up production quickly is most valuable, to take advantage of “scissors” that may cause prices to spike when costs are crashing down.

3. Option value increases with the time to realization of the option. Uncertainty is often “cumulative” in the sense that the longer the future time period we are trying to consider, the more things that can happen cumulatively and push actual outcomes away from our forecast. With greater uncertainty, flexibility becomes more valuable,

so assets that can stay “flexible” for a longer time have a higher option value than those that harden like concrete shortly after their deployment.

4. Option value decreases with input prices, other things being equal. This is at least one intuitive point. Everything else equal, higher input prices, or costs, reduce margins and thus decrease the ability to make profits during upturns.

5. Option value increases with the difference between the weighted-average cost of capital and the risk-free rate of interest. We are accustomed to thinking of the cost of capital as another input cost, and indeed the preceding point made it clear that higher input prices lower option values. However, financial costs are not like other costs when it comes to options. Flexibility allows the postponement of costs of production until the option is exercised and thus saves on financial resources, for which we have to pay the premium above the risk-free rate. This saving is reflected in the relationship between option value and the cost of capital differential.

The fundamental intuition underlying option value can perhaps best be conveyed with a picture. The central idea is that if prices are random and volatile, flexibility protects the asset owner from extreme price movements and creates profit opportunities when prices rise above costs. This creates value.

Figure 1 is a stylized example of the distribution of prices in an electricity market where average (expected) prices for electricity and fuel costs (using natural gas) equal \$20/MWh. We have represented the probability distribution of the margin between price and variable cost ($P_t - VC_t$) as a black and green curve. The green half of the curve corresponds to points where this margin is negative. The black part shows the distribution of the margin if the plant just operates when price exceeds variable cost.⁵

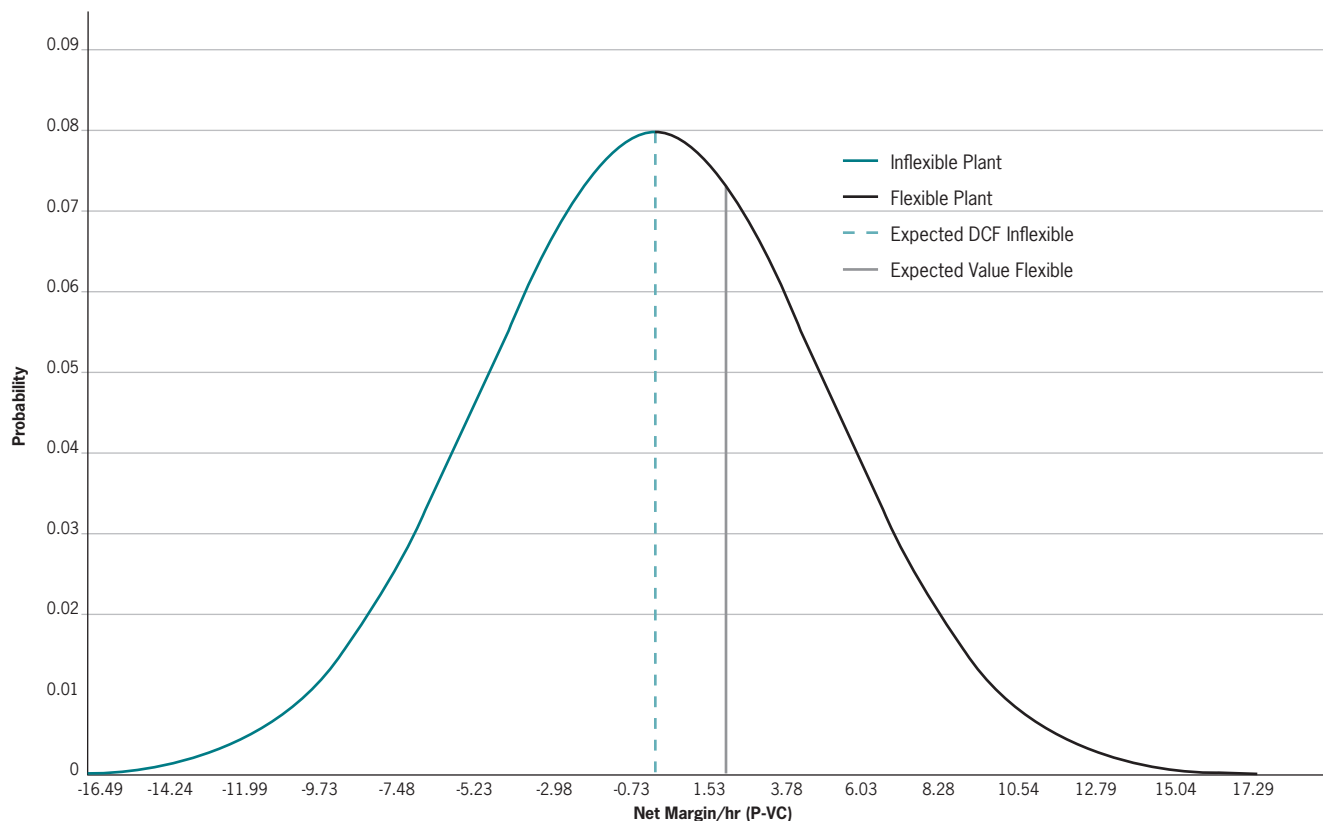
In this example, the expected future discounted cash flow of a plant running continuously is shown by the point of maximum probability of the $P_t - VC_t$ schedule (the bell-shaped black and green curve). Since this schedule follows (here, by assumption) a normal probability density function, the point of maximum probability also corresponds to the mean, or average value, of the distribution. To illustrate how options-based valuation can be counterintuitive, we have set this mean at the point where $P_t - VC_t$ equals zero. This means that under the typical DCF approach followed by most companies and taught in business and economics courses, this asset would be worthless. But if our plant can shut down

4. In the case of a gas turbine this is often referred to as the “spark-spread” option, because the plant has the option of selling/storing the gas at market if it is not profitable to generate. The fact that access to a flexible generation plant can be modeled as a series of European options means that, contrary to Tom Copeland and Vladimir Antikarov's claims (this issue), our use of a modified Black-Scholes method is appropriate. Also, since operational decisions only constrain future decisions for a limited period of time (which we incorporate into our model), we do not have to worry about compound

options in this case. In addition, apart from the cost of purchase of the option (related to plant construction and operation costs, which are largely fixed), this option does not have negative values, as the plant is simply not run if the cost of gas exceeds the revenue from electricity. For this same reason, no dividends are paid in our setup—cash flows are only produced by the plant if the option to run it is exercised.

5. Expressed mathematically, the black line and the portion of the horizontal axis to the left of the black line represent the distribution of the function $\text{Max}(P_t - VC_t, 0)$.

