BEFORE THE STATE CORPORATION COMMISSION
OF THE STATE OF KANSAS

In the Matter of the Application of Black	**)**
Hills/Kansas Gas Utility Company, LLC,	**)**
d/b/a Black Hills Energy, for Approval of	**) Docket No. 25-BHCG-298-RTS**
the Commission to Make Certain Changes	**)**
in its Rates for Natural Gas Service	**)**

DIRECT TESTIMONY

PREPARED BY

ROBERT H. GLASS, Ph.D.

UTILITIES DIVISION

KANSAS CORPORATION COMMISSION

May 9, 2025

I. STATEMENT OF QUALIFICATIONS

Q. What is your name?

A. Robert H. Glass.

Q. By whom and in what capacity are you employed?

A. I am employed by the Kansas Corporation Commission (KCC or Commission) as Chief of the Economics and Rates Section within the Utilities Division.

Q. What is your business address?

A. 1500 S.W. Arrowhead Road, Topeka, Kansas, 66604-4027.

Q. What is your educational background and professional experience?

A. I have a B.A. from Baker University with a major in history. I also have an M.A. and a Ph.D. in economics from the University of Kansas. For 22 years, I was employed by the Institute for Business and Economic Research at the University of Kansas, which later became the Institute for Public Policy and Business Research. My primary duty was doing economic research.

Q. Have you previously submitted testimony before this Commission?

A. Yes. I provided testimony as a Staff consultant for Docket Nos. 91-KPLE-140-SEC and 97-WSRE-676-MER. As an employee of the Commission, I have testified in numerous rate case and non-rate case dockets, which can be made available upon request.

II. INTRODUCTION

Purpose

Q. What is the purpose of your testimony?

A. The purpose of my testimony is to sponsor Staff's recommendations regarding billing determinants normalization.

Black Hills' and Staff's Adjustments

Q. What Black Hills Adjustments are you addressing?

A. I will investigate IS-7, Revenue Synchronization, IS-8, Weather Normalization and Irrigation Adjustment, and IS-10, Expected Revenues from new Large Volume Transport customers, each of which are shown below in Table 1.

Table 1

Black Hills' Adjustments		
Adjustment	Name of Adjustment	Amount
IS-7	Revenue Synchronization	$ 136,907
IS-8	Weather Normalization	$ 269,391
	Irrigation	$ (234,694)
	Total	$ 34,697
IS-10	LVTS Revenues	$ 419,027
	Total	$ 590,631

Q. What adjustments are you sponsoring?

A. I am sponsoring Staff's IS-19, Weather Normalization and Irrigation, and Staff's IS-20, Customer Annualization. These adjustments are shown in Table 2 below. Also, I recommend the Commission accept Black Hills' IS-7, Revenue Synchronization adjustment of $136,907 and IS-7, Expected Revenues from new Large Volume Transport customers of $419,027.

Table 2

Staff's Adjustments			
Adjustment	**Name of Adjustment**		**Amount**
IS-19	Weather Normalization	$	2,443,167
	Irrigation	$	(165,451)
	Total	$	2,277,716
	BH Weather Normalization	**$**	**34,697**
	Staff's IS-19 Adjustment	**$**	**2,243,019**
IS-20	**Customer Annualization***	**$**	**121,746**
NOTE*: Black Hills did not do a Customer Annualization.			

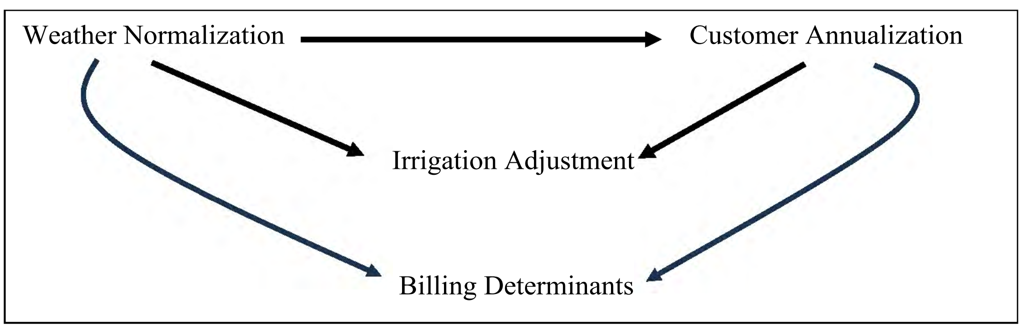
Organization

Q. How is your testimony organized?

A. My testimony is organized in six major sections: (1) Synchronization Adjustment, (2) Large Volume Transport New Customers Adjustment, (3) Weather Normalization Analysis, (4) Customer Annualization Analysis, (5) Irrigation Analysis; and (6) Staff Billing Determinants. I will conclude by recommending the Commission adopt Staff's adjustments for Weather Normalization, Customer Annualization, and adopt Staff's adjusted Billing Determinants for revenue allocation and rate design.

The analysis sections of my testimony, Weather Normalization Analysis, Customer Annualization Analysis, and the Irrigation Analysis, are organized around the flow of data from one section to the next. The weather normalization needs to be done first because it flows into both the customer annualization and irrigation. The customer annualization needs to be done second because part of it flows into irrigation. Irrigation needs to be done after weather normalization and customer annualization because Black Hills' irrigation methodology conflates both weather normalization and customer annualization. Thus, to provide a commensurate comparison with Black Hills' irrigation adjustment, the weather normalization and customer annualization of irrigation must be pulled from where they are calculated and then combined to provide a commensurate irrigation adjustment with Black Hill's irrigation adjustment. All three analysis sections feed into Staff's final billing determinants that are used for revenue allocation and rate design. Figure 1 below illustrates the data flow.

Figure 1



III. ANALYSIS: SYNCHRONIZATION ADJUSTMENT

Q. What is the synchronization adjustment?

A. It is an adjustment to booked revenues, so they are equal to current rates multiplied by test year billing determinants. It can be either negative or positive.

Q. How is the synchronization adjustment calculated?

A. The synchronization adjustment is the difference between booked revenues and test year billing determinants multiplied by current rates.[1]

Q. How large is the Black Hills' synchronization adjustment?

A. The addition of $136,907 to book revenue will make it equal to base rate revenue—current rates times test year billing determinants.

Q. Does Staff agree this is a reasonable approach?

A. Yes. Staff agrees Black Hill's approach is reasonable and recommends the Commission accept Black Hills' adjustment.

IV. ANAYSIS: LARGE VOLUME TRANSPORT ADJUSTMENT

Q. Did Black Hills do a customer annualization adjustment?

A. Black Hills did not do a standard customer annualization adjustment, but it did make an adjustment for new Large Volume Transport Customers that it signed contracts with and were coming online in the near future. Black Hills' adjustment for future customers consists of an increase of three customers, an increase of 36 bills, a volumetric increase of 5,118,400 therms, and a revenue increase of $419,027.

Q. Does Staff agree with this adjustment?

A. Yes. Staff recommends the Commission accept the Large Volume Transport Class adjustment from Black Hills.

[1] Fritel Direct Testimony, p. 5.

V. ANALYSIS: WEATHER NORMALIZATION

Purpose

Q. What is the purpose of weather normalizing gas usage?

A. Weather normalization minimizes the effect of non-normal weather conditions on test year usage and revenue collections. Some uses for natural gas, such as space heating and water heating, are sensitive to temperature—increasing when temperatures fall and decreasing when temperatures rise. Thus, if the test year is cooler than normal, test year usage and revenue will be higher than normal. However, if a test year is warmer than normal, test year usage and revenue will be lower than normal. Ultimately, this would result in rates being set too low when test year temperatures are lower than normal (or too high when test year temperatures are higher than normal) for the utility to collect its approved revenue requirement under normal conditions.[2]

Because test year revenue should reflect normal ongoing operations, the Commission sets rates based on weather-normalized usage. Through the weather normalization process, test year volumes and revenues are adjusted to reflect the difference between actual test year weather and normal weather. Hence, a weather normalization adjustment is applied to test year volumes and revenue, so the test year volumes and revenue are reflective of normal weather.

[2] For example, during periods of colder than normal weather, a natural gas utility will sell more natural gas than they would otherwise have during normal weather. It would be inappropriate to use this above-average usage for setting rates because, as weather returns to normal, the natural gas utility will sell less natural gas than what is needed for the company to recover its revenue requirement at the lower rates.

Process

Q. Please provide the steps for the weather normalization process.

A. Staff's weather normalization process can be divided into four steps. In the first step, historical monthly usage data and customer bills are collected for each of the relevant customer classes. Weather data is also collected for each of the agreed to weather stations within the service territory. In the second step, a regression analysis is performed on the data to develop coefficients called Weather Sensitivity Factors (WSFs), which measure the weather sensitivity of per capita customer usage for each customer class. In the third step, the WSFs are used to calculate volumetric adjustments. In the last step, these volumetric adjustments are multiplied by current rates to adjust for deviations from normal weather during the test year. Each of these steps is discussed in more detail below.

