features

Inferring Individual Asset Values from Aggregate Transaction Data

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abstract

Valuing power generation assets by the sales comparison methodology is complicated by the fact that these assets are generally sold in heterogeneous portfolios. Obtaining a comparable sales value for an individual asset involves inferring such unobservable values from portfolio-level data. The sizes of the assets in question make this a very consequential problem, as errors in valuation can have a substantial impact on a firm's financial performance. This paper examines the role that simple statistical models can play in extracting information on single-asset values from information on bundled transactions.

The ongoing deregulation of power generation in the United States has stimulated numerous transactions for power-generating real property. As regulated utilities divest themselves of these assets, unregulated profit-oriented firms have entered the market and thousands of megawatts of generating capacity have changed hands. Since 1997, the value of these transactions has exceeded \$30 billion and comprised more than 70,000 megawatts (MW) of power. Yet this is only a small fraction of the total generating capacity in the United States. Whatever course deregulation takes, the number and value of these transactions is likely to increase.

These transactions represent a new market, even to firms with past power-generation experience (e.g., the unregulated subsidiaries of utility companies). The competitive structure of the industry has changed in such a way that the dynamics surrounding profitability are now based on market prices rather than on the mandated rates used previously. Accordingly, valuing power plants has become more complicated.

As with other forms of real property, estimating the market value of power-generating real property is generally accomplished by one or more of three methods: income capitalization, replacement/reproduction cost, and comparable sales.[1] For the first two methods, the techniques are standard and information typically is easily available or estimated. The third valuation methodology presents a greater problem. Although the recent surge in transaction volume means that there are now more transactions on which to base an estimate, in absolute terms it is still a small number. Moreover, these transactions are generally for portfolios of several different assets. The challenge, then, becomes how to compare assets of similar technologies across sales of portfolios that differ in mixture and size of assets. The question becomes: What truly represents a comparable sale?

There are two problems in determining comparable sales. The first problem is that even though transactions for power generation assets have become more frequent in recent years, they still trade with relative infrequency compared to other forms of property. Thus, there is often a lack of data on which to base a

1. Appraisal Institute, *The Appraisal of Real Estate*, 12th ed. (Chicago: Appraisal Institute, 2001): 62–65.

comparable sales estimate. This problem was recognized by Grissom and Diaz,[2] who advocated a behavioral approach that simulated asset values as bundles of attributes. Our approach is similar in that it values assets by evaluating various value-generating attributes of the property. The second problem is suggested by Diaz[3]: How are comparable sales selected? In our examination of this problem, the challenge is that comparable assets rarely appear in isolation. Instead, they are bundled with other assets that may not be comparable. The analytical framework we address here and the statistical tools we employ, whether regression (as used in this paper) or factor analysis,[4] are well-suited to the behavioral theory advocated by Grissom and Diaz.[5]

Typically, appraisers of power generation assets select subsets of prior transaction data that "seem like" or "look like" the asset whose value is in question and calculate an average cost per megawatt based on some combination of those values. In this paper, we outline how basic statistical techniques can be used to formalize the extraction of single-asset values from multiple-asset transactions. These techniques provide guidance not only in the construction of meaningful comparable sales figures, but also in quick estimates of market value for individual assets and bundles of assets for bidding. This article outlines the statistical tools used and explores applications to the estimation of single-asset values. It also explores applications that support bidding strategies for portfolios of assets.

Inference and Estimation with Linear Models

The comparable sales question can be represented as follows: Suppose that we wish to determine the comparable sales value of a 1,000 MW coal plant, but have information on only the asset bundles shown in Table 1.

What is the imputed or market-equivalent value of the 1,000 MW coal plant? We can reformulate the problem to clarify the approach:

$$450G + 300C = 575 \qquad (1)$$
$$750G + 800C = 1{,}250 \qquad (2)$$

where:

G = per megawatt price (in millions) of gas assets
C = per megawatt price (in millions) of coal assets

Equations 1 and 2 comprise a linear system and, therefore, can be solved: $G = \$0.630$ and $C = \$0.972$. These numbers, respectively, represent the per-megawatt prices (in millions) of gas and coal assets. Applying these numbers to our 1,000 MW coal plant, we obtain an imputed value of 1,000 MW × \$0.972/MW = \$972 million.