Figure 1 Value of Flexibility w/Uncertainty



when prices are low, namely when the price-variable cost margin is negative, its value will be greater than zero; the center of mass of the black function is shifted right. The difference between the DCF and the expected cash flows of the flexible plant is calculated as the value of flexibility. An important insight of real option theory is that the cash flows are appropriately discounted at a rate based on the weighted average cost of capital, but the value of flexibility should be discounted at the risk-free rate of interest.

Using real option valuation techniques starts with modeling the dynamic nature of input and output prices for the asset we are trying to value—more specifically, we need estimates of the mean and variability (normally measured as the variance or standard deviation of the distribution) of such prices for the relevant periods of time of use of the option embedded in the asset to be valued. (Of course, we will use historic data to forecast the likely values that will be realized in the future.) For the purposes of estimating a mean or “expected price” of electricity, it is important to recognize

the time-specific and seasonal nature of electricity prices. In the application described in this article, we describe an econometric model of hourly supply and demand conditions developed and used in an actual case of valuation of a tolling contract.⁶ The model gives as output the expected price for each hour, given the time of day, month, season, holiday/workday, weather, and expected supply and demand conditions, as well as the probability distribution of price forecasts in any given hour.

Flexibility of the kind described above for electricity generation assets has become a reality over the last quarter of a century through the development of new electricity generation technology. Specifically, the adaptation of combustion turbine technology for use in a static framework, where the turbine shaft is connected to a generator, has made it possible to build generation plants combining great flexibility with high levels of efficiency in the conversion of fuel into electricity, as well as minimal environmental impact. Combustion turbines and their related generation technologies are capable

6. Under a tolling contract, the owner of an electricity generation “rents” the facility to the tollor, who procures the fuel on its own and “converts” it into electricity using the plant.

of operating under very different regimes according to conditions and needs with little stress on turbine components, relative at least to other thermal technologies such as steam boilers, which experience significant stress if ramped up and down frequently.⁷ In addition, turbines can be easily fitted with combined cycle equipment that uses turbine exhaust heat to produce steam and run it through a steam turbine, not unlike the turbocharger in a piston engine. This results in a high level of fuel efficiency when the combustion turbines are operating at high enough levels of output to release enough exhaust heat for steam generation.

Flexibility has also been incorporated into contract design and asset management. Following along the lines of the transformation of production processes in many other industries through the development of *maquila* and other product assembly subcontracting, the emergence of deregulated electricity markets has led to the development of tolling and similar contracts for access to electricity generation plants. Tolling contracts, in particular, confer the benefits and risks of flexibility on to the supplier of the key raw material—fuel—which assumes the cost of fuel supply but also reaps electricity revenues in exchange for a conversion toll or rental payment for the facilities.⁸

The last element that has enabled practical asset valuation using real options techniques is the seemingly unstoppable trend toward greater computational power in microcomputers thanks to continuous improvements in microprocessor capacity. We will only make a brief mention here, to point out that as a result of advances in computational power, it is now possible to process data-intensive models like the one we present below in a matter of a few minutes, thus rendering them suitable for business environments in which extensive sensitivity analyses and variations must be checked and contract details negotiated before capital is committed to a project or tied up in a contract.

The rest of the paper explains the practical implementation of options valuation techniques in the case of a tolling contract providing access to an electricity generation plant with a significant degree of operating flexibility. We begin by discussing the choice of the proper version of the Black-Scholes framework in order to reflect adequately the underlying time structure of the fuel and electricity prices that give rise to option value in the first place. The next section shows how

we go about computing the various inputs required by the model, such as price volatilities and correlations. A third section discusses the treatment of additional complications often found in real-world situations, such as start and stop costs that in fact do impose financial and technical limitations on flexibility for power plants. Results for a range of values of key input parameters are presented in a fourth section. We then compare the option values we obtain with actual market transactions to provide a “reality check.”

Choice of Models: Understanding the Characteristics of Contract-Related Uncertainty

There are two initial steps in the application of the real options framework to the valuation of a tolling contract. The first step involves choosing a model of the underlying dynamic processes for the random (stochastic) variables that will drive the cash flows of the project—electricity and gas prices in this example. The second step involves choosing (or developing) a model that will reflect the value of the embedded operating option of the generating plant in question. It is important that the chosen models correctly account for the characteristics of the processes that affect the cash flows of the tolling contract. The cash flows are driven by spot price levels of electricity and gas. The levels and volatility of spot prices are in turn driven by the conditions in the markets for inputs (natural gas) and for outputs (electricity). It is not an overstatement to say that this is a crucial part of the application of a real options valuation approach, at least within the Black-Scholes framework we are using here. The well-known Black-Scholes formula is based on a stringent set of assumptions—particularly about the types of random processes that drive the prices of financial securities, in the original version of the model—that are unlikely to be correct in most real options applications. Yet because of the mathematical complexity underlying the Black-Scholes formula and the deceptive simplicity of the formula itself, it is easy to apply it as a “recipe” and ignore the assumptions. This is a good way of producing misleading valuations.⁹

The Model for Gas and Electricity Price Movements

In choosing a dynamic process for electricity and gas prices, it is important to understand that these commodity prices

7. The relevance for our example is that little degradation of the equipment is expected with flexible use of turbine technology for electricity generation.

8. These contracts constitute, in effect, a form of partial ownership of generation plant on the part of the user, since one of the defining elements of ownership is *usufructum*—free use of the products or “fruits” of an asset, which in the case of tolling contracts includes flexibility and arbitrage between electricity and fuel (natural gas or diesel-type oil).

9. See, for example, Timothy J. Luehrman, “Investment Opportunities as Real Options: Getting Started on the Numbers,” *Harvard Business Review*, July-August (1998), pp. 51-67. On the other hand, the paper by Adam Borison (this issue) provides an excellent discussion of the issues surrounding the choice of an appropriate real options valuation technique. Our use of a modified version of the “Classic” approach (as labeled by Borison) conforms to the assumptions of the model as specified by Borison. First and foremost,

spot and futures markets for natural gas and electricity in North America and Western Europe are highly liquid. A variety of financial instruments, including “spark-spread” options, are traded in these markets, allowing diversified investors to construct a replicating portfolio for a tolling contract. Second, we use an adaptation of the Black-Scholes formula for the stochastic structure of gas and electricity price movements, including the co-movement of the two sets of prices, as explained below. Our estimation of net present values of cash flows are not related to the use of what Borison calls the “MAD” method, but are meant instead to provide a baseline valuation in order to highlight the additional value revealed by the use of real options analysis. Lastly, although there is private risk in tolling contracts (such as plant maintenance decisions), in our opinion it is too small relative to the market risk to merit additional valuation using the “Revised Classic” or the “Integrated” methods discussed by Borison. In any case, we leave this as a potential refinement of our model for interested readers to pursue.