Data Collection

Data Sources

Q. Who provided the customer usage and customer bill data?

A. Black Hills Energy (Black Hills) provided the number of customer bills and the billed usage data[3] and customer bill data for its Sales and Transportation classes.[4]

[3] Ideally, the data provided for weather normalization would be usage data. But in many cases, such as this docket, the only readily available data is billing data. The problems with billing data are multiple. For example, there can be a billing error in one month that is corrected in a different month, which reduces the correlation between weather and the billing data. Also, all customers are not billed on the same day of the month—instead, there is a monthly billing cycle. For these reasons and other reasons, billing data tends to be "noisy." Through aggregation and averaging, some of the deficiencies in the data are reduced in classes with many customers, but smaller classes can still problems. In this regard, compensating errors are helpful.

[4] Black Hills provided data for the Residential Sales Class, Small Commercial Sales and Transport Classes, Small Volume Sales and Transport Classes, Large Volume Sales, Transport, and Interruptible Classes, and the Irrigation Transport and Interruptible Classes. The data for the 10 customer classes was from October 2014 through September 2024, although in some cases there were no data for particular weather stations for

Black Hills also assigned the members of the customer classes to their closest first-order weather station.[5] With this data, Staff was able to calculate the per capita usage by weather station for each customer class.

Q. What is the source of weather data Staff used for its analysis?

A. Staff collected daily weather data from the National Oceanic and Atmospheric Administration (NOAA) for the first-order weather stations closest to Black Hills' Kansas customers (Concordia, Dodge City, Goodland, Topeka and Wichita) for the period of October 1994 through September 2024. Staff then calculated test year monthly Heating Degree Days (HDDs), Cooling Degree Days (CDDs), and precipitation, and a 30-year normal (average) for each of these weather variables.

Q. What are HDDs and CDDs?

A. HDDs and CDDs are variables that measure deviations from an established base temperature (in this case, 65 degrees).[6] HDDs measure how cool the average daily temperature was relative to the base temperature, while CDDs measure how warm the average daily temperature was relative to the base temperature.[7] Figure 1 below

all or parts of the period. Staff had data back to January 2011 for the Residential Class from the previous rate case which allowed Staff to extend the time period for regression analysis.

[5] First-order refers to weather stations that are professionally maintained, primarily through the National Weather Service or Federal Aviation Administration. Modernization of the National Weather Service during the 1990s resulted in the consolidation of many manned weather stations and the introduction of Automated Surface Observing System (ASOS) instrumentation throughout the United States. ASOS instrumentation is now in use at the vast majority of first-order sites, which are primarily located at airports. See https://www.weather.gov/top/office for more information.

[6] Degree days are weather variables based on the assumption that when the outside temperature is 65 degrees Fahrenheit, an average person will not require heating or cooling to be comfortable. https://www.weather.gov/key/climate_heat_cool

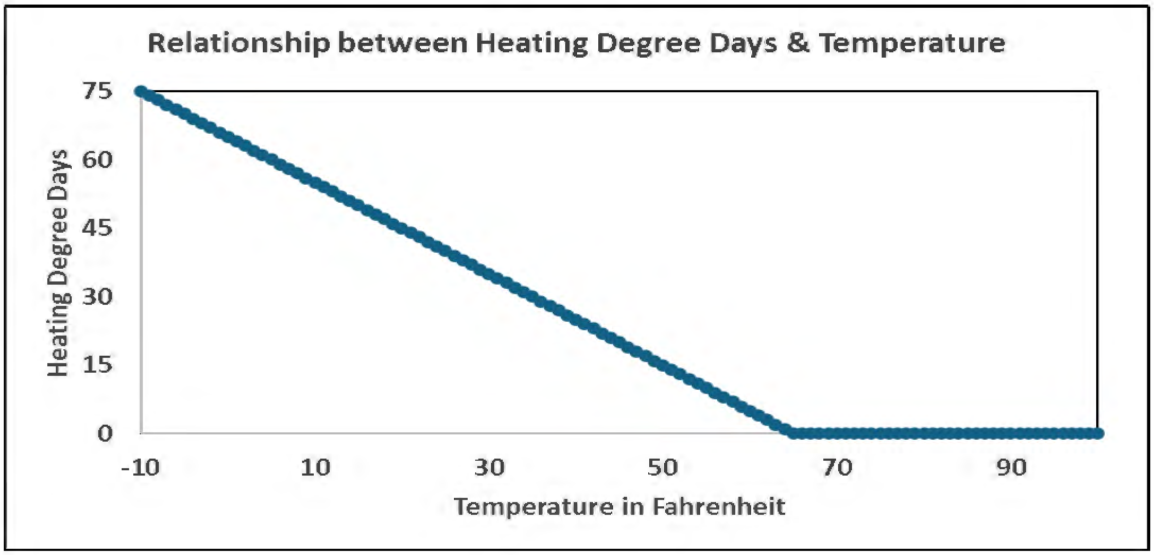
[7] Staff calculated HDD and CDD measures as follows.

$$HDD = \left(65 - \frac{Max + Min}{2}\right) if\ \frac{Max + Min}{2} < 65, otherwise\ HDD = 0$$

$$CDD = \left(\frac{Max + Min}{2} - 65\right) if\ \frac{Max + Min}{2} > 65, otherwise\ CDD = 0$$

shows the relationship between temperature (Fahrenheit) and HDDs; the relationship between CDDs and temperature is the reverse image of Figure 2.

Figure 2



Q. Why were HDDs and CDDs used rather than temperature as weather variables?

A. There are a couple of obvious advantages of using HDDs to measure weather that creates demand for heating. First, HDDs are strictly positive—there is no transition from positive to negative numbers, and second, above the base temperature, in this case 65°, HDDs are equal to zero.

HDDs are a good proxy for customer gas space heating demand—the greater the number of HDDs, the cooler the weather, and thus, a greater demand for space heating. Similarly, CDDs and precipitation serve as proxies for irrigation customers' demand for gas.

Q. What are normal weather variables?

A. We used 30-year rolling averages of the weather variables to represent normal weather.

Q. What is a 30-year rolling average?

A. We begin with the end of the test year, in the case of this docket, that is September 2024 and go back 30 years to October 1994. Thus, the period for calculating the normals is October 1994 through September 2024.

Data Problems

Q. Are there any significant issues with the data collected?

A. The meaningful problems were with the data from Black Hills. And the problems are typical of the problems using billing data. Exhibit -RHG-1 has the details of the major data problems. Here I will only go over one extreme problem and Staff's proposed solution.

Q. What is the extreme example?

A. The Large Volume Firm Class for the Topeka weather station had negative customer usage for October 2022, which is an impossibility. Table 3 below presents the number of customers, the volume of gas usage, and the average usage per customer for the unadjusted data and the adjusted data. The October 2022 data is in red.

Table 3

An Extreme Example & Staff Solution to October 2022 Data Problem						
	Topeka: Large Volume Firm Class					
	Unadjusted Data			Adjusted Data		
Month	Bill Count	Customer Gas Usage	Average Uasge	Bill Count	Customer Gas Usage	Average Uasge
Apr-22	13	127,301	**9,792**	13	127,301	**9,792**
May-22	14	80,441	**5,746**	14	80,441	**5,746**
Jun-22	15	44,150	**2,943**	15	44,150	**2,943**
Jul-22	14	25,485	**1,820**	14	25,485	**1,820**
Aug-22	13	21,738	**1,672**	13	21,738	**1,672**
Sep-22	12	29,548	**2,462**	12	29,548	**2,462**
Oct-22	**4**	**(14,319)**	**(3,580)**	**13**	**41,769**	**3,342**
Nov-22	13	53,990	**4,153**	13	53,990	**4,153**
Dec-22	12	127,034	**10,586**	12	127,034	**10,586**
Jan-23	13	183,331	**14,102**	13	183,331	**14,102**
Feb-23	13	158,694	**12,207**	13	158,694	**12,207**
Mar-23	12	161,969	**13,497**	12	161,969	**13,497**
Apr-23	13	114,044	**8,773**	13	114,044	**8,773**

NOTE: The numbers in parentheses are negative numbers.

NOTE: The data for October 2022 was adjusted by averaging the bill count and customer usage data for September and November 2022.

Q. How did Staff adjust the October 2022 data?

A. Staff first took the simple average of the month before and the month after October 2022 for the bill count and customer usage and then calculated average customer usage by dividing the revised usage amount by the revised bill count. This interpolation resulted in a change in the average customer usage from (3,580) to 3,342 therms per customer.

Q. Did the data adjustment affect the estimation of the weather sensitive factors?

A. Yes. The effect of the adjustment on the estimation of the weather sensitive factors will be discussed in the next section, which is devoted to Staff's regression analysis.

Q. Are there any cases of negative numbers or other adjustments to the customer usage data in the test year data?

A. Yes. The Irrigation Interruptible Class for the Goodland weather station had negative customer usage for December 2023.

Q. How did Staff handle the negative number for Interruptible Irrigation?

A. For the dataset used for regression estimation, Staff used the same method as described above to estimate a new value to replace the negative number. But, for the billing determinants for the test year, Staff left the negative number in the billing determinants. A general rule of thumb is that rate analysts do not change the initial billing determinants unless an error is found. The negative number could represent an overbilling in another month in the test year, causing an adjustment to overstate the test year billing determinants. And test year billing determinants are aggregated into annual numbers for the calculation of rates, so the negative number should remain part of the annual number.

