Appendix 4C
FUEL PRICE FORECASTING

TABLE OF CONTENTS

TABLE OF TABLES

SECTION 1: CONSENSUS FORECASTING APPROACH DISCUSSION

1.1 INTRODUCTION

An investigation was performed to identify the best possible commodity forecasts to use in GMO fuel pricing models. The investigation sought to determine if there was an individual Consultant/Forecaster among the Consultants whose forecasts are currently purchased by GMO that was consistently better performing than other Forecasters, and that the consistency was not only maintained across time but also from multiple perspectives from which a forecast might be utilized or upon which the forecasts can be compared and judged. Such an investigation was previously performed by Kansas City Power & Light, and used the same data sources available to GMO. That analysis confirmed what academic and governmental research had already demonstrated which is that a consensus forecast is the most consistent performer.

The investigation identified a wide variation among forecasters from year to year as to which was the "Best". A more detailed investigation revealed significant academic research in the area for forecasting and forecast averaging. This academic research not only proved the robust nature and reliability of forecast averaging, but showed that an average of forecasts can significantly reduce forecast risk through incorporating the information available to a greater number of forecasters. It also indicated that averaging a small number of forecasters is all that is required to utilize most of the gains from increasing the number of forecasters. The reasons behind the superior performance of forecast averaging are numerous, but are summarized in a simplified manner by Ilan Yaniv, who wrote, "A subjective estimate about an objective event can be viewed as the sum of the "truth", random error, and constant bias."[1] The result of the averaging process is that the random errors, and to an extent the bias as well, cancels each

[1]Yaniv, Ilan, Hebrew University of Jerusalem, "The Benefit of Additional Opinions", Current Directions in Psychological Science, 2004, No.13, p.76-79

other out when forecasts from multiple sources are averaged, which produces a result that can be summarized from the Yaniv example as the "truth" plus a random error significantly smaller than in the individual sources on which the averages are based.

Testing the academic results against existing Powder River Basin coal price forecasts showed that in practice, the academic results were repeated with real world data, implying that combining existing Consultant's forecasts into an average forecast produces a composite forecast that consistently has the highest probability of accuracy on an annual basis.

1.2 BACKGROUND

In developing long-term forecast prices for any commodity it is necessary to review a variety of data sources in the effort to gain an adequate knowledge of the current and future factors likely to influence the supply and demand for the commodity. Quite often this requires referring to certain industry experts, often impartial industry specific consultants or economists that have collected significant information about the commodity in question and have significant knowledge and experience within the industry. These industry experts generally have many years in the industry analyzing and forecasting supply, demand, and price for a select few commodities in which they specialize. As such these experts often produce some of the most widely influential and accepted price forecasts within their area of expertise.

When planning decisions require making projections of future market supply, demand, or price, experts are often the only available resource upon which future projections can rely. However, when presented with several different expert sources from which to choose, the question will invariably arise as to which experts' forecast should be chosen. Usually this is based upon some measure of which expert is most "accurate".

Selecting the most "accurate" of all experts is certainly the most desirable pathway if the accuracy could be known a priori, but unfortunately this idyllic concept encounters several problems. The problems include determining the relativistic frame of reference from which the relative accuracy can be measured and compared, so as to provide the colloquial "apples to apples" comparison. For example, the forecaster that is most accurate in the near term may be different from the one that has the smallest number of periods in error, and both of these references may differ from the expert whose forward curve has the smallest mean error relative to the actual forward once that actual forward is known.

Additional difficulties may arise even within a relative frame of reference, because forecast experts are much like Wall Street mutual fund managers. This year's best performer in a specific reference category may not be next year's best performer in that category. These differences likely result from the annual or periodic variance in information quality and quantity accessible to each forecaster, as well as the differences in weight that each forecaster may place on that variable information.

If the relativistic definition of forecast accuracy is the forecast that is least wrong (i.e. has the smallest error to actual), then without perfect information it is difficult, if not impossible, to consistently select the most accurate forecaster for each year, since the best forecast can't be identified until after the actual value is known.[2] Since such identification is not feasible, the consistently best performing forecast a priori is often a simple average of several individual forecasts.[3] This alternative suggests that logic for the preferred solution may be found in a comparison with Portfolio Theory.