Applying Real Options Techniques: A Roadmap

The use of real options techniques for the valuation of tangible and intangible assets need not be beyond the reach of business decision makers. With currently available desktop computing technology and a systematic procedure, it is perfectly possible to compute real options values with an acceptable level of reliability for investment decision making. Here are the steps we follow to apply real options to a tolling contract:

1. Identify the characteristics of the option to be valued: Is the value of the asset affected by significant uncertainty in the operating environment (e.g., high volatility in gas and electricity prices)? What is the source of flexibility to respond to unexpected changes in the variables that affect asset value (e.g., the operating flexibility of gas turbines)? What is the nature of the uncertainty in these variables (e.g., do output prices follow a random walk, or are they driven by “fundamentals” in the longer run)? If several variables are subject to high uncertainty, are their values correlated?
2. Choose the most appropriate options valuation model, according to the type of uncertainty identified in the previous step (e.g., a modified Black-Scholes formula to account for mean reversion and uncertainty in both input costs and output prices).
3. Compute the expected value of the asset:
 - a. Establish the basic assumptions concerning the operating parameters of the asset (e.g., plant capacity, conversion efficiency, variable operating and maintenance needs, fixed costs, and plant operating regime and constraints).
- b. Establish the basic assumptions concerning the expected values or forecasts of the prices and costs affecting asset value, especially those affecting option value (e.g., projected annual trend in electricity and fuel prices; predictable seasonal, weekly, and daily profile of electricity and gas prices).
- c. Build the model (usually a spreadsheet model) of the asset operation, revenues, and costs over the desired evaluation horizon (e.g., ten years) and establish the discount rate to be used to compute present discounted values.
4. Compute the option value of the asset:
 - a. Estimate the volatility and correlation (if applicable) of the variables affecting option value (e.g., volatility and correlation of gas and electricity prices).
 - b. Adjust volatility estimates for specific characteristics of the uncertainty affecting the variables (e.g., when prices are mean-reverting—that is, driven by “fundamentals”—adjust volatilities for decreasing value over longer forecast horizons; when there are operating constraints, adjust for these).
 - c. Run option value model.
5. Conduct sensitivity analysis to validate models and test the robustness of expected and option values to varying parameter values and assumptions.

may have characteristics that make them dissimilar to other financial asset prices, such as equities. Since market supply and demand conditions will determine levels and volatilities of gas and electricity prices, it is natural to attribute part of the changes in electricity and gas spot prices to predictable factors, and part to unpredictable or stochastic factors. We incorporate these factors into our valuation model.

It is also important to recognize the *relationship* between electricity and gas prices when choosing our dynamic model. Cash flows from plant operations will be influenced by any linear relationships between input and output price—in other words, by the covariance between electricity and gas prices. In the case of natural gas and electricity, the rationale for a relationship between electricity and gas prices is fairly well understood. Natural gas prices are related to electricity prices by their “substitutability” across different types of energy (e.g., use of natural gas and

electricity for heating) and obviously by the use of natural gas as an input for electricity generation—in economic parlance, the derived demand for natural gas.

We therefore model electricity and gas price dynamics as follows. We posit that the appropriately modeled electricity and gas prices, once we account for the typical variation they experience across the seasons of the year, follow a *first-order autoregressive process*, or AR(1). This means that, in contrast to the standard model of stock prices, shocks to electricity and gas prices are not persistent. In fact, we further assume that electricity and gas prices are “mean-reverting.” This is the most important departure from the standard Black-Scholes model, which assumes that the prices of shares follows a random walk. Mean reversion is a fundamental characteristic of price movements in commodity markets. Unlike financial assets, which have potentially unlimited supply and demand, energy commodities are

expected to more closely follow “fundamentals” that are driven by supply and demand conditions.¹⁰ Production costs are very clear in the case of commodities, whether it be the cost of mining and smelting iron ore or the cost of raising and slaughtering hogs to produce pork bellies. This means that large deviations in commodity prices from production costs are rarely sustainable over an extended period of time; eventually, prices “revert” back to a “mean” more or less closely related to cost. Electricity in this regard should be no different from other commodities in a deregulated market. Large deviations from the cost of generating a kilowatt-hour trigger either entry by new producers eager to exploit the arbitrage profits between production cost and price, or exit by inefficient existing producers that can no longer cover their fixed production costs, and so prices should revert to some long-run mean trend.

We also assume that the relationship between electricity and gas prices is positive (both prices move together, for the reasons mentioned above) and linear (the price-cost margin remains fairly steady at different price ranges, implying that we can measure the relationship adequately using the sample covariance between the two prices). Finally, we assume that the errors of the model are normally distributed (the normal distribution function occurs naturally in many random processes; we can in any case test for the validity of this assumption).

The Spark-Spread Valuation Model

As for a valuation model, it is possible to adapt the well-known Black-Scholes formula to the special circumstances of the tolling contract as described above. This is known in the energy industry as the “spark-spread” model, which measures the value related to the “spread” or margin between the price of a “spark” of electricity and that of a “spark” of natural gas (the variable cost of a gas-fired generation plant). The latter can be expressed in dollars per MWh of electricity by simply multiplying the price of natural gas delivered at the plant by the inverse of the thermal efficiency of the plant, which tells us how many units of gas are needed to generate one MWh of electricity.

To understand the basis for the adaptation of the Black-Scholes formula to the spark-spread model, it is useful to consider the intuition behind the spark-spread model further. It can be easily shown that the value of an option on a “spread” between two prices can be interpreted in the same manner as an option on a price when, as we are assuming, the two prices

have a linear relationship. In this case, the applicable volatility is simply the sum of the volatilities of the individual price series minus the covariance between the two price series. With this intuition, plus some fancier mathematics to account for mean reversion, the Black-Scholes formula can be adjusted for a mean-reverting AR(1) process.¹¹ We use this formulation to conduct our valuation.

Parameter Estimation

Electricity Price Profiles. A significant amount of variation in electricity and gas prices can be predicted using standard econometric models. To the extent that the asset we are valuing can take advantage of such systematic variation to earn higher average revenues, this exercise would give us the *expected* value of the asset rather than its pure *option* value. By definition, the latter corresponds to *unpredictable* future events rather than to the predictable ones we use as the basis for the expected value calculation. To underscore the potentially large differences between expected and option values, we first compute the expected value and then the option value of the contract. The option value is estimated using the conditional volatility from the expected value calculation—in other words, the volatility that cannot be “explained away” using the econometric model.

Following this logic, then, the first estimation step is the construction of a time series of “expected” prices for electricity and gas (see Figure 2). We start with long-run forecasts of the annual average price of electricity and gas in the market of interest to us, in this case continental Europe. These forecasts correspond to the long-run equilibrium prices in the market, and as such are normally obtained using models of supply and demand “fundamentals,” such as economic growth rates and prices of substitute energies for the demand side, or installed equipment costs, interest rates, and operating costs for the supply side. Because of the complexity of developing such a model, and the significant interactions with other sectors and even of the world economy as a whole, these price forecasts are normally developed by specialized forecasting firms, which commercialize them, or by public agencies and universities. For these same reasons, in the example discussed here we did not attempt to develop these forecasts, but rather obtained long-run price forecasts from a third party.