Q. Did Black Hills change any of the billing determinants?

A. Yes. Staff noticed that the numbers extracted from the billing data worksheet provided by Black Hills were not the numbers found in the initial monthly billing determinants for the Large Volume Transportation Class.[8] Black Hills was asked

[8] Staff extracted the monthly number of bills and customer gas usage from tab WP-2 from Fritel workpaper KSG Direct Exhibit EJF-2,3,4.xlsx. The adjusted Large Volume Transport Class test year billing determinants can be found in tab WP-12 in Fritel workpaper KSG Direct Exhibit EJF-6,7,8.xlsx.

about this in Staff Data Request No. 163. Black Hills acknowledged that they had used another dataset for the Large Volume Transportation billing determinants. "The billing data used for the weather normalization, customer growth and billing determinants are based upon the usage month ("BF Rev Mo"), with one exception. That exception is Large Volume Transportation customers." They did this because they wanted to "to align the customer counts and usage with the month in which they actually occur. Due to the nature of transportation customers and their billing, the revenue month ("revmo") aligns with their actual usage months." For other classes the actual usage month and the revenue month do not necessarily align.

Q. Does Staff accept Black Hills' correction to the data issue with the Large Volume Transportation Class?

A. Yes. The intent of the correction is what Staff would like in all cases―matching as close as possible actual usage with the month it was used in. The resulting Large Volume Transportation test year data looks much more reasonable.

Regression Analysis

Q. What is Regression Analysis?

A. Regression Analysis is a bundle of statistical techniques used to estimate the strength of the relationship between a dependent variable and one or more independent variables.

Q. What is the purpose of performing a regression analysis on weather variables and natural gas usage?

A. Analysts employ regression analysis to derive statistical estimates of weather variables impact on average customer gas usage.

Q. How does regression analysis accomplish estimating the impact of the weather variables on average customer gas usage?

A. The coefficients estimated for the independent weather variables in the regression equation (WSFs) represent the estimated impact of each independent variable on the dependent variable. Put another way, as the independent variables change, the estimate of the dependent variable changes proportionally, and the estimated value of the dependent variable captures the variance explained by the independent variables. The change in the dependent variable that is not accounted for the change in the independent variables is the unexplained variance, which presents itself in the error term. One of the criteria used to evaluate regression equations is how much of the dependent variables' variance the independent variables explain.[9]

Q. What type of regression analysis does Staff use?

A. We use linear regression analysis to estimate the WSFs. The equation below is an example of a simple weather normalizing equation.

$$\boldsymbol{y = a + WSF_1 * HDD + WSF_2 * HDD(-1) + \varepsilon}$$ [10]

In the equation above, the a is the intercept term, the ε is an error term, HDD and $HDD(-1)$ [11] are the independent weather variables, and WSF_1 and WSF_2 are the weather sensitive parameters to be estimated. Using the data described in the ***Data Collection*** section of this testimony, Staff then estimates the WSFs. Attached to

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[9] Ordinary least squares (OLS) estimation minimizes the sum of the squared differences between the actual data and the predicted value of the dependent variable and is the best linear unbiased estimator. There are other methods for estimating the coefficients when OLS has problems, but it is the usual starting point.

[10] In the irrigation equations, the CDD and perception variables are added and nearly always the parameters on the HDD variables indicated the HDD variables are not statistically significant for estimating irrigation demand.

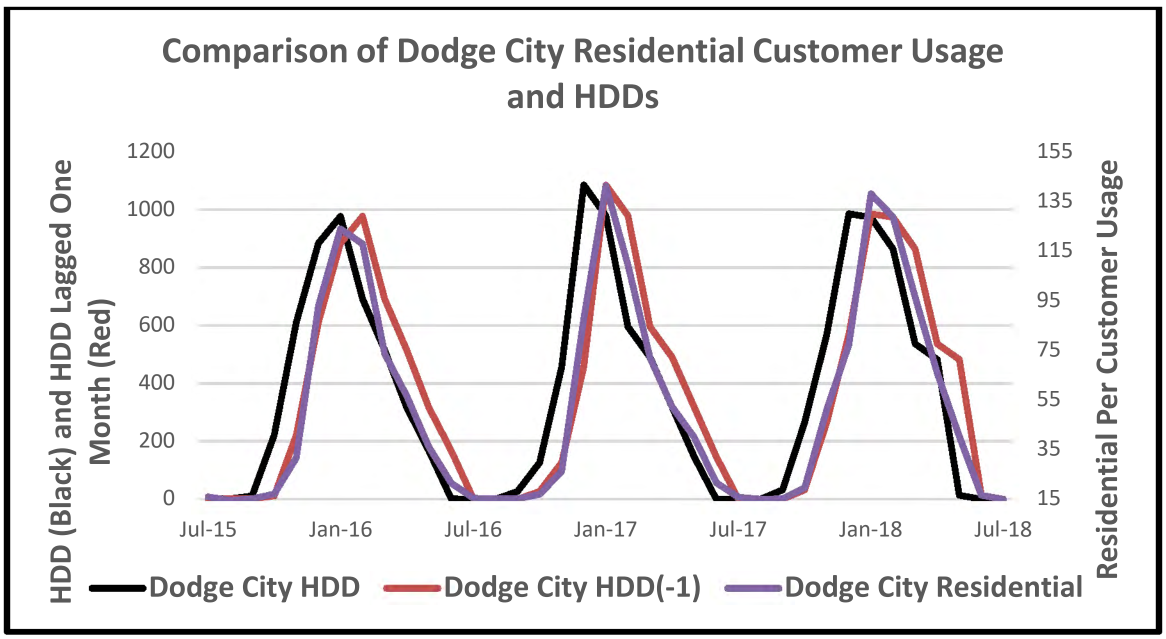
[11] A lagged variable (-1) is the previous month's value when looking at the current month. For example, if the month is October, September HDDs would be the lagged HDDs.

this testimony as Exhibit RHG-2 is a more detailed description of Staff's weather normalization regression analysis methodology.

Q. How does a linear equation capture non-linear seasonal components to average customer gas usage?

A. The HDD and HDD(-1) track average customer usage well for rate classes with a large number of customers. As an example, below in Figure 3 is a graph showing the relationship among HDDs, HDDs(-1), and Residential average customer usage for the Dodge City weather station.

Figure 3



The graph is for only 37 months, July 2015 through July 2018, because if the full dataset was used, then the graph looks like three curves layered on top of each other. The point is the weather variables do an excellent job of explaining the movement of average customer usage when the average customer usage is well-behaved.

The Effect of Bad Data on Regression Estimation

Q. How does bad data affect the regression estimation?

A. Bad data thwarts regression analysis or any kind of statistical analysis. A general truism of statistics is that statistical analysis can only be as good as the data used—"garbage in, garbage out."

To illustrate this point, we will return to the Topeka weather station example of a negative customer usage in October 2022 for the Large Volume Firm Class. Table 4 below shows the estimation of the WSFs using two datasets: the whole dataset available for the regression estimation, October 2014 through September 2024, and a shortened estimation period of February 2022 through September 2024.

Table 4

The Effect of Adjusting the Data on Regression Estimation				
Weather Sensitivity Factors	October 2014 - September 2024			
	Unadjusted		Adjusted	
	Coefficients	Std. Error	Coefficients	Std. Error
TOP_HDD	1.374	0.662	1.537	0.613
TOP_HDD(-1)	9.764	0.663	9.490	0.614
Sum of Coefficients	11.138		11.027	
	February 2022 - September 2024			
TOP_HDD	0.798	1.099	1.640	0.638
TOP_HDD(-1)	11.848	1.050	10.683	0.610
Sum of Coefficients	12.646		12.323	

Q. Why are there two estimation periods?

A. One of the statistical tests that Staff uses is a test of whether there are breakpoints in the estimated model's results—points where the estimated parameters change significantly. The Large Volume Firm Class for the Topeka weather station had multiple breakpoints. And as a result, Staff shortened the estimation period to eliminate the breakpoints from the estimation period.[12]

Q. What is the effect of the adjustment on the estimation result?

A. For the whole dataset, the adjustment changes the relative size of the WSFs with the current period HDD coefficient increasing from 1.374 to 1.537 and the previous period declining from 9.764 to 9.490. But the sums of the coefficients, basically the net effect of the HDD variables, for the estimates are about 1%: the difference in the sums of the coefficients is 11.138 vs. 11.027.

However, the regression estimation from the shorter period does show some substantial differences. First, the sum of the WSF values is larger between the unadjusted and adjusted datasets: with the unadjusted dataset 12.646 and 12.323 for the adjusted dataset.

Second, the standard error for the current period HDD with the unadjusted dataset is large compared to the coefficient value, 0.798 vs. 1.099. That means that potential negative values of the HDD coefficient value and the adjusted coefficient value lie within one standard deviation of the estimated HDD coefficient value. In a normal distribution, approximately 68% of the data falls within one standard deviation of the mean which is the estimated coefficient value in this case, and the mean converges to a standard distribution. If this were the dataset and model chosen by Staff, the current HDD variable would be eliminated from the model because by traditional frequentist standards it is insignificant.