Portfolio theory holds that by diversifying investments through placing smaller amounts in numerous assets, rather than investing everything in a single risky asset, the risk of loss is greatly reduced, while the average expected performance

[2] Yaniv, Ilan, Hebrew University of Jerusalem, "The Benefit of Additional Opinions", Current Directions in Psychological Science, 2004, No.13, p.76-79

[3] Clemen, Robert T. and Winkler, Robert L., "Combining Economic Forecasts" Journal of Business & Economic Statistics, Jan.1986, v.4, No.1, p.39-46

may improve. Such improvement comes not from increasing the odds of making the right pick every time, but rather from decreasing the odds of making the worst pick, and spreading the risk implications of the worst pick across the entire portfolio, thereby minimizing its impact. In much the same way, placing reliance on a portfolio of individual forecasts by industry experts should reduce the price risk resulting from the inevitable forecasting error, while the incorporation of each experts' additional unique information should improve overall forecast performance across many different frames of reference. Robert Clemen, Professor of Decision Sciences at Duke University, expressed this concept when he wrote, "no matter how many methods an expert uses, the results are limited by the expert's personal set of information. In contrast, a new expert has a possibly distinctive set of information, which, at least in principle, could provide further improvement even if many experts have already been consulted."[4]

Additionally, the simple average of a portfolio of expert price forecasts provides something no individual forecast can provide, and that is a method for measuring the statistical variability, or uncertainty, in the forecast price. Most individual forecasters do not provide a probabilistic range around their forecast price, and only JD Energy provides a high and low case (without probabilities), but with a portfolio of forecasts the range and variability can be calculated quantitatively for the average forecast, which permits establishing confidence intervals as the upper and lower ranges around the base case composite.

1.3 <u>SUPPORTING RESEARCH</u>

Whether referred to as average forecast, consensus forecast, or combinatorial forecast, the concept of combining forecasts has been the subject of numerous academic investigations during the last four decades. Considerable academic research tested various methods for selecting and/or combining forecasts and estimates. Some of the most extensive research on the subject during the past

[4] Clemen, Robert T. and Winkler, Robert L., "Multiple Experts vs. Multiple Methods: Combining Correlation Assessments", Decision Analysis v.1, No.3, Sept. 2004, p.167-176

20+ years is the work of Dr. Robert T. Clemen and Dr. Robert L. Winkler, of the Fuqua School of Business at Duke University. Dr. Clemen demonstrated the extensive nature of this forecasting research in a paper published by the International Journal of Forecasting in 1989, which is titled: "*Combining Forecasts: A Review and Annotated Bibliography*." In this paper, Dr. Clemen compiles a list of 209 research documents totaling more than 2000 pages, plus 11 books and theses, all investigating and demonstrating the scientific validity for combining forecasts. Since the publication of this paper an additional eighteen years of research by Robert Clemen and others has continued to demonstrate the superior benefits of combining forecasts in numerous applications ranging from psychology and medicine to engineering and economics, with the central conclusion being that forecast accuracy is significantly improved by combining multiple individual forecasts and that the simple averaging of forecasts often produces results superior to more complicated combinatorial methods.[5]

When averaging multiple forecasts there are several assumptions that apply. The two most important assumptions are:

A Priori belief that all expert forecasts are interchangeable provided the forecasters are all of the same caliber (implied by simple average). The closer to the time period being forecast, the lower the expected forecast error to actual, and the lower the general variation among forecasters

The extensive academic research into the methods and practice of combining forecasts has produced many highly supportive results. The following list compiles eight consistent findings that are most relevant to the combining of available energy price forecasts.

1.4 ACADEMIC RESEARCH RESULTS:

- Simple average of forecasts can significantly improve results

[5] Clemen, Robert T., "Combining Forecasts: A Review and Annotated Bibliography", International Journal of Forecasting, v.5, 1989, p.559-583

- Simple averaging has been demonstrated to be more robust and perform better than more complex methods
- Increasing number of individual forecasts decreases variability, implying a large risk reduction
- Increasing number of experts increases accuracy
- Increasing number of forecasting methods increases accuracy
- Gains are greater from adding more experts than from adding more methods, with improvement from each additional expert equal to approximately four additional methods
- Majority of forecasting improvement occurs from the first 3-4 experts, with rapidly diminishing returns from addition of more experts
- Simple averaging method and complex Bayesian statistical method will converge to the same forecast result when number of forecasts is large (n>=30)