Of course, this example is overly simple. It presumes, among other things, that the true values of assets are both known with certainty and completely determined by fuel type. In practice, these values are not known with certainty and do not remain constant on a per-megawatt basis. Power-generation plant values differ based on location, technology, age, environmental legacies, and numerous other factors not considered in this example. Accordingly, we cannot simply use algebra to extract individual asset values from these transaction groups. Instead, the situation in Equation 1 is more accurately expressed as shown in Equation 3, and we must turn to statistical methods such as regression.[6]

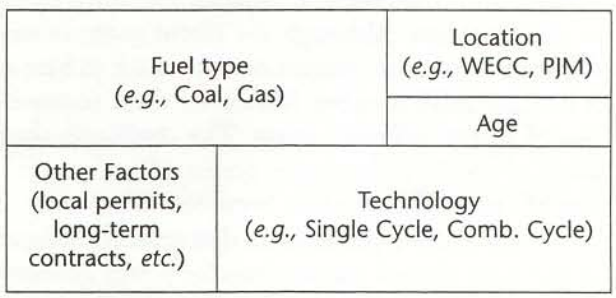
$$450G + 300C + \text{Other Factors} + \text{Residual} \qquad (3)$$

The statistically equivalent statement is that there are multiple sources of variance in transaction values (as illustrated in Figure 1). In this article, we assume that although there are regional and techno-

Table 1 Two Sample Asset Bundles

	Gas	Coal	Purchase Price (in millions)
Bundle 1	450 MW	300 MW	\$575
Bundle 2	750 MW	800 MW	\$1,250

Figure 1 Sources of Variance in Total Plant Value



2. Terry V. Grissom and Julian Diaz III, "Valuation Without Comparables," *The Appraisal Journal* (July 1991): 370–376.
3. Julian Diaz III, "The Process of Selecting Comparable Sales," *The Appraisal Journal* (October 1990): 533–540.
4. The factor analysis approach may more directly answer the questions raised by Diaz, *Ibid.*
5. Grissom and Diaz, *Ibid.*
6. Even this structure may be overly simple. Values also may be a function of nonlinear relationships between the variables.

logical differences between different transaction bundles, there are general values for different fuel type assets that are preserved across the transactions. The question is, how much variance can be explained by fuel type alone? Intuitively, how big are the areas depicted in Figure 1? Our hypothesis is that fuel type is the largest source of variance and, therefore, useful for estimating the market value of power-generation assets. That is, the fuel type tells more about the per-megawatt value of the plant than any other information.

Clearly, there are several other factors apart from fuel type that influence power-generation asset values. Nevertheless, there are numerous practical reasons for limiting attention to a small subset of value-influencing factors. In many cases, acquiring specific information about the factors is costly. Even when information cost is not a consideration, certain pieces of information may not be available because they are proprietary or undisclosed. We seek to determine how accurately we can estimate asset values starting with the most general information available. If greater accuracy is desired, then new factors can be introduced.

The goal is to develop a methodology for extracting the common information contained in portfolio transaction data. In essence, we seek an answer to the question: What would the portfolio's individual assets' values be if they were traded individually on the market? In the analysis that follows, we develop a series of models based on data on power-generation asset transactions since 1997 and illustrate an application of the models to the determination of comparable sales estimates for appraisal. The database contains complete information on 39 transactions among three different fuel types: coal, gas, and oil.[7] These transactions are listed in Table 2.

A typical approach to comparable sales valuation might simply examine the average per-kilowatt (kw) cost of plants that have sold. For these 39 transactions, the values range from \$29/kw to \$1,398/kw, with an average of \$403/kw.