The next task was to form the predictable “profile” of electricity and gas prices—that is, the profile determined by systematic seasonal and daily factors. For our example,

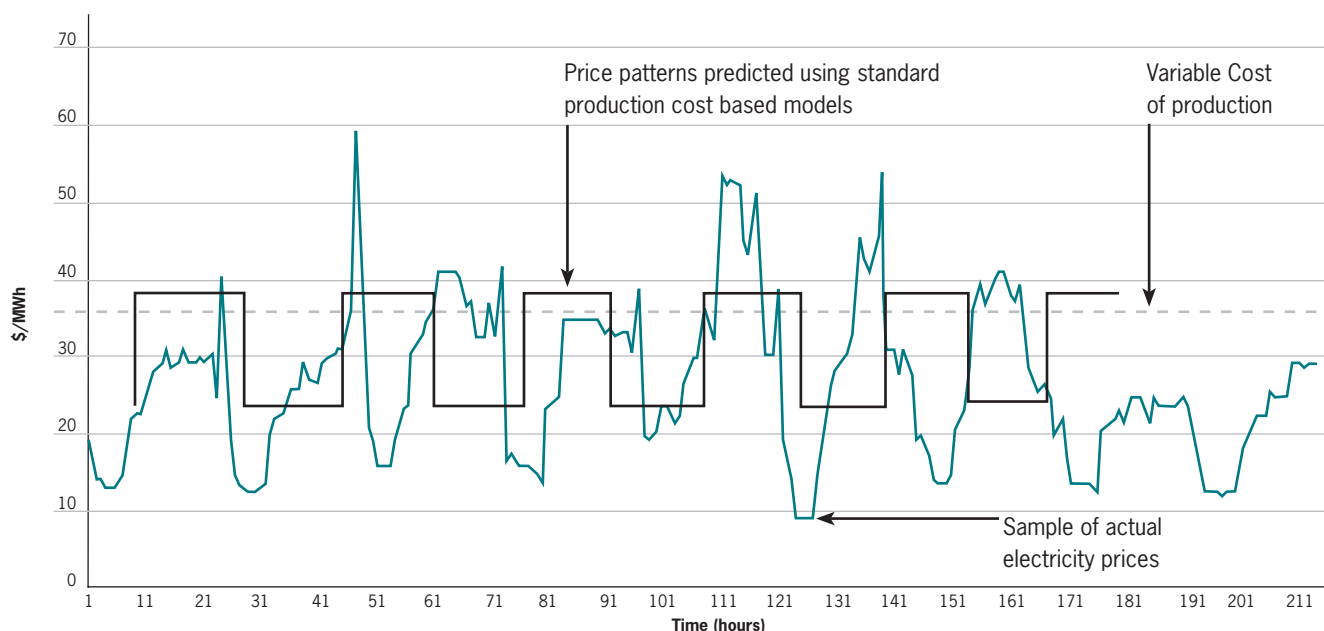
10. Robert Pindyck tests whether energy commodities are mean-reverting and whether they follow the rational fundamentals models. He finds weak evidence that energy commodities follow fundamentals and are mean-reverting, but rejects the model for commodities such as gold. He fails to reject a unit root (i.e., a random walk evolution) in gas prices, although this is likely due to the shorter time series of data available. See Robert S. Pindyck, “The Present Value Model of Rational Commodity Prices,” *The Economic Journal* 103 (1993): 511-530, and “The Long Run Evolution of Energy Prices,” *The Energy Journal*, Vol. 20, No. 2 (1999).

11. See Andrew Lo and Jiang Wang, “Implementing Option Pricing Models When Asset Returns are Predictable,” *The Journal of Finance*, Vol. 50, No. 1 (1995), pp. 87-129. Their adjusted volatility formula is:

$$\sigma^2 = \frac{s^2(r_1)}{\tau} \frac{\ln(1+2\rho_1(1))}{(1+2\rho_1(1))^{\tau} - 1}$$

where ρ is the autocorrelation coefficient sampled at τ intervals, and s is the unconditional variance of returns sampled at unit intervals (r_1).

Figure 2 **Electricity Price Profiles**



we developed a profile using 1997-1998 data on system marginal electricity prices from the England and Wales electricity pool.¹² The predicted profile of hourly electricity spot price patterns consists of the predicted values from the regression of a natural logarithm of the hourly England and Wales Pool price (which we represent as $\ln P_e(t)$ in our formulas) on a matrix of dummy variables representing seasonal (monthly), daily, or hourly factors. The seasonal variables capture differences in demand across the seasons due to differences in heating and air conditioning uses throughout the year, while the daily variables capture workday/holiday demand differences, and the hourly variables, peak, shoulder, and off-peak demand patterns. We then created a time-series of 8,760 proportional adjustment factors with a mean of 1. The vector of proportional adjustment factors can then be multiplied by the expected mean electricity price for each year to produce a time series with the correct mean and modeled hourly profiles.

A similar methodology as described above for the electricity price data was used for the natural gas price data, with the exception that we only assumed seasonal variations (as opposed to seasonal, daily, and hourly variations for electricity prices), since natural gas prices exhibit far less short-term volatility than electricity prices due to the

storability of natural gas. The gas profiles were created using 1998-1999 natural gas price futures contract data from the International Petroleum Exchange (IPE) in Amsterdam, which reflect natural gas market conditions in continental Europe. Note again that the profiles represent (proportional) shifts in the annual average data, and thus can be applied to any *level* of expected prices.

The range for the proportional adjustment factors for predicting electricity prices was 0.4 to 1.82, while the range for gas prices was about 0.8 to 1.2. Since, as pointed out, these factors were estimated for an average price of 1 (so that they could be readily applied to any price forecast by multiplying the average annual price by predictive factors corresponding to each hour in the year), these numbers mean that the smallest electricity price was predicted to be about 60% below its mean while the largest was predicted to be about 82% above its mean, whereas the range for predicted gas prices was about 20% above and below the mean. Gas prices have lower overall volatility than electricity prices because gas can be stored, while electricity cannot.