1.5 USAGE

The practice of combining forecasts is widely used and accepted by central bankers, corporate executives, and government agencies around the world. Examples of this acceptance are the numerous consumers of forecasting products from a firm called Consensus Economics (www.consensuseconomics.com). Since 1989 Consensus Economics has applied the theory of combining multiple expert forecasts to produce an average monthly forecast for important macroeconomic variables such as GDP, PPI, CPI, currency exchange, etc, that are relied upon by both governments and industry. Since the focus of their business is forecasting broad economic indicators for more than 70 countries worldwide, they do not produce specific energy related forecasts such as Powder River Basin coal or Henry Hub natural gas. However, the concepts supporting their forecasting method are well researched, and as prior academic research has demonstrated, can be applied to improve forecasts for a wide range of variables and commodities. Consensus Economics web site provides links to additional supporting research. However, Consensus Economics is not the only source to report the acceptance of forecast averaging on the part of government Central Bankers. In a 2001 paper titled, “Testing for Forecast Consensus”, U.S. Federal Reserve Chairman Ben Bernanke is quoted as saying that consensus forecasts can be used to add credibility to monetary policy.[6]

There are many reasons for using a combination of expert forecasts, but the most common are:

- Incorporate additional distinctive information
- Simple averages do not require data fitting
- Simple averages do not require complex relativistic comparisons of expert accuracy
- Numerous academic studies prove that the average of multiple expert judgments is superior to individual judgments
- Random error by forecasters is averaged, cancelling individual biases
- A Portfolio of individual forecasts minimizes potential forecast error, thereby reducing risk
- Variation of individual forecasts around an average provides a reasonable measure of implied forecast uncertainty

1.6 TESTING

As part of the effort for determining the highest quality forecast available it is apparent that academic research findings should be tested on available consultant

[6] Gregory, Allan W., Smith, Gregor W. and Yetman, James, “Testing for Forecast Consensus, Journal of Business and Economic Statistics, Jan. 2001, v.19, Issue 1, p.34-43

forecasts. Given that coal is the largest expense component of a fuel portfolio, and since the coal market is less liquid and there are fewer coal forecast sources available than for the more open and heavily traded crude oil and natural gas markets, it is clear that testing should be performed using Powder River Basin coal price forecasts, and specifically the 8400 BTU coal forecast since that is, by tonnage, the largest quality component within the coal portfolio. The forecasts analyzed were from John Dean Energy, Hill & Associates, and Energy Ventures Analysis.

The Consultant forecasts for PRB coal were chosen to test the academic findings against actual data. The forecasts were selected on the basis of the following five criteria:

- Forecasts from consultants used and respected throughout utility and mining industries
- Forecasts from consultants routinely used by and readily available to GMO
- Forecasts that project ten years or more into the future
- Forecasts of same region and coal type
- Forecast series immediately available at least as far back as 2002-03

Three forecasting sources met all of the criteria. The three sources were JD Energy, Energy Ventures Analysis Inc., and Hill & Associates, with the limiting factors being the unavailability of JD Energy forecasts prior to 2003, and changes in the Hill and Energy Ventures coal product definitions between 2000 and 2003.

Forecasts from the three consultants, plus an average of the three forecasts, provided four forecasts that could be compared and tested from several relative perspectives. The four forecasts were then compared for accuracy against the yearly average of actual Coal Daily settlement prices for PRB 8400 BTU coal.

1.7 MEAN SQUARED ERROR

Although there are many relative perspectives from which the forecasts can be compared, the first comparison chosen was to mathematically compare the statistical “fit” or deviation of the historic forecast curves to the actual price curve. The analysis did this through calculation of the Mean Squared Error (MSE) for each of four forecast curves for each forecast year beginning with the 2003 forecasts. MSE essentially measures the deviation of the entire curve from the actual curve, with the lowest MSE value representing the curve with the smallest overall deviation. The data on which the test was performed is displayed in Appendix I, and the results are tabulated below in Table 1.