[12] More explanation of breakpoints is provided later in the current section of this testimony.

Third, all of the model test statistics, such as the adjusted R^2, F-statistic, loglikelihood function, and the information criteria, indicate that the model performs much better with the adjusted dataset than with the unadjusted dataset. Therefore, Staff concludes that adjusting and shorting the dataset provides a better estimate of the WSF coefficients.

Q. Even though the adjustment adds to the total customer usage, the WSFs are smaller with the unadjusted dataset than with the adjusted dataset. Please explain the reason for this unintuitive result.

A. Although the result seems unintuitive, there is an explanation for this conundrum, but it requires some explanation. As the variance in the dependent variable decreases, the coefficient values of the independent variables in a regression model tend to decrease. This is because when the variance in the dependent variable is smaller, there's less variation for the independent variables to capture. This leads to a smaller coefficient for each independent variable because it represents the proportion of the total variance explained by that particular variable. There are exceptions to this observation, but this case follows the usual behavior.[13]

Other Potential Problems with Regression Analysis

Q. Were there any other regression estimation issues?

A. Yes. Here are the three major problems.

(1) Even including the weather variables, it was not possible to capture all the seasonal effects in the data. Because the data was collected at regular

[13] Since the method of estimation used is OLS, the coefficients are calculated to reduce the variance of the dependent variable, average customer usage. The standard deviation of average customer usage, the square root of the variance, in the unadjusted shortened dataset is 5,002 while in the adjusted shortened dataset it is 4,705. With a larger variance, a larger coefficient is needed to minimize the variance.

intervals over an extended period of time, seasonal serial correlation was usually present in the data.[14]

(2) In addition, the HDD and HDD(-1) variables for all weather stations had unit roots as did most of the average customer usage variables.

(3) Finally, after estimating a model, Staff checked for breakpoints in the estimation—points where estimated parameters changed significantly

These issues and Staff's resolution are discussed in Exhibit RHG-2, which contains a fuller description of our weather normalization regression analysis.

Volumetric Adjustment

Q. Please describe the process used to calculate the volumetric usage adjustments.

A. To calculate the appropriate adjustment to usage, the actual weather variables were subtracted from the normal weather variables for each month of the test year.[15] These calculated differences were multiplied by the WSFs and then multiplied by the number of class customer bills for each month since the WSFs were estimated for per capita customer usage. The result is the estimated change in usage attributable to deviations from normal weather.[16] This calculation is done for each

[14] Autocorrelation is the correlation of a time series variable with earlier and later value of itself. For example, the best predictor of next period US Gross Domestic Product (GDP) is current period's GDP plus or minus a small percentage change because US GDP is autocorrelated. Seasonality in time series data are regular patterns in the data. For example, air conditioning usage increases in the spring through the summer and then decreases in the fall through the winter.

[15] The reason for subtracting the actual weather variables from the normal weather variables is that if the weather was colder than normal, the resulting subtraction would be negative and reduce the customer usage. If it were warmer than usual, the reverse would happen.

[16] $(Volumetric\ Adjustment) = \left[\left(\binom{Normal}{HDDs, CDDs, or\ Precipitation} - \binom{Actual}{HDDs, CDDs, or\ Precipitation}\right)(WSF)\right] * (Customer\ count)$

customer class for each weather station, and the sum of all those adjustments is the total weather normalized volumetric adjustment.

Revenue Adjustment

Q. Please describe the process used to calculate the revenue adjustment.

A. The process began with the volumetric sales adjustments for each customer class. The volumetric sale adjustment was then multiplied by the appropriate rate for that customer class.[17] The result is the estimated revenue adjustment necessary to adjust test year revenues to reflect weather-normalized volumetric sales for that class. The sum of all those adjustments is the total weather-normalized revenue adjustment.

Results

Q. What were the results of Staff's weather normalization analysis?

A. Staff's total volumetric adjustment is 12,715,734 therms[18] which translates into a revenue adjustment of $2,443,167.

Q. How do Staff's adjustments compare to Black Hills weather normalization adjustments?

A. The answer to this question is a little more complex than it appears. Black Hills' weather normalization adjustments are 1,381,083 therms that translate into a revenue adjustment of $269,391.

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[17] $(Revenue\ Adjustment) = \begin{pmatrix} Volumetric \\ Adjustment \end{pmatrix} * \begin{pmatrix} Applicable \\ Tariff\ Rate \end{pmatrix}$

[18] A therm is a measure of the heat energy. For contrast, a BTU is the fundamental unit of heat energy. "One BTU is the amount of heat it would take to raise the temperature in one pound of water by one degree Fahrenheit." A therm has slightly more heat energy on average than the BTUs created by buring 100 cubic feet of natural gas in the United States. https://naturalgasplans.com/difference-between-ccf-mcf-therm/

Q. Are Staff's and Black Hills' weather normalizations commensurable?

A. No. Black Hills' adjustments are not commensurable with Staff's adjustments. Black Hills only weather normalized Residential, Small Commercial, Small Volume Firm, and Large Volume Firm Classes. It made a normalizing adjustment for Irrigation Interruptible and Transport, but it was not formally a weather normalization adjustment.[19] We weather normalized all sales and transportation classes that gave reasonable results including the two irrigation classes. The appropriate weather normalization comparison is to include all the sales and transportation classes except for the irrigation classes, which can be found in Table 5 below.

Table 5

Staff and Black Hills Weather Normalization				
	Staff		Black Hills	
Customer Classification	Volumetric Adjustment	Revenue Adjustment	Volumetric Adjustment	Revenue Adjustment
Residential	8,524,700	1,726,337	1,024,730	207,518
Small Commercial	1,732,242	350,796	212,191	42,971
Small Voluum Firm	1,539,149	240,200	97,281	15,182
Large Voluum Firm	238,501	18,930	46,881	3,721
Large Voluum Interuptible	1,662	132		
Small Commercial Transport	74,233	12,496		
Small Voluum Transport	602,928	94,093		
Large Voluum Transport	2,317	184		
Total	12,715,734	2,443,167	1,381,083	269,391

[19] Staff and Black Hills' irrigation adjustments will be discussed after Staff's customer annualization discussion.

Q. How much larger is Staff weather normalization adjustment than Black Hills' adjustment?

A. Staff's weather normalization adjustment is a little over 9 times larger than Black Hills' adjustment. If only the classes weather normalized by both Black Hills and Staff are considered, our adjustment is about 8⅔ larger.

Q. Why is Staff's weather normalization adjustment so much larger than Black Hills' adjustment?

A. The primary reason is that Staff's WSFs (the coefficients in from the regression equations) are much larger than Black Hills' WSF. Table 6 below shows Staff's estimated coefficients for the last rate case (21-BHCG-418-RTS) along with Black Hills' and our estimated coefficients for this rate case for the four rate classes that we both estimated.

Table 6

Comparision of Staff & Black Hills Heating Coefficients
Dockets No. 21-BHCG-418-RTS and 25-BHCG-298-RTS

Docket and Weather Station	RESIDENTIAL			SMALL COMMERCIAL			SMALL VOLUME FIRM			LARGE VOLUME FIRM		
	HDD (a)	HDD-1 (b)	SUM (c)=(a)+(b)	HDD (d)	HDD-1 (e)	SUM (f)=(d)+(e)	HDD (g)	HDD-1 (h)	SUM (i)=(g)+(h)	HDD (j)	HDD-1 (k)	SUM (l)=(j)+(k)
STAFF: 21-BHCG-418-RTS												
Concordia[1]	(0.01)	0.12	0.11	**0.01**	**0.20**	**0.20**	**0.01**	**0.20**	**0.20**	**0.01**	**0.20**	**0.20**
Dodge City	0.04	0.08	0.12	0.07	0.20	0.27	0.45	1.00	1.45	**0.00**	**0.00**	**0.00**
Goodland	0.02	0.11	0.13	0.04	0.25	0.28	0.31	0.75	1.06	**0.00**	**0.00**	**0.00**
Topeka	0.03	0.09	0.12	0.09	0.32	0.41	0.09	0.32	0.41	0.00	23.70	23.70
Wichita	0.04	0.09	0.13	0.18	0.37	0.55	0.18	0.37	0.55	1.29	11.85	13.14
25-BHCE-298-RTS												
STAFF												
Concordia	(0.02)	0.11	0.10	(0.03)	0.19	0.16	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Dodge City	0.04	0.08	0.12	0.07	0.20	0.28	0.47	1.18	1.65	**0.00**	**0.00**	**0.00**
Goodland	0.03	0.06	0.09	0.03	0.24	0.26	0.14	0.76	0.90	**0.00**	**0.00**	**0.00**
Topeka	0.03	0.10	0.13	0.06	0.24	0.30	0.34	1.33	1.67	1.64	10.68	12.32
Wichita	0.04	0.10	0.14	0.10	0.22	0.33	0.67	1.48	2.15	3.04	19.30	22.33
BLACK HILLS												
Concordia	0.00	0.03	0.03	0.00	0.04	0.04	0.00	0.06	0.06	0.08	0.00	0.08
Dodge City	0.01	0.02	0.02	0.01	0.04	0.05	0.08	0.21	0.29	1.68	0.89	2.57
Goodland	0.00	0.02	0.03	0.00	0.05	0.06	0.07	0.15	0.22	0.16	0.00	0.16
Topeka	0.00	0.02	0.02	0.01	0.04	0.05	0.05	0.23	0.28	0.25	1.99	2.24
Wichita	0.01	0.02	0.02	0.02	0.04	0.05	0.10	0.25	0.35	0.16	3.90	4.06

NOTE[1]: Concordia commercial classes were all estimated as one large group and then the estimated coefficients were applied to all commercial classes. Black Hills did this for all the weather stations, but Staff only did this for Concordia and then estimated the other weather station classes individually.