Our first model for estimating the market value of comparable sales of power-generation assets that are part of a portfolio involves performing a regression analysis using three independent portfolio variables: megawatts of coal, oil, and gas transacted. In this case, we estimate the model in Equation 4, which we shall refer to as the Basic Model.

$$\text{VALUE} = \beta_1 O + \beta_2 C + \beta_3 G \qquad (4)$$

where:

O = per megawatt price of oil assets

C = per megawatt price of coal assets

G = per megawatt price of gas assets

The results are presented in Table 3 and a comparison of the predicted to actual values is displayed in Figure 2.[8] If the model had perfect accuracy, we would expect to see all of the points lie along the 45-degree line. Nevertheless, despite the simplicity of this model, it is able to explain more than 79% of the variation in actual costs (equivalent to a correlation of 0.89 between actual and predicted values).[9]

Having established a plausible working model, we might ask how a model could be structured to improve the adjusted R^2, as well as the model's realism.[10] The first step is to determine if the hypothesized value relationship in Equation 4 is incomplete or wrong. For example, the value relationship may only be linear in the logarithm of the sizes[11] (scale

7. These transactions are most likely not exhaustive, although they are compiled from sources believed to be reliable. Transactions for which complete data was not reported were excluded. Due to their limited number, transactions that contained nuclear or hydroelectric facilities and nontraditional power sources (*e.g.*, biomass, wind) also were excluded. A total of 11 transactions were dropped from the database for one or both of these reasons. Where possible, data was checked for accuracy against multiple sources. When discrepancies were found, the numbers reported were those listed in official documents such as Federal Energy Regulatory Commission (FERC) filings (as opposed to company press releases). The few transactions listed that involved more than one state were listed either by North American Electric Reliability Council (NERC) region or by the state in which the plurality of megawatts were located. Facilities that could use multiple fuel sources (*e.g.*, oil and gas or oil and coal) were listed under the fuel source predominantly used at the time of the transaction. Prices listed include, to the extent reported, the assumption of any debts, transfers of any assets as consideration, and allowances for future contracting.

8. In cases for which the models estimate (unfeasibly) a negative value, we have replaced the negative value with a zero. There were five such cases in the basic model; this adjustment was not necessary for the expanded model.

9. The reader will note that we have forced our regression to run through the origin since an intercept value has no meaning in this context. For example, a power plant that cannot generate power should have no value.

10. Because of the small ratio of data points to independent variables, a better diagnostic measure may be the "adjusted R^2" statistic, $\overline{R^2}$. $\overline{R^2}$ penalizes unnecessarily complex linear models by adjusting for the degrees of freedom in the model; see Sanford Weisberg, *Applied Linear Regression* (New York: John Wiley, 1985). A polynomial of degree $n-1$ could perfectly fit n data points, although it would have no theoretical underpinning and would result in poor out-of-sample performance. The adjusted R^2 similarly recognizes that simply adding independent variables to a regression model—particularly one with relatively few data points—can inflate the traditional measures of model goodness-of-fit. Let n be the sample size and k be the number of independent variables:

$$\overline{R^2} = \frac{R^2 - k(1 - R^2)}{n - k - 1}$$

Using this measure results in an adjusted R^2 of 79.1% for the basic model and 83.3% for the expanded model.