Table 1: Forecast Error Minimization as Measured by MSE – from Best to Worst ** Confidential **

[redacted]

On a percentage basis the MSE results in the above table are as follows:

Table 2: Forecast Error Measured by MSE as Percentage of Total Forecasts ** Confidential **

[redacted]

Measuring the relative forecast error by MSE shows that ** XXXXXX ** forecasts had the smallest error in 50% of the forecast years measured, but ** XXXXXX ** also produced the worst forecast 25% of the time. This sample set suggests that choosing ** XXXXXX**as the preferred forecast would have resulted in the best or second best forecast 75% of the time, but would not have had a top performing forecast since before the price spikes of 2005-06, and would also have resulted in being saddled with the worst forecast 25% of the time. Looking for the next best performer from the MSE perspective, the Average of the forecasts stands out. The Average was the best performer 25% of the time, and like ** XXXXXX ** it was best or second best 75% of the time, but unlike ** XXXXXX **, the Average was never the worst performer. Just as the academic research suggests, the Average

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forecast seems to have minimized the risk of error, and consistently performed better than the forecast from any other source. It is apparent that “before the fact” it was not possible to know which of the three consultants would perform best in a given year, and even the consultant with the highest probability of performing well still had a very risky probability of being the absolute worst choice a whopping 25% of the time. Only the Average appears to provide a reasonably confident assurance, “before the fact”, that the forecast will be of good quality.

1.8 COUNT OF FORECASTS

Another perspective for measuring the quality of a forecast is to look at the absolute number of times the forecaster was correct, independent of the statistical fit of the total dataset. This does not measure the overall relationship between points forming a curve as with the MSE, rather this method just looks at all the years forecast by a consultant in a given forecast year, and counts each year of the forecast independent of the other years, simply measuring how many times the forecaster got relatively close to actual over the duration of the forecast.

Since forecasters being absolutely correct for any given year are akin to a golfer hitting a hole-in-one (but with smaller probability), it is not probable that a small sample will provide any statistically perfect information, and true to this theory the present data set does not have any perfect matches between forecast and actual. However, since the more achievable goal seems to be the minimization of forecast error, it is reasonable to count the number of occurrences within a minimum error of actual to see how often a forecaster gets within the proverbial ballpark. The test dataset produces a count of at least one forecaster for each forecast year if the minimum error is no more than 10% from actual. With the test dataset, each consultant has four measurable forecast points for the 2003 forecast, three for the 2004 forecast, two for 2005, and one for 2006, summing to a total number of ten possible points.

Table 3: Count of Forecast Points Within 10% of Actual (PRB 8400)
**** Confidential ****

[redacted]

Measuring accuracy by counting the total number of forecasts that fall close to the actual value indicates that the best forecaster may be ** XXXXXXX **, since that consultants forecasts for this sample set were within 10% of actual more of the time (40%) than any other forecaster, and is within 10% of actual for at least one year of the measurable forecast in three of the four forecasts. However, ** XXXXXXX ** was by far the worst overall forecaster when measured by MSE, as demonstrated in Table-1 and Table-1A. Likewise, the forecaster with the largest number of best MSE forecasts, ** XXXXXX **, appears by the Count method to be the worst performer, with only one close forecast point out of ten possible points and only one forecast year (2005) having any forecast points within 10% of actual. When looking at performance from this perspective and comparing it to the MSE perspective, it is evident that the overall best and worst performers from one perspective trade places when viewed from the other perspective.

Further analysis of the Count method shows that the second best performance measured by this metric is the Average of forecasts. The Average had 30% of all points within 10% of actual, and was most consistent with three of the four forecasts having at least one year falling within 10% of actual. The Average produced the second best overall results by both the Count metric and the MSE metric, while the best and worst performers swapped positions, suggesting that the Average may be the most consistent performer. These results seem to confirm what the voluminous academic research has already shown, which is that the most robust forecast is consistently achievable by averaging multiple forecasts, and that the average of forecasts will minimize the risk of forecast error.

1.9 FIRST YEAR OF FORECAST

A third metric from which to measure a forecaster is their ability to correctly forecast the near-term or immediate future. Just as it is easier to predict what the weather will be tomorrow than it is to predict the weather a month or a year from today, due to familiarity or temporal proximity, it should also be less difficult to predict the next forecast period than one ten years in the future. Being closer to tomorrow than to next month, it is easier to know with a higher probability tomorrow's most likely outcomes. Likewise, there should be an expectation that the first year of a commodity price forecast be more accurate than later years simply because of more high quality information with higher probability outcomes.

Furthermore, given the time value of money, the early years of a price forecast are weightier and therefore error risk is potentially more costly than in later years when time provides room to maneuver by exercising alternative options, and inflation erodes financial value. Therefore, the first year of a forecast is, financially speaking, the most valuable or costly forecast year depending on your point of reference. It also provides the starting point for all remaining forecast years in a forecast curve, so being as accurate as possible in year number one should help provide a firm foundation for the remainder of the forecast curve.