NOTE (General): Zeros indicate that either their was no data for the class or we were unable to find an adequate model to estimate the class.

NOTE (General): Because Black Hills estimated all of the Commercial classes together in the 21-BHCG-418 docket, any comparison of Black Hills commercial estimations in the 21-418 docket with Staff and Black Hills' commercial estimations in the current docket, are not commensurable.

Q. How large are the differences between Staff's WSFs and Black Hills' WSFs?

A. Table 7 on the next page shows the result of dividing Staff's WSFs by Black Hills' WSFs. The blank space in Table 7 are a result of Black Hills eliminating estimated coefficients that are negative because it results in dividing by zero. Notice how large the difference in the coefficients is.

Q. Why the large difference between Staff's and Black Hills' WSFs?

A. Staff has been unable to identify the reason for the large difference. Staff uses Eviews statistical software to do our econometric estimation. Black Hills revealed that they used the R statistical software to do their estimation. We estimated the four classes that Black Hills estimated in both Eviews and R. Our results were similar—the first two digits for the estimations were almost always the same for Eviews and R. However, as noted above, our estimates of the WSFs in this docket are close in most cases to our estimates in the last Black Hills rate case.

Table 7

Comparision of Staff & Black Hills Heating Coefficients: Docket No. 25-BHCG-298-RTS
Staff estimated coefficients divided by Black Hills estimated coefficients

Weather Station	RESIDENTIAL		SMALL COMMERCIAL		SMALL VOLUME FIRM		LARGE VOLUME FIRM	
	HDD (a)	HDD-1 (b)	HDD (d)	HDD-1 (e)	HDD (g)	HDD-1 (h)	HDD (j)	HDD-1 (k)
STAFF/BLACK HILLS								
Concordia		4.38		4.55		0.00	0.00	
Dodge City	5.36	5.27	5.49	5.02	6.07	5.61	0.00	0.00
Goodland	7.57	2.71	7.52	4.37	1.97	5.09	0.00	
Topeka	5.81	5.66	9.54	6.04	6.99	5.76	6.59	5.37
Wichita	6.85	5.62	6.82	6.15	6.63	5.91	19.19	4.94

NOTE: Black Hills eliminated negative coefficients when calculating its weather normalization. That is the reason for the blank cells. Staff retained the negative coefficients if the absolute value of the negative coefficient was smaller than the positive coefficient. Staff's reason for retaining the negative coefficient is that the incorporation of the current and lagged value ot the HDD variables results in the data choosing the relative weights of each variable. If the negative coefficient is eliminated, then the equation needs to be reestimated so that the proper impact of the weather on average usage is estimated. That is the reason that it is the sum of the coefficients that reveals the impact of the weather.

Q. Are Black Hills's WSFs from the previous rate case similar to their WSFs in this rate case?

A. In the 21-BHCG-418-RTS docket, Black Hills estimated the Residential Class separately, but combined the data for Small Commercial, Small Volume Firm, and Large Volume Firm Classes and made one estimation for each weather station. And then used those WSFs for all three classes from the same weather station. So, the only commensurable comparison is with the Residential Class between the last rate case and this rate case. Table 8 below shows the comparison between the last rate case and the current rate case for the WSFs for the Residential Class.

Table 8

Black Hills Residential Heating Coefficients: Dockets No. 21-BHCG-418-RTS & 25-BHCG-298-RTS

Weather Stations	HDD (a)	HDD-1 (b)	SUM (c)=(a)+(b)
21-BHCG-418-RTS			
Concordia	(0.010)	0.113	0.103
Dodge City	0.036	0.082	0.118
Goodland	0.018	0.110	0.128
Topeka	0.021	0.096	0.118
Wichita	0.033	0.097	0.131
25-BHCE-298-RTS			
Concordia	(0.003)	0.026	0.023
Dodge City	0.008	0.015	0.023
Goodland	0.004	0.023	0.027
Topeka	0.005	0.018	0.023
Wichita	0.006	0.017	0.024

Q. How do the WSFs compare across the two rate cases?

A. The best comparison is to compare the sum of the coefficients. Notice that the WSFs from the previous rate case are about 4 to 5 times larger than the coefficients in the current rate case.

VI. ANALYSIS: CUSTOMER ANNUALIZATION

<u>Purpose</u>

Q. What is the purpose of annualizing customer bills?

A. Because test-year revenue should reflect normal ongoing operations, the Commission sets rates based on the current number of customers and their usage. Through the customer annualization process, test year customer bills, volumes, and revenues are adjusted to reflect the number of customers in each customer class Black Hills was serving at the end of the test year. In other words, the adjustment represents the revenue Black Hills would have received if the number of customers at year-end had received service throughout the entire test year.

<u>Process</u>

Data Collection

Q. Who supplied Staff with the customer bills and customer usage for customer class by weather station?

A. As discussed above, Black Hills supplied monthly customer bills and usage for its Sales and Transportation Classes by weather station.

Customer Coefficient Calculation

Q. What is the customer coefficient?

A. The customer coefficient represents the change in the number of customers each month, assuming the change occurred at a constant rate throughout the test year.

Q. How did Staff calculate the customer coefficients?

A. Staff calculated customer coefficients by subtracting September 2023 customer bills from September 2024 customer bills for each class by weather station. This value was then divided by twelve to evenly spread the difference across the test-year months.[20]

Customer Bill Adjustment

Q. Please describe how the customer coefficients are used to calculate annualized monthly customer bills?

A. Beginning in October 2023 of the test year, the customer coefficient is multiplied by 11.5 (November 2023 by 10.5, and so on) and continues until the actual customer bills and annualized customer bills are equal.

Q. Why did Staff annualize customer bills using this method?

A. We annualize customer bills using this method for two reasons. First, it simulates the number of customers Black Hills was serving at the end of the test year as if they were served throughout the entire test year. Second, by multiplying by 11.5 and so on, Staff is approximating the change in the number of bills resulting from the increase/decrease of customers joining at different times throughout the month

[20] $Customer\ Coefficient = \frac{September\ 2023\ Customer\ Count - September\ 2022\ Customer\ Count}{12}$

instead of all joining at the beginning of the month. This is the same method Staff has used in other recent gas rate cases.

Volumetric Adjustment

Q. How did Staff calculate the volume adjustment?

A. In order to derive annualized monthly volumes, Staff multiplied the annualized customer bill times the monthly weather normalized volumes per customer across each rate class and corresponding weather station. The use of the weather normalization volumes and the interaction between weather normalization and customer annualization is illustrated in Figure 4 on the next page.

Revenue Adjustment

Q. How did Staff calculate the revenue adjustment?

A. In order to arrive at monthly adjusted revenues, we added the product of the annualized monthly volumes and the corresponding volumetric charge to the product of the annualized customer bill and the corresponding basic service charge. The final test year adjustment is the sum of adjusted revenues across all months in the test year associated for each customer class and weather station.

Figure 4

Interaction between Staff Models

The Interaction between Staff's Statistical Heating Coefficient Models and Staff's Calculation of Weather Normalization and Customer Annualization Model

Staff's Weather Normalization Regression Models

$$\left(\frac{\begin{matrix}Volumetric\\Usage\end{matrix}}{\begin{matrix}Bill\\Count\end{matrix}}\right) = \beta_0 + \beta_1 * HDD_t + \beta_2 * HDD_{t-1} + \begin{pmatrix}Seasonal\\Adjustment\end{pmatrix} + \varepsilon_t$$

β_1, β_2 are the heating coefficients

Staff's Weather Normalization and Customer Annualization Model

(1) ***The calculation of the per capita volumetric weather adjustment:***

$$\begin{pmatrix}Per\ Capita\\Volumetric\\Weather\\Adjustment\end{pmatrix} = \left[\begin{pmatrix}Normal\\Weather\\Variables\end{pmatrix} - \begin{pmatrix}Actual\\Weather\\Variables\end{pmatrix}\right] * \begin{pmatrix}Heating\\Coefficents\end{pmatrix}$$

(2) ***The calculation of the aggregate volumetric weather adjustment:***

$$\begin{pmatrix}Aggregate\\Volumetric\\Weather\\Adjustment\end{pmatrix} = \begin{pmatrix}Per\ Capita\\Volumetric\\Weather\\Adjustment\end{pmatrix} * \begin{pmatrix}Bill\\Count\end{pmatrix}$$

(3) ***The calculation of the aggregate volumetric customer annualization adjustment:***

$$\begin{pmatrix}Aggregate\\Volumetric\\Customer\\Annualization\end{pmatrix} = \left[\left(\frac{\begin{matrix}Volumetric\\Usage\end{matrix}}{\begin{matrix}Bill\\Count\end{matrix}}\right) + \begin{pmatrix}Per\ Capita\\Volumetric\\Weather\\Adjustment\end{pmatrix}\right] * \begin{pmatrix}Bill\\Count\\Adjustment\end{pmatrix}$$

Changes in Bill Count and Volumetric Usage

(1) Changes in both can affect the heating coefficients by affecting the left-hand side
(2) Changes in the number of bills can affect aggregate volumetric weather adjustment
(3) Changes in volumetric usage can affect aggregate volumetric customer annualization adjustment

Results

Q. What customer annualization adjustment is Staff recommending?

A. Staff's calculation of the customer annualization results for changes in customer bill, volumetric, and revenue adjustments are shown in Table 8 below. The Large Volume Transport Class and the two irrigation classes are not included. The Large Volume Transport Class will be discussed later in this section and the irrigation customer annualization adjustments will be added to the irrigation weather normalization adjustment and discussed in the next section. The customer bill adjustment is 363, volumetric adjustment is 209,411 therms, and a total revenue increase is $121,746.