11. Log-transforms can also be used to reduce variance and pull in extreme values for data that is widely dispersed.

Table 2 Database of Power Generation Asset Transactions

Transaction	State	Package Cost ($ millions)	Aggregate $/kw	Total MW	Coal MW	Oil MW	Calif Gas MW	Non-Calif Gas MW
Commonwealth - Edison	IL	$4,800	$716	6,708	3,590	231	–	2,887
Potomac - Southern	MD	$2,750	$529	5,202	2,875	1,485	–	842
SCE - AES	CA	$781	$197	3,956	–	–	3,956	–
PG&E - Southern	CA	$801	$296	2,702	–	156	2,546	–
PG&E - Duke	CA	$501	$189	2,645	–	165	2,480	–
SCE - Reliant	CA	$237	$104	2,276	–	–	2,276	–
ConEd - Keyspan	NY	$597	$275	2,168	–	–	–	2,168
Boston Edison - Sithe	MA	$536	$268	2,000	–	735	–	1,265
GPU - NYSEG	PA	$1,800	$955	1,884	1,884	–	–	–
ConEd - Orion	NY	$550	$296	1,855	–	–	–	1,855
Dynergy - Central Hudson	NY	$903	$508	1,779	–	1,779	–	–
Potomac - PPL	PA	$1,572	$919	1,711	1,711	–	–	–
Cajun Electric	LA	$1,026	$601	1,708	1,488	–	–	220
SCE - Reliant 2	CA	$43	$29	1,500	–	–	1,500	–
ConEd - NRG	NY	$505	$347	1,456	–	–	–	1,456
NYSEG	NY	$950	$667	1,424	1,424	–	–	–
Niagara - NRG	NY	$355	$261	1,360	1,360	–	–	–
Transalta	WA	$554	$413	1,340	1,340	–	–	–
SDG&E	CA	$356	$296	1,204	–	–	1,204	–
Commonwealth - Dominion	IL	$186	$168	1,108	1,108	–	–	–
NRG - Conectiv	var.	$643	$595	1,081	1,081	–	–	–
United Illuminating	CT	$272	$258	1,056	571	485	–	–
Cogen Technologies	NJ	$1,450	$1,398	1,037	–	–	–	1,037
SCE - NRG	CA	$88	$86	1,020	–	–	1,020	–
Commonwealth - Southern 2	MA	$462	$470	984	–	–	–	984
Montaup - FPL	ME	$91	$147	620	–	620	–	–
Intercontinental Energy	MA	$533	$888	600	–	–	–	600
SCE - Destec	CA	$30	$56	530	–	–	530	–
Commonwealth - Southern	IN	$68	$139	490	490	–	–	–
Chase Manhattan	ND	$150	$330	455	455	–	–	–
PPL - WPS	PA	$106	$246	431	431	–	–	–
Dominion Energy	TX	$110	$264	414	–	–	–	414
Niagara Mohawk - PSEG	NY	$48	$119	400	–	400	–	–
Sierra Pacific - NRG	NV	$273	$955	286	286	–	–	–
Eastern Utilities - Southern	MA	$75	$268	280	–	–	–	280
SCE - Thermo Ecotek	CA	$10	$34	280	–	–	280	–
Montaup - NRG	MA	$55	$367	150	110	–	–	40
Brooklyn Union	NY	$105	$875	120	–	–	–	120
Dow Chemical	CA	$13	$186	70	–	–	70	–

Sources: Financial Times Energy, Global Power Report, Electric Light & Power, RDI, Wall Street Journal, company press releases.

Table 3 Basic Regression Results

Regression Statistics	
Multiple R	91.0%
R^2	82.8%
Adjusted R^2	79.1%
F-Statistic (p-value)	57.95 (0.00)
Observations	39

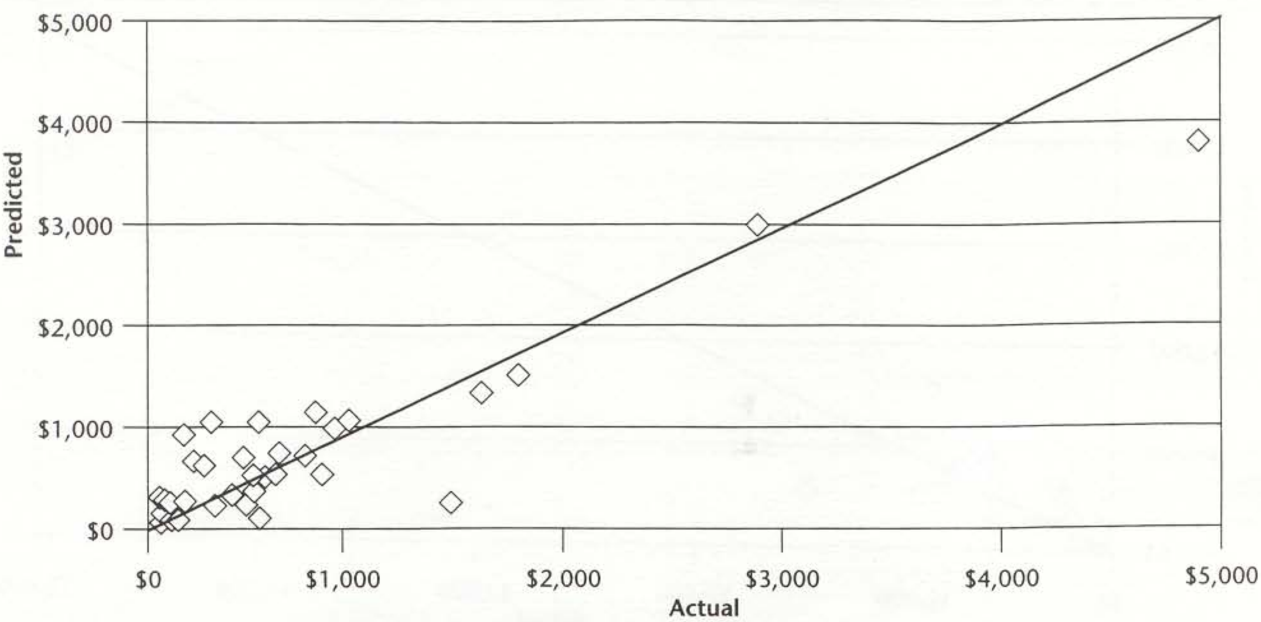
	Coefficients	Standard Error	t Stat	P-value
Coal MW	0.79	0.07	11.97	0.000
Oil MW	0.33	0.16	2.14	0.039
Gas MW	0.30	0.05	5.86	0.000