The reference data, consisting of forecasts from ** XXXXXXXXXXXXXXXXXX **, and an average of these forecasts, shows that ** XXXXXX ** got the most first year forecasts closer to actual than others. A tabulation of first year forecast accuracy is displayed below in Table 4 and Table 5:

Table 4: First-Year Forecast Accuracy (PRB 8400, Calendar Years 2003-2006) ** Confidential **

[redacted]

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Table 5: First-Year Forecast Accuracy as Percent of All Test Case Forecasts ** Confidential**

[redacted]

Testing the forecasts from yet a different perspective, the results once again show the best performer will vary from year to year, and from this particular perspective (best first year accuracy) the top performer differs from the top performers in the previously tested MSE and “Count of Points” perspectives. The results displayed in Table-3 and Table-3A demonstrates that all test case forecasts were best in accuracy at least once, with the exception of ** XXXXXXXXXXXXXX **, with two first year bests, had more first year accuracy bests than the other forecasts at 50% of the sample set, and a total of 75% of first and second best. The next best first year forecast performer was the Average of forecasts, with one best and two second bests, for a total percentage of first and second best performances of 75% just like ** XXXXXXX **. While the best performer from the “Count of Points” accuracy tests, ** XXXXXXXXX **, was only the third best performer in the first year of the forecasts tested. ** XXXXXXXX **, which was the most accurate performer by the MSE statistical testing method, proved to have the worst accuracy in 100% of the first year forecasts.

The first year accuracy test once more demonstrates the superiority of the Average of forecasts. The simple Average produced the best outcome 25% of the time, and either best or second best 75% of the time, while never producing a worst outcome. With other forecasts swinging wildly from best to worst depending on the relative perspective from which their performance is considered, the Average consistently performed as either a best or second best choice, regardless of perspective. Furthermore, given that it is the only choice that could “before the fact” be consistently expected to perform with a high degree of accuracy, it appears as the best forecast choice among the forecasts that were available for testing.

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1.10 SUMMARY

In summary, the results of the accuracy tests applied to available PRB 8400 coal forecasts demonstrated findings consistent with the academic research of forecast averaging, and indicate that the most consistent forecast across a variety of reference points is the simple Average of available expert/consultant forecasts. The results are tabulated in Table 6 below:

Table 6: Results of Accuracy Testing by Method (PRB 8400, Calendar Years 2003-2006) ** Confidential **

[redacted]

Results displayed in Table 6 are consistent with academic research that indicates the Average forecast is simply the best choice in terms of probable accuracy independent of the method for determining that accuracy. The robust nature of the statistical Average forecast is noted by its consistent performance across each of the perspectives considered. Additionally, as noted in the results for each perspective, the forecaster that is labeled “Best” under each perspective in Table-4, also had a demonstrated probability of being “Worst” in at least one out of four forecasts for that perspective, while the Average was never “Worst” in any year of any forecast from any perspective tested, which implies that the Average is truly the “Best” available forecast. Simply stated, if the objective is to minimize forecasting risk and individual bias, employ the maximum amount of available market information, and consistently have a high probability of choosing a good performing forecast for each time period, then the best forecast is the Average of a portfolio of individual forecasts. The Average forecast also provides something the other individual forecasts lack, which is the added benefit of being able to statistically determine a range of possible forecast outcomes based upon desired confidence intervals.

1.11 <u>REFERENCES:</u>

Clemen, Robert T. and Winkler, Robert L., “Combining Economic Forecasts”, Journal of Business & Economic Statistics, Jan.1986, v.4, No.1, p.39-46

Clemen, Robert T., “Combining Forecasts: A Review and Annotated Bibliography”, International Journal of Forecasting, v.5, 1989, p.559-583

Clemen, Robert T. and Winkler, Robert L., “Multiple Experts vs. Multiple Methods: Combining Correlation Assessments”, Decision Analysis v.1, No.3, Sept. 2004, p.167-176

Consensus Economics

www.consensuseconomics.com

Gregory, Allan W., Smith, Gregor W. and Yetman, James, “Testing for Forecast Consensus, Journal of Business and Economic Statistics, Jan. 2001, v.19, Issue 1, p.34-43

Sternstein, Martin, PhD, “Statistics”, 1996, Barron’s Educational Series Inc., Hauppauge, NY 11788,   ISBN: 0-8120-9311-9