Table 9

Staff's Customer Annualization			
Customer Classification	Customer Bill Adjustment	Volumetric Adjustment	Revenue Adjustment
Residential	328	267,574	127,002
Small Commercial	50	84,315	33,875
Small Voluum Firm	(7)	(78,227)	(17,668)
Large Voluum Firm	1	104,411	12,547
Large Voluum Interuptible	0	0	0
Small Commercial Transport	(2)	(6,643)	(1,585)
Small Voluum Transport	(9)	(162,019)	(32,425)
Total	363	209,411	121,746

Q Did Black Hills do a customer annualization adjustment?

A. No. The three new customers in the Large Volume Transport Class discussed above are the only change in the number of customers made by Black Hills.

VII. ANALYSIS: IRRIGATION ADJUSTMENTS

Black Hills' Method for Normalizing Irrigation

Q. Why is there an irrigation adjustment separate from the other class adjustments?

A. Black Hills estimated an irrigation adjustment using a different normalization process than the process generally used for either weather normalization or customer annualization.

Q. What method did Black Hills use to estimate its irrigation adjustments?

A. Black Hills used a three-step method to estimate its irrigation adjustments.

Step 1. Black Hills used a ten-year average of the monthly average usage per customer as normal irrigation conditions.

Step 2. Black Hills calculated the difference between the ten-year average and the actual test year average customer usage.

Step 3. Black Hills took the difference between the ten-year average and the test year average usage and multiplied by the delivery (volumetric) charge.

Q. What is Black Hills justification for using a different method for estimating an irrigation adjustment?

A. Black Hills justifies its use of a ten-year average of annual average usage as a "normal" by pointing out that, "A ten-year average takes into account multiple considerations that can affect irrigation usage from year-to-year, including HDDs, localized precipitation, crop rotations, improved efficiency, and various other factors."[21] Earlier in his testimony, Mr. Fritel notes again that multiple causes could

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[21] Ethan Fritel, Direct Testimony, Docket No. 25-BHCG-298-RTS, pp. 15-16.

have caused the increased irrigation during the test year, however he does suggest that "the higher irrigation usage during the Test Year was likely the result of drier conditions that resulted in the need for increased irrigation."[22]

Staff's Objections to Black Hills' Method of Estimating an Irrigation Adjustment

Q. Does Staff think this method is appropriate for normalizing irrigation?

A. No. Staff determined that using the standard weather normalization and customer annualization methods provide a better estimate of the irrigation adjustment.

Q. Why?

A. (1) Using the average of average usage for 10 years for normalization is more than just weather normalization and customer annualization. It is protection from technological improvements in irrigation such as drip irrigation and smart irrigation with soil sensors. It is protection from secular trends in the natural gas industry.

(2) There have been substantial changes in both the number of customers and the average customer usage over the 10 year period. Figure 5 below shows the change in the average annual number of customers for Sales and Transportation Irrigation Customers, and Figure 6 below Figure 5 shows the annual average use per customer for both classes.[23] Because of the substantial changes, it is not average annual customer usage that should normalized, but the major cause of the changes in average annual customer usage, which leads to number (3).

[22] *Ibid*. p. 15.
[23] The data underlying Figures 5 and 6 are from Exhibit EJF-5.

Figure 5

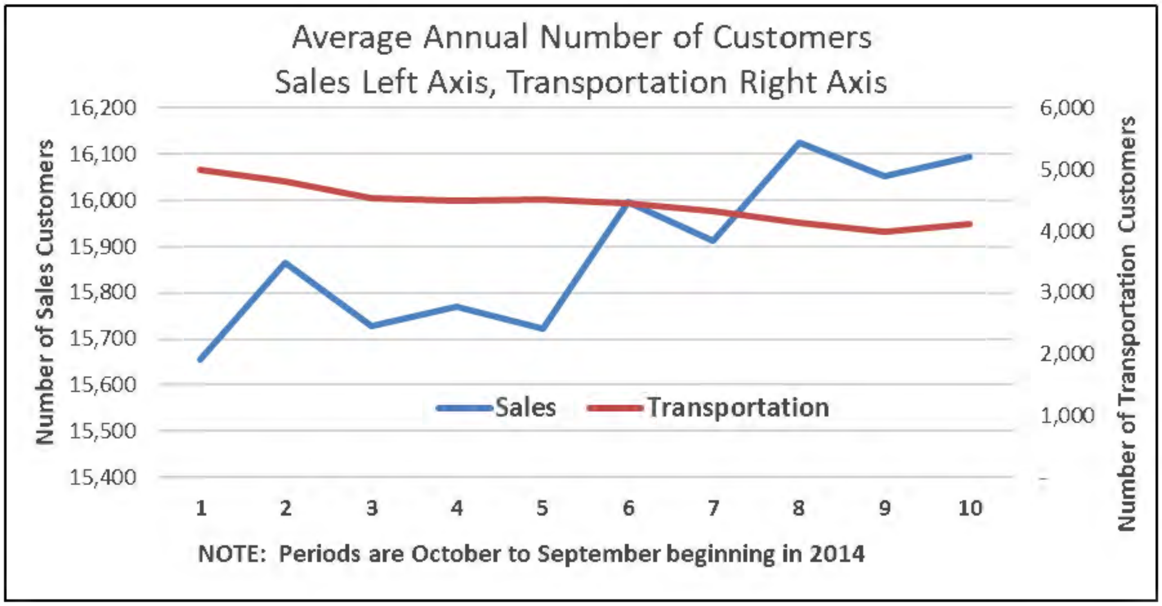
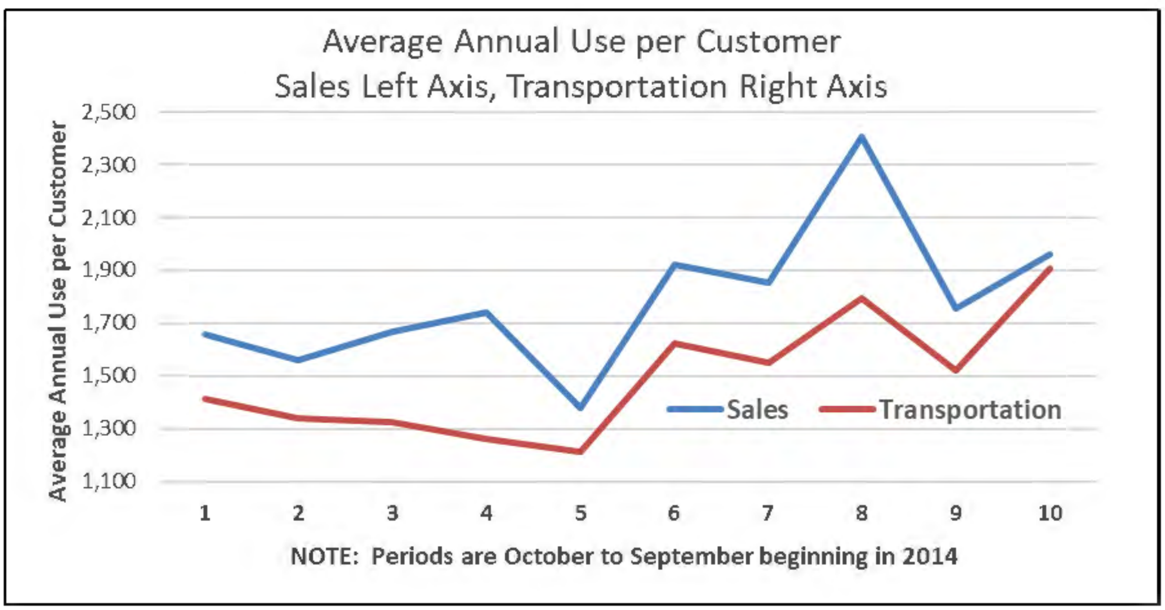


Figure 6



(3) Kansas has been in a drought for the past few years, as Figure 7 below illustrates, which would explain increased irrigation. The brown areas below zero in the graph show months below average wetness using the Palmer Drought Severity Index whose classification is shown in Table 10 below Figure 7.