economies); indeed, the linear model may simply not be appropriate, necessitating the use of nonlinear regression methods.[12] Alternatively, if regulatory intervention has caused markets to become segmented geographically, we may wish to incorporate the physical location of the assets in the model. Any number of possible scenarios could be examined. To illustrate these principles, we will focus on a single expanded model.

Our expanded model illustrates the value of incorporating factors in support of different hypotheses. Specifically, we explore the hypothesis that gas plant values

12. Douglas M. Bates and Donald G. Watts, *Nonlinear Regression Analysis and Its Applications* (New York: John Wiley, 1988).

Figure 2 **Predicted vs. Actual Values for the Basic Model**



differ markedly depending on whether or not they are located in California. Clearly, events in the California energy market have made it unique. However, it is important to keep in mind that most of the transactions used here were completed prior to 1999 during a period of significant uncertainty about the consequences of deregulation in California. By partitioning the transactions geographically in this manner, we can quantify that uniqueness.[13] The geographic variable model is shown in Equation 5, where θ is represented as in Equation 6.

$$\text{COST} = \beta_1 C + \beta_2 O + \beta_3 \theta G + \beta_4 (1 - \theta) G \quad (5)$$

$$\theta = \begin{cases} 1 \text{ Located in California} \\ 0 \text{ else} \end{cases} \quad (6)$$

The results are illustrated in Table 4 and Figure 3. Although there appears to be only a minor increase in explanatory power (the correlation between the actual values and those predicted by the expanded model increased from 0.89 to 0.94), the values of the coefficients reveal a significant change. The two sets of coefficients (which are the per-megawatt prices of each asset type) are listed in Table 5.

As Table 5 indicates, values for coal and oil change moderately. However, the basic model's value for gas assets shifts in a very important fashion. Essentially, it reveals that there is no *single* value for gas assets. The previously estimated value (independent of geographic location) is almost an average of the actual region-dependent values. Gas plants inside of California are worth less than half as much as those located outside of the state on a per-megawatt basis. Clearly, when there are differences this extreme, there are important implications for comparability in a valuation setting.[14]

We must stress that the model's estimates are not statements about intrinsic value. Rather, they are simply representative of the market environment at the time of the transactions; this model treats all previous sales as equally representative. To the extent that, in the past, some buyers have over- or underpaid for assets, this model captures that over- or underpayment. The model is meant to replicate market transactions, not justify them.

The market-equivalent values provided by this approach can help to reveal where asset-specific or intangible strategic factors may have significant influence in valuation (see Figure 4). An example of this is given by

13. With respect to gas power plant values in California, two issues appear paramount. First, regulatory uncertainty over the efficiency of the then new, wholesale electricity market may have depressed values as investors required higher discount rates as compensation for bearing those additional risks. Second, as part of deregulation, the existing investor-owned utilities were required to divest themselves of their generation assets. The forced divestiture of such a large collection of assets may have depressed prices for gas assets in particular, since California does not have many coal- and oil-fired power generation facilities (gas, nuclear, and hydroelectric generation dominate).