Volatility Estimates. Volatility is the standard deviation in the log of the price series. The previous profiling exercise amounts to “deseasonalizing” the data. Using the deseasonalized electricity and gas time series from

12. The choice of a price series to model turned out to be a nontrivial task, because the setting for the tolling contract was continental Europe. Although a continental price series was available from the Amsterdam power exchange, this market was still perceived to be in its infancy and had not operated for a full year at the time. After some investigation, we determined that the England and Wales pool data represented the predictable

nature of electricity prices for continental Europe better than other alternatives such as CalPX data from California, due to the similarity between the U.K. and the continent in seasonal temperatures, daylight hours, and broad-based industrial demand, which are the primary drivers for predictable electricity use.

the England and Wales pool and the IPE, respectively, we estimated conditional volatilities for mean-reverting processes for both electricity and gas prices.¹³ In addition, we estimated the correlation between the IPE gas prices and the England and Wales electricity prices, which resulted in a value of 0.198.¹⁴

Accounting for Mean Reversion: Volatility Term Structure. Another key adjustment of our volatility estimates was needed to account for mean reversion in gas and electricity prices. As already explained, we valued the tolling contract using the Black-Scholes option pricing formula, adjusted to account for mean reversion and the particularities of the spark-spread model. We adjusted for mean reversion by incorporating a term structure for the volatilities of electricity and gas prices (see Figure 3).¹⁵ In other words, we assumed that the expected volatilities decline over time due to mean reversion, in contrast to the Black-Scholes formula, which assumes a constant volatility.¹⁶ The intuition is that mean reversion causes expectations about the future to converge to their long-run supply and demand conditions.

If our intuition is true, then the variance of prices as given by 12-month-ahead futures contracts should be smaller than the variance of, say, prices for a one-month-ahead contract. There is empirical evidence of a volatility term structure in the “strips” of futures contract price data. This allowed us, for instance, to estimate a volatility term structure for natural gas by calculating separate volatilities for natural gas contracts with different maturities: one-month ahead, two months ahead, ..., 12 months ahead, and so forth.

For our spark-spread formula, we need the total volatility in both the relative prices of electricity and variable costs (natural gas prices). For natural gas prices, our estimates were computed using IPE futures contract data. The electricity term structure was estimated using futures contract data for 1996-1998 from contracts traded at the California-Oregon Border (COB) hub.¹⁷ Since we are assuming a linear relationship between gas and electricity prices, the total volatility is equal to the volatility of

variable costs plus the volatility in electricity prices minus twice the covariance between the two series.¹⁸

In addition, we have created a confidence interval for our estimated electricity price volatilities taking advantage of the availability of data on electricity prices for California, New England, the mid-Atlantic states (New Jersey, Pennsylvania, and Maryland), and Alberta, assuming as above mean-reverting processes in electricity prices. The mean volatility from these markets was 0.204. If we assume the standard deviations *across markets* to be distributed log-normally, we can estimate lower and upper confidence limits for the 90% confidence interval of *approximately* 0.13 (lower limit) and 0.38 (upper limit) for the standard deviation or volatility. In other words, there is only a 5% probability that the electricity price volatility is below the lower limit and a 5% probability that it is above the upper limit.

Other Parameter Inputs

- *Real risk-free rate of interest.* The nominal yield on LIBOR and Eurodollar deposits was about 6.10% and 6.13%, respectively, at the date of the analysis.¹⁹ The rate of interest on United States three-month Treasuries was 5.53%. The current rate of inflation (average annual rate over the 12 previous months) in the country where the tolling plant is located, according to *The Economist*, was 1.3%, versus 2.3% in the U.S. We took the real risk-free rate to be 5.0% on an annual average basis, as the three-month Eurodollar deposit rate less the rate of inflation in the country.²⁰

- *Convenience yield.* We also used the IPE data to estimate a convenience yield for natural gas. This was done by taking the average difference in the natural logarithm of the one-month-ahead and two-month-ahead futures contract data, plus the risk-free rate of interest, taken as 5%. 1998 and 1999 IPE data were used. The resulting estimate was 1.23% (continuous rate).²¹

- *Degradation of plant with use.* It was assumed, in accordance with data from our client, that the plant's efficiency level would be maintained throughout the life of the contract by the plant operator. This parameter was thus set to zero, but it can be easily incorporated into the model by lowering

13. The precise methodology can be found in Avinash Dixit and Robert S. Pindyck, *Investment Under Uncertainty* (Princeton, NJ: Princeton University Press, 1994). The case for using the deseasonalized mean-reverting model is made in Dragana Pilipovic, *Energy Risk: Valuing and Managing Energy Derivatives* (New York: McGraw-Hill, 1997).

14. It is reasonable to calculate correlation between British electricity prices and Amsterdam gas prices because the British gas network is highly interconnected with the continental networks, and British gas prices are largely deregulated, so that gas prices in Britain can be expected to track IPE prices very closely. It is also of note that this number was calculated using the “raw” (i.e., not deseasonalized) data. Since the number used was positive, it tended to reduce the total volatility. This was a conservative approach. As the deseasonalized price series were necessarily uncorrelated, with daily and monthly fluctuations having been removed, had we used an estimate from the deseasonalized series, we would have overstated the total volatility and the option value.

15. The idea of a term structure of volatilities is described in Pilipovic (1997), cited earlier.

16. The assumption of constant volatility over time, used by Black and Scholes,

implies that the volatility of the option, T periods in the future, grows proportionally to the square root of T .

17. COB data were employed because trading in COB contracts has a much longer history, and represents one of the more liquid electricity futures contract markets as measured by the average number of contracts traded daily.

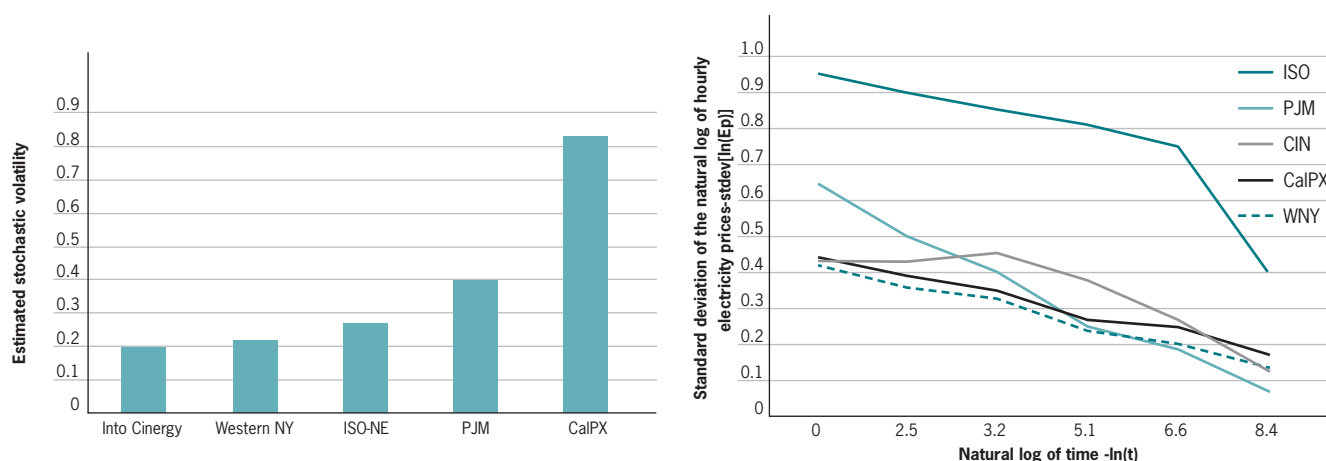
18. In algebraic terms, this can be written $v^2 = \sigma_e^2 + \sigma_g^2 - 2\rho\sigma_e\sigma_g$; our point estimates of these three parameters, using the data and methodology described above in Section 1, are $\sigma_e = 0.32$, $\sigma_g = 0.015$, $\rho = 0.198$, or $v^2 = .101$.