Figure 7

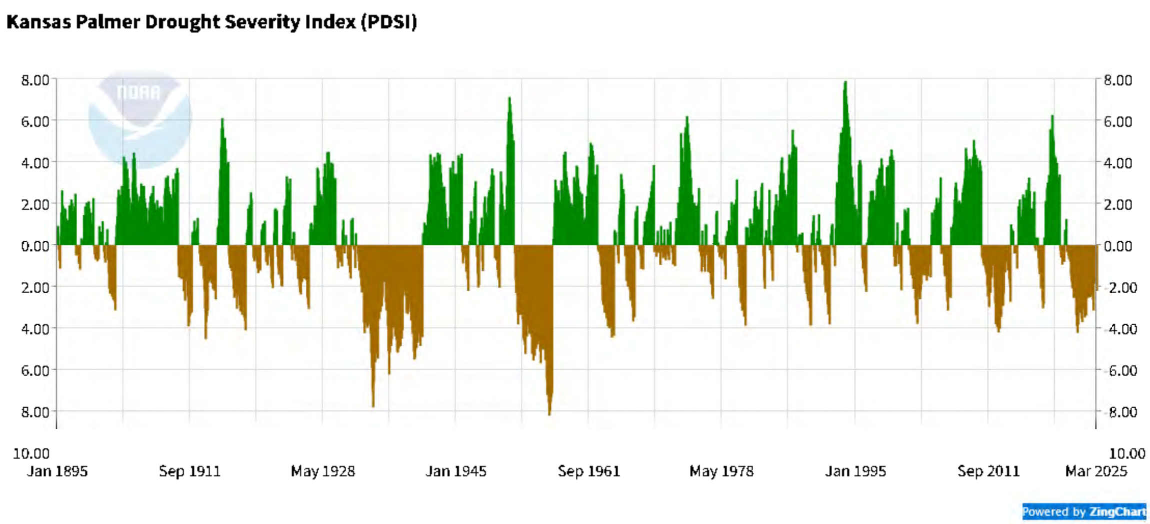


Table 10

Classification of the Palmer Drought Severity Index (PDSI) Near Normal Conditions Are 0.49 to (0.49)			
Wet Conditions		**Dry Conditions**	
PDSI value	**Classification**	**PDSI value**	**Classification**
0.5 to 0.99	Incipient Wet Spell	(0.5) to (0.99)	Incipient Dry Spell
1.0 to 1.99	Slightly Wet	(1.0) to (1.99)	Mild Drought
2.0 to 2.99	Moderate Wet	(2.0) to (2.99)	Moderate Drought
3.0 to 3.99	Very Wet	(3.0) to (3.99)	Severe Drought
4.0 or more	Extremely Wet	(4.0) or Less	Extreme Drought
NOTE: Numbers in paranthesis and red are negative numbers.			

Figure 7 illustrates that 10 years is not long enough to get the full Kansas drought cycle. Thus, using a shorter period of time for calculating an irrigation normal is inadequate. Just to capture the current cycle, one would need to go back to 2011 or 2012. And the drought part of the cycle is not over yet.

Staff's Irrigation Adjustment

Q. How did Staff estimate its irrigation adjustments?

A. We used the same techniques we did to estimate the adjustments in the other classes. First, we weather normalized the irrigation classes using primarily precipitation, but also cooling degree days (CDD), which capture the warmth of Spring, Summer, and Autumn. Second, we used customer annualization to capture the changes in customer bill count. Table 11 shows our results.

Table 11

Staff Irrigation Adjustment					
Customer Classification	Weather Normalization		Customer Annualization		
	Volumetric Adjustment	Revenue Adjustment	Customer Count Adjustment	Volumetric Adjustment	Revenue Adjustment
Irrigation Interruptible	(1,929,031)	(103,743)	(258)	(366,214)	(33,518)
Irrigation Transport	(408,730)	(21,981)	(54)	(70,262)	(6,209)
Total	(2,337,761)	(125,725)	(312)	(436,476)	(39,727)

Q. How does Staff's irrigation adjustment compare to Black Hills' adjustment?

A. Table 12 compares our irrigation adjustments to Black Hills's irrigation adjustments. Staff's adjustments are in the same direction as Black Hills' adjustments, but substantially smaller in absolute value terms.

Table 12

Staff and Black Hills Irrigation Adjustment				
	Staff		Black Hills	
Customer Classification	Volumetric Adjustment	Revenue Adjustment	Volumetric Adjustment	Revenue Adjustment
Irrigation Interruptible	(2,295,246)	(137,261)	(3,099,240)	(166,677)
Irrigation Transport	(478,991)	(28,190)	(1,264,726)	(68,017)
Total	(2,774,237)	(165,451)	(4,363,967)	(234,694)

<u>**Recommendations**</u>

Q. Now that Staff's weather normalization, customer annualization, and irrigation analysis are complete, do you have any recommendations?

A. Yes. I recommend the Commission accept our weather normalization and irrigation adjustment (Staff IS-19) of $2,243,019. Additionally, I recommend the Commission accept our customer annualization adjustment (Staff IS-20) of $121,746.

Q. Because Staff used both the weather normalization analysis and the customer annualization analysis to create the irrigation analysis, did you make sure to not include any double counting?

A. Yes. First, we pulled the irrigation classes out of both the weather normalization and customer annualization analysis. Next, to make a separate irrigation adjustment, we combined the weather normalization and customer annualization for the irrigation. The combining of Staff's weather normalization and irrigation adjustments allowed for a commensurate comparison to Black Hills IS-8 adjustment. Put another way, Staff's IS-19 and Black Hills IS-8 adjustments are commensurable.

VIII. ANALYSIS: BILLING DETERMINANTS

<u>Staff's Proposed Billing Determinants</u>

Q. Have you put together a table that shows the initial billing determinants and Staff's adjustments?

A. Yes. Table 13 on the next page shows the initial billing determinants, the same initial billing determinants used by Black Hills, and then shows Staff's adjustments to those billing determinants. The initial number of bills are shown in column (a). Column (b) has Staff's customer bill adjustment from its customer annualization. Column (b) also includes Black Hills Large Volume Transport Class customer additions: 3 customers, 36 bills. Column (c) combines the initial number of bills with Staff's bill adjustments. Column (d) has the initial customer usage in therms. Column (e) has Staff's customer usage adjustment from our customer annualization. Column (f) has Staff's customer usage adjustment from our weather normalization analysis. Finally, Column (g) has Staff's final estimate of customer usage, adding together Columns (d), (e), and (f).

Table 13

Staff's Billing Determinants							
Customer Class	Number of Bills	Staff's Customer Adjustment	Staff's Adjusted Number of Bills	Customer Usage (Therms)	Staff's Customer Adjustment (Therms)	Staff's Weather Norm Adjustment (Therms)	Staff's Adjusted Customer Usage (Therms)
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Residential	1,271,308	328	1,271,636	61,963,635	267,574	8,524,700	70,755,908
Small Commercial - Sales	116,091	50	116,141	12,196,387	84,315	1,732,242	14,012,944
Small Commercial - Transportation	2,452	(2)	2,451	604,152	(6,643)	602,928	1,200,438
Small Volume Firm	15,397	(7)	15,391	12,889,053	(78,227)	1,539,149	14,349,976
Small Volume Transportation	5,511	(9)	5,503	6,600,794	(162,019)	602,928	7,041,703
Large Volume Firm	505	1	506	3,879,337	104,411	238,501	4,222,250
Large Volume Transportation	1,429	36	1,465	59,860,668	5,118,400	2,317	64,981,385
Large Volume Interruptible	181	0	181	2,410,164	0	1,662	2,411,826
Subtotal	1,412,874	399	1,413,273	160,404,190	5,327,811	13,244,429	178,976,430
Irrigation Service	16,095	(258)	15,837	31,586,269	(366,214)	(1,929,031)	29,291,023
Irrigation Transportation	4,123	(54)	4,069	7,860,659	(70,262)	(408,730)	7,381,668
Total Sales and Transportation	1,433,092	87	1,433,179	199,851,118	4,891,335	10,906,668	215,649,121

Q. How do Black Hills' final billing determinants compare with Staff's estimates?

A. Table 14 on the next page has Black Hills' final billing determinants. Columns (a) and (b) have the initial number of bills and customer usage. Column (c) has only the 36 additional bills from the new Large Volume Transport customers, and Column (d) has the expected usage by these new customers. Column (e) has Black Hills weather normalization and their irrigation adjustment. Finally, Columns (f) and (g) have the final estimated number of bills and customer usage.