Yaniv, Ilan, Hebrew University of Jerusalem, “The Benefit of Additional Opinions”, Current Directions in Psychological Science, 2004, No.13, p.76-79

Forecast Sources:

** <u>Hill & Associates (now Wood Mackenzie)</u>

<u>Powder River Basin Coal Supply, Demand, and Prices 2003-2013, November 2003</u>

<u>Powder River Basin Coal Supply, Demand, and Prices 2004-2015, November 2004</u>

Powder River Basin Coal Supply, Demand, and Prices 2005-2015, November 2005

Powder River Basin Coal Supply, Demand, and Prices 2006-2015, November 2006

JD Energy

Quarterly Coal Forecast, December 2003

Quarterly Coal Forecast, September 2004

Quarterly Coal Forecast, May 2005

Quarterly Coal Forecast, August 2006

Note: The JD Energy Quarterly Coal Forecast varies in its date of issuance and may not be issued four times in a given year, so for a given calendar year the "Quarterly" Forecast closest to the August to November time period was chosen to coincide as close as possible with the Energy Ventures and Hill forecasts.

Energy Ventures Analysis

The Long-Term Outlook Vol.2, August 2003

The Long-Term Outlook Vol.2, August 2004

Long-Term Outlook for Coal and Competing Fuels, August 2005

The Long-Term Outlook Vol.2, August 2006 **

Appendix I

A) Powder River Basin 8400 BTU Coal Price Forecasts ** <u>Confidential</u>**

[redacted]

Forecasts Used in Calculating Average for Analysis Confidential****

[redacted]

[redacted]

[redacted]

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C) Forecast Averages and Standard Deviations Confidential****

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SECTION 2: COAL

2.1 FORECASTS

A composite coal price forecast was created by combining the forecasts from the Energy Information Administration (EIA), Energy Ventures Analysis (EVA), JD Energy, and Hanou Energy Consulting (HEC), S&P Global Platts (S&P) and IHS Markit (IHS). Each source provided a base case forecast in either nominal or real dollars. All forecasts were converted to nominal dollars using Moody's Analytics' GDP implicit price deflator.

Once all coal price forecasts are in nominal dollars the forecasts are combined by equal weight to create a composite price forecast representing the expected or base case consensus among the major forecast sources. The variation of individual forecasts within the composite are then used within a t-distribution to mathematically calculate high and low forecast price curves representing the 90th and 10th percentiles of the t-distribution. The three resultant price curves with their probability of occurrence are base 50%, high 25%, and low 25%.

2.1.1 ENERGY INFORMATION ADMINISTRATION

Office of Integrated Analysis and Forecasting

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Washington, D.C. 20585

"Annual Energy Outlook 2017"

2.1.2 ENERGY VENTURES ANALYSIS INC.

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1901 North Moore Street, Suite 1200

Arlington, VA. 22209-1706

“FUELCAST: 2016 Long-Term Outlook”

2.1.3 JD ENERGY INC.

JD Energy, Inc.

P.O. Box 1935

Frederick, MD. 21702-0935

“Long-Term Coal Price Forecast 2017-2045”

2.1.4 HANOU ENERGY CONSULTING, LLC

1204 Sterling Drive

Annapolis, MD. 21403

“Powder River Basin Coal Supply, Demand, and Prices 2017-2036”

2.1.5 IHS MARKIT

IHS Markit (IHS)

4th Floor Ropemaker Place

London EC2Y9LY

United Kingdom

“2017 US Steam Coal Market Update – August 2017”

2.1.6 MOODY’S ANALYTICS

7 World Trade Center

250 Greenwich Street

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Moody’s Analytics www.economy.com *DataBuffet* accessed 9/26/2017

2.1.7 S&P GLOBAL PLATTS – FORMERLY PIRA ENERGY GROUP

S&P Global Platts – formerly PIRA Energy Group

2 Pennsylvania Plaza, 25th Floor

New York, NY 10121

Long Term Coal Price Forecast was sourced from Energy Price Portal Long Term Coal Price Forecast - June 1 2017

SECTION 3: NATURAL GAS

3.1 FORECASTS

A composite Henry Hub natural gas price forecast was created by combining the forecasts from the EIA, EVA, IHS, and S&P. Each source provided a base case forecast in either nominal or real dollars. The forecasts that were provided in real dollars were converted to nominal dollars using Moody's Analytics' GDP implicit price deflator.