19. From the February 9, 2000 edition of *The Wall Street Journal*.

20. Although it is perhaps more common to use three-month U.S. Treasuries as the benchmark for risk-free interest rates, recent U.S. government surpluses have disturbed the normal supply and demand conditions in these markets. The reason for using a real rate is that the project was located in a country where government debt was not as riskless as U.S. treasuries, making it advisable to use the U.S. rate as a basis.

21. This is a simplification, as the convenience yield is potentially stochastic.

Figure 3 Indicative Trends in Electricity Price Volatility for Various U.S. Power Markets



plant efficiency in the energy conversion formulas (which express natural gas use in terms of \$/MWh) as we estimate option values further into the future.

- *Risk aversion discount rate.* According to the methodology of real options valuation, we have set this parameter to zero. In the spreadsheet tool we prepared for computational purposes (see below), we nonetheless added the capability to set this parameter to nonzero values. The appropriateness of setting this parameter to zero depends in part on the degree to which the “toller” (the user of the plant) is capable of managing the overall risk profile of its portfolio of real assets as a whole. In case of imperfect diversifiability of these assets, the discount rate can be adjusted accordingly.

Additional Constraints to Plant Operation

In order to make the model as realistic as possible, we modified to take into account the operating limitations that even highly flexible technologies like combined cycle gas turbines (CCGTs) face in actuality. These limitations fall under two major types: flexibility costs (the plant cannot instantaneously move from stop to full capacity, and for this reason it may lose some profit opportunities or be forced to remain in operation between price spikes despite losing money during the off-peak hours); and flexibility limitations (the number of starts per period may be limited to avoid severe degradation of the plant caused by repeated thermal stresses as the plant heats up and cools down). Incorporating operating constraints is important as it might have a material adverse impact on the estimated value of the asset—logically enough, greater operating rigidity lowers option value. A recent paper estimated

that, on average, ignoring operational constraints could cause total spark-spread-based plant values to be overestimated by about 14%.²²

Flexibility Costs (Start and Stop Costs)

The data for start and stop costs were provided by the project developer. The nature of starting and stopping costs for a CCGT flows from less-than-optimal thermal efficiency as the plant ramps up or down. From the information furnished by the developer, we estimated that during a start-up taking the plant from zero to full output over an interval of an hour and a half, its average efficiency is just 33% of the maximum efficiency level, while during a ramp-down to zero from full output lasting for a little less than half an hour, average efficiency is only 40% of the maximum level.

The total starting and stopping costs for the plant in any given year are dependent on two main parameters. First is the forecast or expected number of starts and stops in a year, and second is the forecast price of electricity and cost of gas at the time of the expected start/stop. The expected electricity price and expected variable cost were obtained from the electricity price and variable cost profiles and levels estimated as described above. Based on these forecast data, any time the expected variable cost exceeded (was below) the predicted electricity price, the plant was forecast to stop (start), given that it was running (stopped) in the preceding hour. Note that gas prices do not change hourly, so hourly fluctuations in the price-cost margin are driven entirely by electricity prices.

However, we must take account of the possibility that the plant operator would optimally rather stay on in some

22. See Chung-Li Tseng and Graydon Barz, “Short-Term Generation Asset Valuation: A Real Options Approach,” Working paper, University of Maryland Dept. of Civil Engineering (1999).

periods, given that the plants are already running, than incur the stop-start costs. To do this, the following heuristic was employed. For each predicted stop, the analysis computes the sum of predicted cash flows from the next 12 hours of operations (the need for this is due to the possibility of operating in some hours when electricity prices are slightly below variable costs). The expected cash flows from running are then compared to the expected cash flows from starting and stopping. The smaller of the two, the stop/start costs and the running costs, is then taken as the expected optimal operating cost. The expected optimal costs are then summed over the entire year and the annual totals are discounted at the risk-free rate. These data represent the total expected discounted costs associated with optimal starting and stopping of the plant given the expected energy prices.

Flexibility Limitations (Limited Number of Starts and Stops)

The second major operational concern even in a highly flexible gas-fired combined cycle plant was the limited ability of the plant to start and stop. Specifically, the plant is predicted to have the guaranteed capability to stop and restart only once a day. As described above, we again can rely on the partly predictable nature of hourly electricity prices and daily gas prices to simplify the problem. Given these predicted profiles, we can calculate the expected number of starts/stops expected in any given day and over the year in general.

Under the reference case electricity and gas price forecasts, and including the predicted profiles created from the U.K. Pool and IPE price data *without* constraints or considering start/stop costs, the model predicts between 230-275 starts and stops a year. In addition, as expected, the model does not predict more than one start or stop a day. Flexibility constraints will necessarily reduce the number of starts and stops, as will the addition of starting and stopping costs as part of the plant operating logic. Therefore, we can conclude that the flexibility constraint is not *expected* to be binding. This is not to say that additional adjustments to the valuation do not have to be made. Although the model in general, without constraints, predicts a maximum of one start/stop a day, this only accounts for the *predictable* part of price fluctuations. The option value of the plant specifically derives value from the fact that the plant will shut down *whenever* prices are low, and start whenever they are high. Obviously, when the plant faces start and stop costs and has limited flexibility, the ability to capture option value is reduced, and the modeling must reflect this constraint.

To account for the impact of the limited flexibility of the plant on the option value, we reduced the total volatil-

ity input²³ by multiplying by a proportional adjustment factor equal to $1/\sqrt{n}$, where n is the expected number of running hours. Specifically, in the case of a single start/stop per day, n equals 12.