14. In addition, there are important questions about the applicability of using pre-deregulation sales to estimate post-deregulation values. We assert that a model that incorporates a sequential or temporal element to the analysis may have substantial value, although we do not explore such modifications here.

Figure 3 **Predicted vs. Actual Values for the Expanded Model**

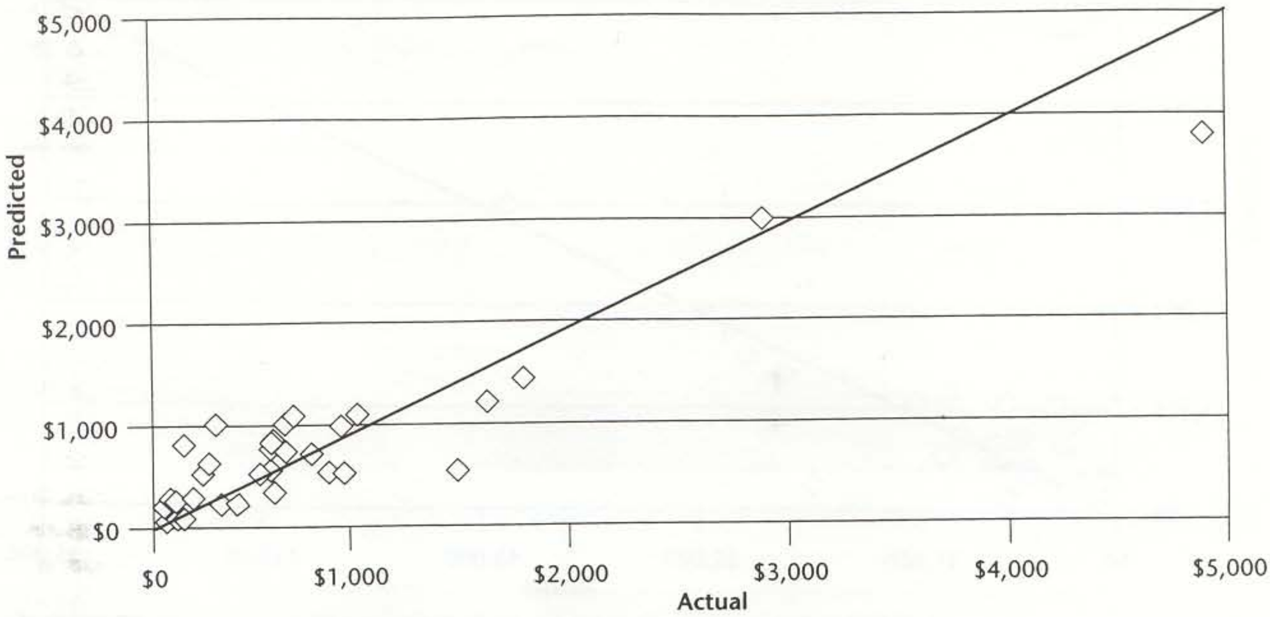


Table 4 **Expanded Model Results**

Regression Statistics				
Multiple R				93.4%
R^2				87.3%
Adjusted R^2				83.3%
F-Statistic (p-value)				59.91 (0.00)
Observations				39

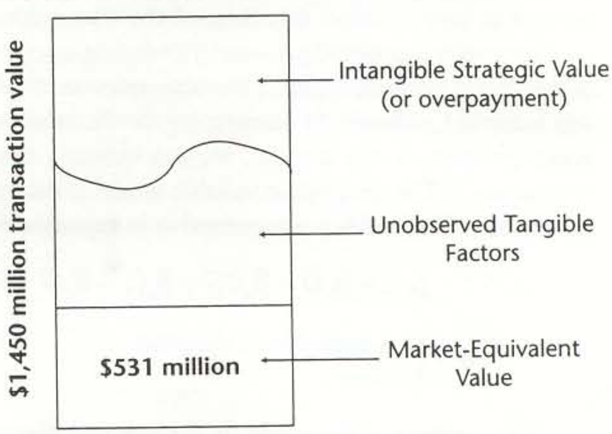
	Coefficients	**Standard Error**	***t* Stat**	***P*-value**
Coal MW	0.72	0.06	11.81	0.000
Oil MW	0.31	0.14	2.27	0.029
Gas (Calif.) MW	0.19	0.05	3.51	0.001
Gas (Non-Calif.) MW	0.51	0.08	6.71	0.000