Once all natural gas price forecasts are in nominal dollars the forecasts are combined by equal weight to create a composite price forecast representing the expected or base case consensus among the major forecast sources. The variation of individual forecasts within the composite are then used within a t-distribution to mathematically calculate high and low forecast price curves representing the 90th and 10th percentiles of the t-distribution. The three resultant price curves with their probability of occurrence are base 50%, high 25%, and low 25%.

The New York Mercantile Exchange (NYMEX) forward price curve for Henry Hub natural gas goes forward five years; for two of those five years the NYMEX price is used as the base forecast for natural gas, with the consensus forecast gradually taking over from the NYMEX curve for year three (2019). This gradual change occurs by decreasing the weighting of the NYMEX price by 25% and increasing the weighting of the consensus price by 25% for each year starting in year three (2019), such that the forecast price is 100% consensus by year six (2022), and the consensus forecast remains the forecast basis through the end of the forecast horizon. The high and low consensus forecasts differ from the base forecast in the treatment of NYMEX forward prices during the first five years of the forecast. When calculating the statistical distribution that determines the high and low price forecasts, the NYMEX forward prices are treated as an equal weight component of the consensus for the five years that the NYMEX forwards are present, rather than being the sole basis of the forecast.

3.1.1 ENERGY INFORMATION ADMINISTRATION

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3.1.2 ENERGY VENTURES ANALYSIS INC.

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Arlington, VA. 22209-1706

"FUELCAST: 2017 Long-Term Outlook"

3.1.3 IHS MARKIT

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United Kingdom

"September 22, 2017 IHS Energy North American Monthly Gas Briefing"

3.1.4 MOODY'S ANALYTICS

7 World Trade Center

250 Greenwich Street

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Moody's Analytics www.economy.com *DataBuffet* accessed 9/26/2017

3.1.5 S&P GLOBAL PLATTS – FORMERLY PIRA ENERGY GROUP

S&P Global Platts -formerly PIRA Energy Group

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Henry Hub natural gas price forecast was sourced from Energy Price Portal Long Term Natural Gas Price Forecast – August 15, 2017

SECTION 4: FUEL OIL

Oil fired power generation is not at the present time a major source of electricity generation, and there are no present price forecast scenarios between 2017 and the 2040's in which oil would become the lowest cost fuel option for generating electricity compared to other fossil fuels.

4.1 FORECASTS

A composite crude oil price forecast was created by combining the forecasts from the EIA, EVA, PIRA and IHS. Like with our coal and natural gas forecasts, each source provided their forecast in either nominal or real dollars. The forecasts that were provided in real dollars were converted to nominal dollars using Moody's Analytics' GDP implicit price deflator.

Once all oil price forecasts are in nominal dollars the forecasts are combined by equal weight to create a composite price forecast representing the expected or base case consensus among the major forecast sources. The variation of individual forecasts within the composite are then used within a t-distribution to mathematically calculate high and low forecast price curves representing the 90^{th} and 10^{th} percentiles of the t-distribution. The three resultant price curves with their probability of occurrence are base 50%, high 25%, and low 25%.

The New York Mercantile Exchange (NYMEX) forward price curve for New York Harbor ULSD (HO) futures contract is used for first part of the forecast for no.2 oil. Since the historic correlation between the price of NYMEX HO and NYMEX WTI Crude oil is very strong (>0.95), forecast sources for crude oil are more available and tend to have longer forecast horizons than available no.2 oil forecasts, the consensus crude oil forecast is then used to project no.2 oil through the rest of the forecast horizon. This is done with the assumption that the strong price correlation will continue and the rate of price change in no.2 oil will be approximately the same as that observed in crude oil; by applying the monthly rate of change in the crude oil price to the prior month’s no.2 oil price, an expected no.2 oil price is projected from the consensus crude oil forecast.

4.1.1 IHS MARKIT

IHS Global Inc. (IHS)

4th Floor Ropemaker Place

London EC2Y9LY

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“September 2017 IHS Energy North American Monthly Gas Briefing”

4.1.2 ENERGY INFORMATION ADMINISTRATION

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4.1.3 ENERGY VENTURES ANALYSIS INC.

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4.1.4 MOODY'S ANALYTICS

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Moody's Analytics www.economy.com *DataBuffet* accessed 9/26/2017

4.1.5 S&P GLOBAL PLATTS – FORMERLY PIRA ENERGY GROUP

S&P Global Platts -formerly PIRA Energy Group

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Long Term Oil Price Forecast – June 17, 2016