To see why is this approximately correct, consider what happens if the plant can shut down only once over the next 24 hours. Once the plant is up and running, it will not shut down when electricity prices fall a little below gas prices; it is better to run and sustain short-run losses than to incur costs associated with stopping and starting. It will not be optimal to shut the plant down unless the expected margin (the sum of $Pe(t) - VC(t)$ expectations for the next 12 hours) is less than the expected costs associated with starting and stopping the plant over this same period. Therefore, although prices may be volatile around their predicted values, the plant will receive what amounts to the *average* margin $Pe(t) - VC(t)$ over the near term when it is expected to run. The end result is that the *effective* volatility in prices faced by the plant has been reduced. The size of that reduction is $1/\sqrt{12}$ for the case of a single start and stop per day.²⁴

Another way to grasp the intuition behind this volatility reduction is to consider the case where a flexible plant currently sells all its energy forward on daily futures contracts. Now suppose the plant managers were interested in selling energy into a newly created spot market where prices are set every hour. As the market is new, the managers have only the *daily*

Table 1 Assumptions Summary

Operating Assumptions	
Conversion Efficiency	55.0%
Start Costs	plant operates at 33% of max efficiency for 1.5 hours after start
Stop Costs	plant operates at 40% of max efficiency for 0.5 hours from full to zero output
Operating Regime	max one start/stop cycle every 24 hours
Availability	92.0%
Modeling Parameters	
Volatility in power prices	0.320
Volatility in natural gas prices	0.015
Correlation between power prices and natural gas prices	0.198
Risk free rate of interest (real)	5.0%
Convenience Yield (continuous rate)	1.2%
Degradation of Plant Use	0
Risk aversion discount rate	0

23. Recall that we calculate the volatility as the standard deviation of the margin $\ln P_e(t) - \ln VC(t)$ (electricity price over natural gas cost), after correcting for systematic seasonal changes and after adjusting for mean reversion (declining volatility over longer

forecast periods).

24. In general, the standard deviation of the distribution in any sample mean falls in proportion to the square-root of sample size, n .

Table 2 **Sensitivity Analysis and Comparison**

Case	Volatility		Price Correlation	Average Annual Run Time	FDCF w/Optimal Start-Stop	Option Value	Total Value
	Electricity Price	Gas Price					
Low Margin (SWEP)	0.088	0.004	0.054	4,318	(20,640,245)	4,348,294 137,311,889	(16,291,952) 116,671,643
	0.132	0.042	0.557				
5% Margin	0.088	0.004	0.054	4,858	6,457,256	5,117,937 144,564,399	11,575,193 151,021,655
	0.904	0.042	0.557				
10% Margin	0.088	0.004	0.054	5,542	30,803,830	4,963,546 144,708,372	35,767,375 175,512,202
	0.904	0.042	0.557				
Base Case	0.088	0.004	0.054	6,460	43,587,837	2,214,803 93,074,632	45,802,640 136,662,468
	0.904	0.042	0.557				
15% Margin	0.088	0.004	0.054	5,938	57,623,836	4,495,533 143,642,370	62,119,369 201,266,206
	0.904	0.042	0.557				
High Margin (APX)	0.904	0.042	0.557	8,200	630,642,814	82,257,719 668,501	712,900,534 631,311,315
	0.004	0.004	0.054				

futures price data at market closing—which tells them how much prices move from day to day—to use in inferring the *hourly* volatility—how much can prices move from one hour to the next. How would we do this? In general, the *hourly* volatility will be the volatility in the *daily* price data divided by $\sqrt{24}$. The reason is that prices have a lot more room to move between the daily close of the market every 24 hours than they do over a shorter period such as one hour—hence, the hourly volatility is less than the daily volatility. Intuitively, the probability that demand for electricity will change drastically, or that a generation unit or a transmission line will fail, is lower from one hour to the next than for the next 24 hours, which reflects the cumulative effect of all that can happen over that 24-hour period. Therefore, as we shorten the time interval under consideration, the amount prices can move is necessarily reduced. Next, note that introducing *inflexibility* within each 24-hour time period has the same effect as shortening the time period, so we can model such inflexibility by reducing the volatility the plant faces. Table 1 summarizes our assumptions.

Results and Sensitivity Analysis

In this section, we present our results over a range of key parameter values and then compare them with actual transaction values as an additional check for the validity of our results. Option values are calculated by feeding the input data and parameters discussed above into a spreadsheet model that applies the modified Black-Scholes formula for every hour over a ten-year period and discounts the hourly values at the risk-free rate to obtain the total figure for the asset.²⁵ The spreadsheet also calcu-

lates the expected value of the price-cost margin accruing to the asset over the ten-year period, computed on the basis of the annual average electricity and gas price curves, the modeled profiles of electricity and gas price variation over the year, and the plant operating restrictions (start and stop costs and limitations).

We calculated the variation in option values for a range of values of the two parameters that are the primary drivers for the value of the project. The first is the volatility of electricity prices and variable costs (natural gas prices). These are one of the primary drivers of option value, and option value can be expected to represent a large proportion of the value of the contract. The second parameter is the long-run average margin between electricity prices and variable cost.

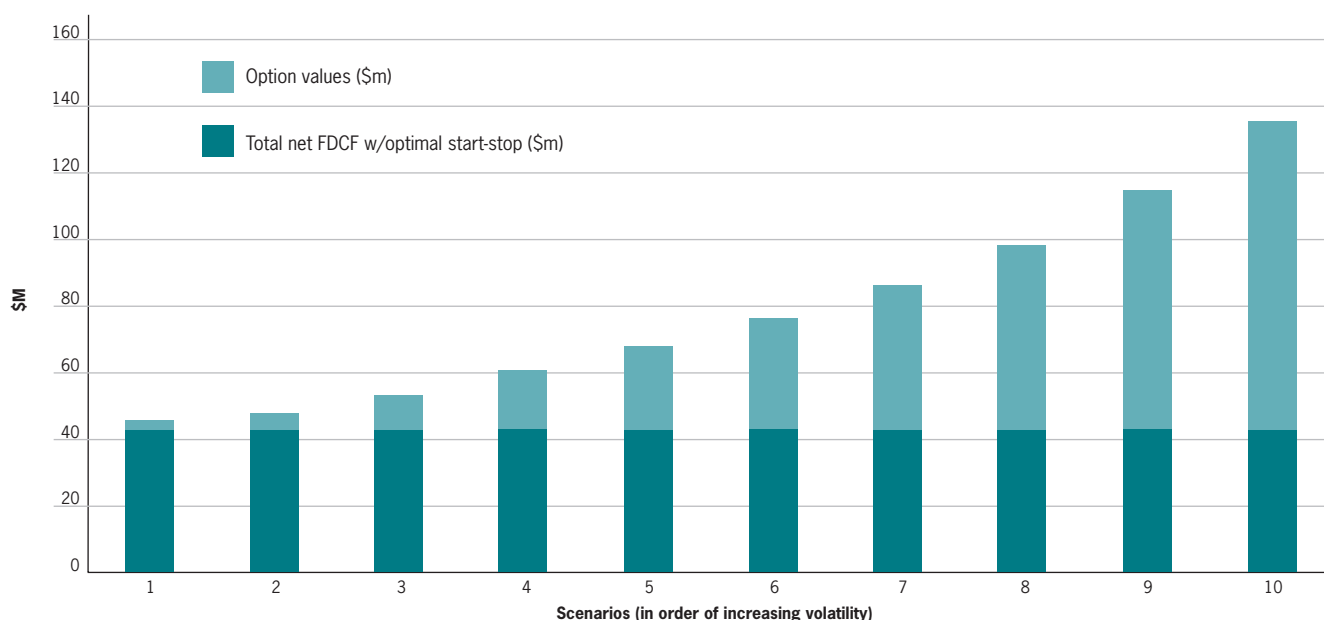
The sensitivity analysis supports some very important points. First, although the project value is highly sensitive to volatilities, its profitability need not depend on volatility. Table 2 shows that the low-volatility cases are profitable with a mere 5% average annual margin between electricity prices and variable costs. Only in the low-margin case does the low-volatility scenario yield a negative project value.