Table 5 **Comparison of Coefficients Between Basic and Expanded Models**

	Basic	**Expanded**
Coal	0.79	0.72
Oil	0.33	0.31
Gas (Calif.)	0.30	0.19
Gas (Non-Calif.)		0.51

one of the poorest fits in the expanded model. The Cogen Technologies sale of 1,037 MW of gas assets to Enron in 1999 was priced at $1.45 billion, including assumption of debt.[15] The expanded model,

Figure 4 **Estimated Division of Value Components in a Transaction**



however, indicates that the assets had a market-equivalent value of only $531 million (±$161 million).[16] This means that the market, based on historical sales, would have valued the portfolio in the $370 to $692 million range. Thus, the difference of close to a billion dollars reflects the premium paid by Enron to acquire those assets. As analysts noted at the time, the deal was at the high end of recent transactions, but was intended to position Enron for access to the PJM market.[17] Whether or not the

15. *Financial Times*, "U.S. Generation Asset Sales Market Status Report," in *Financial Times Energy* (London: Financial Times, 1999).

16. The amount in parentheses reflects the 95% confidence interval for the average value of the dependent variable.

17. *Financial Times, Ibid.*

"toehold option" value of Enron's purchase can be realized is an empirical question likely to be of intense current interest. The model's indication is simply that Enron paid a substantial premium (roughly $1 billion) over then-current market prices (more than 11 standard errors above the market-equivalent price).

These valuation issues are precisely the type of information that the sales comparison approach is intended to reveal. To the extent that there are differences between the income-capitalization approach (which best indicates the value of a facility as an ongoing concern) and the sales comparison approach, it may be reflective of strength or weakness in the market. This may indicate whether it would be beneficial to take advantage of generous market prices and divest of an asset or maintain it as an operating project. The goal of this discussion, however, is to illustrate how estimates of individual asset market sales values can be inferred from portfolio transactions data. The models developed here demonstrate that this is feasible, although other formulations of these models are possible and may better serve other specific hypotheses.

Bidding Valuation of Heterogeneous Portfolios

Most power-generation real property asset transactions are conducted as auctions, during which several bidders will make purchase offers for a particular portfolio of assets. In such situations, it is important not only to have an accurate idea of what the buyer's internal value for the asset is, but also what the other bidders are likely to pay. Knowing the other bidders' valuations can help to alleviate the well-known "winner's curse." The winner's curse reflects the tendency for the winners of certain types of auctions to have overpaid for the asset in question.[18] The term reflects the fact that the "winner" of the auction, having agreed to pay more than anyone else was willing to pay, actually may be worse off if the winning bid exceeds the value of the asset. Historical transaction data provides some information on the valuations of other bidders, but rarely for portfolios of assets that are substantially similar. Again, the challenge is to extract the value process underlying the reported prices and apply that process to new portfolios.

Using the regression approach developed here, bidders can approximate what the average winner of previous auctions has paid for heterogeneous portfolios of assets. We emphasize the term "winner" because the model does not claim to represent the behavior of all bidders, but rather only the bidder who eventually acquired the asset. This is important to the extent that it can provide an upper limit on reasonable bids. It should be noted, however, that the winning bid may not be reflective of the asset's true value. Appraisers are often after the most probable highest bid, which, because of the winner's curse mentioned above, may not be the winning bid. However, appraisers face this dilemma in any auction environment, and it seems most appropriate to take such issues into account during the final reconciliation of value indications.[19]

Suppose, for example, that a portfolio containing 800 MW of coal assets and 600 MW of gas assets (400 MW in California and 200 MW outside California) came up for bid. What is a reasonable estimate of the market value? Using a simple, nonstatistical approach, the first step would be to look at recent transactions for substantially similar portfolios. In the last several years, there have been no substantially similar transactions. Instead, we must turn to less similar transactions in an attempt to determine comparability. We will consider three transactions, given in Table 6. Each transaction is missing some element of comparability: PG&E-