On the upside, small increases in volatility have a big impact on contract value when the base value is moderate. Volatility can make a seemingly unprofitable project quite profitable, as shown by the low-margin scenario and by Figure 4, which displays the breakdown between predicted and option value for ten increasing-volatility scenarios within the base case gas and electricity price forecasts. On the other hand, if electricity prices turn out to be high relative to gas prices, the project is seen to be very profitable. But as option theory suggests, in this case the option value falls relative to

25. The spark-spread valuation tool is written in MS Excel® 97/VBA. The software was developed on a system with a 266 MHz Pentium II® processor with 300 MB RAM running

MS Windows NT® operating system. A similar or more advanced hardware and software system should be used with the tool. The size of the file is about 20 MB.

Figure 4 Free Cash Flow Versus Option Value, Base Case



total contract value because the plant is likely to run “at full steam,” and thus there will be little potential for unexpected windfalls—that is, little “option” value.

We conclude that the project has a very high potential for profitability, with very little downside. Only the low-volatility scenario in the lowest margin case shows a negative project value. However, the probability that margins will be very low *and* volatilities will be very small is remote, so the project is very unlikely to be unprofitable. Our best estimate of project value is given by the base case, ranging from \$45.8 million for low volatility to \$136.7 million for high volatility.

These results are sensitive to the model parameter estimates, but sensitivity analysis has shown that within a reasonable range of parameter estimates, the project’s viability is maintained. Moreover, we have defined the range of sensitivities using what we believe to be conservative estimates for the margins, 5% for the low end and 15% for the high end. The modeling results will also be sensitive to other assumptions of the analysis, but in general we have adopted conservative assumptions wherever the data do not allow us to clearly reject the conservative approach. For example, we did not rely on the Black-Scholes assumption of constant volatility but instead estimated volatility term structures (rate of decay over time in volatility) using data on electricity and gas futures contracts. We also employed mean-reverting process estimates and incorporated this methodology into the analysis, which also had the effect of reducing value.

Moreover, we compared the values we obtained for the project with prices in recent asset sales for gas plants in dereg-

ulating markets. On a per kW capacity basis, the project is worth about \$216/kW. Assets in New England that were purchased in recent years by Sithe and US Gen went for an average \$/kW value of \$200-\$350/kW, with some of the more efficient plants going as high as \$1,400/kW. Thus the project is well within the range of other assets of its kind. In addition, our analysis has shown that average variable costs for gas plants were very close to the average New England electricity prices, suggesting that Sithe and others must have considered option value, whether explicitly or implicitly, when bidding for these assets.

Conclusions

In the preceding pages, we have shown how real options valuation methods can be applied when valuing intangible assets, such as tolling contracts, that consist of claims on real assets. By focusing on the drivers of option value for the underlying asset, modeling them carefully, and contrasting them to the value we would expect “as if” there were no uncertainty about future outcomes (the *expected value* of the asset), we have shown that the main economic value of the project in fact lies in the flexibility—that is, the option value—of the underlying asset, in this case the combined cycle technology envisaged for an electricity generation plant. Besides extending the usefulness of real options valuation to claims on real assets and providing yet another example of how optionality can radically alter asset values, we have offered a detailed recipe for the construction of a real options valuation model, consisting of model selection, estimation of model inputs, adjustment of the model to

increase its realism, and use of sensitivity analysis to derive a robust range of plausible values.

We are reasonably confident that our analysis demonstrates the potential profitability of the tolling contract. As with any other type of model, the usefulness of a real options valuation model is constrained by two key factors: first, the adequacy of the model to the analysis of the real-world subject we are trying to analyze—not so much “how does the graph resemble the real thing” but “does the graph capture the elements *of importance to the task at hand*”; and second, the plausibility and reliability of the inputs we use to derive model outputs, following the well-known systems logic of GIGO, or “garbage in, garbage out.”

Our real options model is a variation on the standard Black-Scholes formula to account for two deviations from that formula’s assumptions: first, the fact that energy prices, like the prices of other commodities, are generally thought to exhibit mean reversion rather than following a Wiener process (Brownian motion) as in the standard Black-Scholes formula; and second, the existence of two (related) sources of randomness in a production process such as the generation of electricity from natural gas—from volatility in both natural gas prices and electricity prices. Moreover, we have properly accounted for the limitations of plant flexibility—namely the maximum of one start and stop cycle per day as well as starting and stopping costs—by adjusting a key model input, the rate of price volatility; and we have also adjusted volatility rates over time to further account for mean reversion.

Although our recipe (see earlier box insert) is focused on the case of a tolling contract for a combined cycle electricity generation facility, it can be easily adapted to a variety of other situations that could reasonably be modeled as similar to a conversion process of this nature, and where we can find sufficient price data to estimate volatility rates with some confidence. Although no other commodity exhibits the level of short-term price volatility of electricity (due to the non-storability of electrical energy), most commodities do exhibit considerable volatility because their production

entails considerable sunk costs (as production capacity is largely fixed once facilities are built) and competition is strongly price-centered (commodities being, by definition, undifferentiated products). In addition, for many commodities we have long price series, dating back decades if not longer in some cases. Variable production costs often depend on a major input or feedstock, like crude oil or bauxite, whose price is also highly variable. Under these circumstances, we can use the above model to value physical assets, contractual claims on such assets, or alternative production technologies. Some technologies may offer considerable flexibility, such as certain chemical products where feedstock combinations can be easily altered to yield different compounds. The main adaptation of the model to the case of commodity production facilities, or claims on such facilities, is the existence of inventories as important buffer mechanisms and as an input into the model, the convenience yield.

GREGORY SWINAND is a Managing Consultant at London Economics and Indecon, an economics consulting firm based in Dublin, Ireland. He holds a Ph.D. in Economics from Boston College and a B.A. in economics from the University of Massachusetts at Amherst.

CARLOS RUFIN is Assistant Professor of Strategic Management and Associate Director of the Institute of Latin American Business at Babson College in Wellesley, Massachusetts. He received his Ph.D. in Public Policy from Harvard University. He also holds an M.A. in economics from Columbia and a B.A. in political economy from Princeton. While pursuing his doctoral studies, he worked as a consultant for London Economics in their Cambridge, Massachusetts, office, and continues to consult on an individual basis to multilateral institutions and other organizations. He has also worked for Levitan & Associates (a Boston-based energy consulting firm), Imperial Chemical Industries, Zeneca, and Stone & Webster Management Consultants.

CHETAN SHARMA works for Cinergy Corporation. He holds an M.B.A. from Indiana University.

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