Table 6 "Comparable" Market Sales Estimation of a Newly Offered Portfolio

	Megawatts by Type				Dollars in Millions		
	Coal	Oil	Gas (Calif.)	Gas (Non-Calif.)	Actual Price (in millions)	Expanded Model	95% Conf. Interval
Hypothetical Transaction	800	0	400	200	???	$757	± $103
PG&E - Duke	0	165	2,480	0	$501	$518	± $272
Potomac - Southern	2,875	1,485	0	842	$2,750	$2,973	± $435
Cajun Electric	1,488	0	0	220	$1,026	$1,191	± $175

18. John Kagel and Dan Levin, "The Winner's Curse and Public Information in Common Value Auctions," *American Economic Review* (December 1986); Richard H. Thaler, *The Winner's Curse* (Princeton: Princeton University Press, 1994).

19. Appraisal Institute, 65, *Ibid.*

Duke has no coal or non-California gas and has oil, Potomac-Southern has oil, but no California gas, and Cajun Electric has no California gas. These three transactions have values ranging from \$189/kw to \$600/kw. The average of these three values is \$440/kw—an amount at which no transaction actually occurred. There is room for enormous subjectivity and bias here; this is the type of subjectivity that we can avoid by turning to formal models.

If the portfolio of assets in question were put up for bid, what is a reasonable estimate of the average winning bid, assuming that the value process in the market is unchanged?[20] Using the expanded model developed in the previous section, we can apply the pricing of Equations 7 and 8 to the portfolio of assets under consideration.[21]

$$\text{Price} = \beta_1 C + \beta_2 O + \beta_3 \theta G + \beta_4 (1-\theta) G \quad (7)$$

$$\text{Price} = 0.72(800) + 0.19(400) + 0.51(200) = 757 \quad (8)$$

The indicated price is \$757 million (± \$103 million), or \$540/kw (± \$73/kw). This price indicates a greater similarity with the Potomac-Southern transaction, which had a value of \$528/kw. Greater attention to aspects of that transaction may be warranted.

Conclusions

We have illustrated briefly the value and efficiency of using formal models in the valuation of assets by the sales comparison approach. By using standard regression tools, easily accessible from most computer spreadsheet packages, the value processes underlying portfolio-transaction prices can be better understood. Moreover, models can be developed that allow the extraction of single-asset values from portfolio-level data. This approach not only increases the accuracy and reduces the subjectivity of the sales comparison approach in appraisals, but also illuminates bidding and market behavior, providing strategic insight to managers on the comparative value of participating in various markets.

In addition, the calculated model coefficients can be related to build costs for the different assets. This measure of value ties the sales comparison ap-

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20. This is an important qualification. If the value process in the market changes over time, care must be taken to examine the intertemporal properties of the model's forecasts. Should, for example, more weight be given to more recent historical observations?

21. With respect to using this approach to forecast possible future bid values, it is important to have a process by which the model's accuracy can be assessed. There are several techniques that can be used to evaluate regression models as forecast tools. For example, specific transactions could be removed from the database and the model refit. One can then examine the performance of the model on the removed data points as a true "out-of-sample" test of the model's accuracy. Many of the same techniques that are used to determine regression model robustness can be adapted to examine forecasting accuracy as well. The interested reader is directed to standard texts in the area for further detail; see Weisberg.

proach to the cost approach to appraisal valuation. For example, what might be the implication of an asset for which the estimated value (i.e., beta coefficient) is greater than the build cost? It may reflect, among other things, the impact of permitting expenses and the ability of older, existing plants to be "grandfathered" in under less stringent requirements. Existing plants would be worth more because construction of new plants could involve more cumbersome and costly permitting.

Finally, although we do not report such results here, there is also significant value in the study of how the coefficients change over time. Examination of the intertemporal properties of the coefficients can provide insights into the cyclical behavior of power-generation asset prices when analyzed in conjunction with fuel prices and regulatory regimes. In fact, our experience has been that there is much to be learned from extending the simple framework we present here with more sophisticated statistical techniques.

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