Table 14

Black Hills Customer Count and Customer Usage							
Customer Class	**Number of Bills**	**Customer Usage (Therms)**	**Customer Additions Bills**	**Customer Additions (Therms)**	**Weather Norm Adjustment (Therms)**	**Adjusted Number of Bills**	**Adjusted Customer Usage (Therms)**
	(d)	(b)	(c)	(d)	(e)	(f)	(g)
Residential	1,271,308	61,963,635			1,024,730	1,271,308	62,988,365
Small Commercial - Sales	116,091	12,196,387			212,191	116,091	12,408,578
Small Commercial - Transportation	2,452	604,152				2,452	604,152
Small Volume Firm	15,397	12,889,053			97,281	15,397	12,986,334
Small Volume Transportation	5,511	6,600,794				5,511	6,600,794
Large Volume Firm	505	3,879,337			46,881	505	3,926,218
Large Volume Transportation	1,429	59,860,668	36	5,118,400		1,465	64,979,068
Large Volume Interruptible	181	2,410,164				181	2,410,164
Subtotal	**1,412,874**	**160,404,190**	**36**	**5,118,400**	**1,381,083**	**1,412,910**	**166,903,673**
Irrigation Service	16,095	31,586,269			(3,099,240)	16,095	28,487,029
Irrigation Transportation	4,123	7,860,659			(1,264,726)	4,123	6,595,933
Total Sales and Transportation	**1,433,092**	**199,851,118**	**36**	**5,118,400**	**(2,982,884)**	**1,433,128**	**201,986,634**

NOTE: Black Hills only weather normalized the Residential, Small Commercial, Small Volume, and Large Volume Sales Classes. Black Hills used another normalizing technique for normalizing the Irrigation Classes.

Although Staff and Black Hills started with the same initial billing determinants, Staff's final number of bills and customer usage were larger than Black Hills'. Table 15 below has a comparison of the total sales and transportation billing determinants.

Table 15

Staff and Black Hills' Final Billing Determinants		
Total Sales and Transportation	**Number of Bills**	**Customer Usage (Therms)**
Initial Billing Determinants	1,433,092	199,851,118
Staff Final Billing Determinants	1,433,179	215,649,121
Black Hills Final Billing Determinants	1,433,128	201,986,634

Staff's final billing determinants have 51 more bills and 13,662,487 therms than Black Hills. The difference in therms is almost all due to Staff's much larger weather normalization adjustment.

IX. CONCLUSION

Q. Please summarize your recommendation.

A. I recommend that the Commission accept Staff's weather normalization and Irrigation adjustment (Staff IS-19) of $2,243,019 and customer annualization adjustment (Staff IS-20) of $121,746. In addition, I recommend the Commission accept Black Hills' revenue synchronization adjustment of $136,907 and Large Volume Transport adjustment of $419,027.

Finally, I recommend the Commission accept Staff' adjusted billing determinants, which include Staff's weather normalization and customer annualization number of customer bills and customer adjustments for use in revenue allocation and rate design.

Q. Does this conclude your testimony?

A. Yes. Thank you.

EXHIBIT RHG-1

DOCKET NO. 25-BHCG-298-RTS

Data Problems with Black Hills'

Number of Bills and Customer Gas Usage

Data Problems with Black Hills' Number of Bills and Customer Gas Usage

Data Problems

Billing Data Problems

We recognize that data problems happen, especially since we are using billing data. Ideally, the data provided for weather normalization and customer annualization would be usage rather than billing data. But usually that is not possible, such as this docket, where the only readily available data is billing data.

There can be multiple problems with billing data because of the billing configuration. For example, there can be a billing error in one month that is corrected in a different month. Because of the correction of billing errors and other reasons, billing data tends to be "noisy." Through aggregation and averaging, some of the deficiencies in the data are mitigated, though aggregation is usually effective if a class is sufficiently large. However, commercial and industrial classes usually have smaller numbers of customers and aggregation is less effective at smoothing the data. All of the major data problems in this docket happened with the commercial and industrial class.

Organization

The specific issues we will discuss are:

(1) October 2022
(2) Large Volume Transport
(3) Large Volume Firm
(4) Concordia—Irrigation Interruptible
(5) Methods Used to Mitigate Problems

October 2022: Multiple Case of Unexpected Data

Dodge City, Goodland, Topeka, and Wichita all have unexpected data for October 2022. The worst situation is Topeka which has six classes with strange data for October 2022.

Topeka

In Table 1 below are the data for October 2022 and the six months before and after for the four rate classes that Mr. Fritel weather normalized. In each class, October 2022 is an outlier or nearly an outlier. In particular, the negative usage by the Large Volume Class is an obvious problem.

Table 1

	Topeka					
	Residential			Small Commercial		
	Cust Count	Usage	Avg Usage	Cust Count	Usage	Avg Usage
Apr-22	36,599	2,148,512	**58.70**	2,407	286,836	**119.17**
May-22	36,695	1,087,590	**29.64**	2,460	139,614	**56.75**
Jun-22	37,127	542,649	**14.62**	2,447	63,612	**26.00**
Jul-22	33,649	362,935	**10.79**	2,275	42,655	**18.75**
Aug-22	33,558	354,744	**10.57**	2,161	41,063	**19.00**
Sep-22	32,672	358,919	**10.99**	2,149	47,744	**22.22**
Oct-22	**8,865**	**459,764**	**51.86**	**489**	**51,107**	**104.51**
Nov-22	32,720	1,044,988	**31.94**	2,180	128,796	**59.08**
Dec-22	32,817	3,141,360	**95.72**	2,194	432,582	**197.17**
Jan-23	32,935	4,136,082	**125.58**	2,199	643,170	**292.48**
Feb-23	32,880	3,807,419	**115.80**	2,202	546,222	**248.06**
Mar-23	32,984	3,041,096	**92.20**	2,216	481,818	**217.43**
Apr-23	32,918	2,058,938	**62.55**	2,207	296,001	**134.12**
	Small Volume Firm			Large Volume Firm		
	Cust Count	Usage	Avg Usage	Cust Count	Usage	Avg Usage
Apr-22	328	353,748	**1,079**	13	127,301	**9,792**
May-22	315	192,744	**612**	14	80,441	**5,746**
Jun-22	325	139,398	**429**	15	44,150	**2,943**
Jul-22	294	94,795	**322**	14	25,485	**1,820**
Aug-22	284	99,543	**351**	13	21,738	**1,672**
Sep-22	283	116,528	**412**	12	29,548	**2,462**
Oct-22	**46**	**96,008**	**2,087**	**4**	**(14,319)**	**(3,580)**
Nov-22	286	202,499	**708**	13	53,990	**4,153**
Dec-22	284	440,647	**1,552**	12	127,034	**10,586**
Jan-23	288	548,576	**1,905**	13	183,331	**14,102**
Feb-23	281	509,358	**1,813**	13	158,694	**12,207**
Mar-23	282	454,124	**1,610**	12	161,969	**13,497**
Apr-23	283	329,235	**1,163**	13	114,044	**8,773**

Two additional rate classes with October 2022 problems are the Small Commercial Transportation and Small Volume Transportation Classes. The same range of data is shown for these two classes in Table 2 below. Again, the October 2022 data stand out.

Table 2

	Topeka					
	Small Commercial Transport			Small Volume Transportation		
	Cust Count	Usage	Avg Usage	Cust Count	Usage	Avg Usage
Apr-22	40	17,500	**437.50**	123	200,407	**1,629.33**
May-22	43	18,371	**427.23**	111	120,503	**1,085.61**
Jun-22	41	9,288	**226.54**	119	93,774	**788.02**
Jul-22	53	10,219	**192.81**	105	60,821	**579.25**
Aug-22	27	6,289	**232.93**	101	55,282	**547.35**
Sep-22	40	7,691	**192.28**	102	62,380	**611.57**
Oct-22	**33**	**14,172**	**429.45**	**25**	**62,548**	**2,501.92**
Nov-22	41	10,197	**248.71**	99	108,357	**1,094.52**
Dec-22	41	20,076	**489.66**	100	238,458	**2,384.58**
Jan-23	41	29,865	**728.41**	99	299,785	**3,028.13**
Feb-23	40	24,553	**613.83**	100	269,827	**2,698.27**
Mar-23	40	25,683	**642.08**	99	256,146	**2,587.33**
Apr-23	41	18,846	**459.66**	97	185,539	**1,912.77**

Dodge City

For Dodge City and Wichita, the same two classes, Small Commercial Transportation and Small Volume Transportation, also have strange numbers for October 2022. See Tables 3 and 4 below.

Table 3

	Dodge City					
	Small Commercial Transport			Small Volume Transportation		
	Cust Count	Usage	Avg Usage	Cust Count	Usage	Avg Usage
Apr-22	80	15,765	**197.06**	235	301,823	**1,284.35**
May-22	79	6,145	**77.78**	234	158,946	**679.26**
Jun-22	82	2,807	**34.23**	228	108,263	**474.84**
Jul-22	75	1,268	**16.91**	226	78,842	**348.86**
Aug-22	75	1,301	**17.35**	214	69,184	**323.29**
Sep-22	75	1,804	**24.05**	209	68,856	**329.45**
Oct-22	**48**	**2,934**	**61.13**	**85**	**110,751**	**1,302.95**
Nov-22	74	8,440	**114.05**	196	144,165	**735.54**
Dec-22	74	34,705	**468.99**	193	347,968	**1,802.94**
Jan-23	74	45,608	**616.32**	192	452,345	**2,355.96**
Feb-23	74	43,282	**584.89**	192	417,657	**2,175.30**
Mar-23	75	35,787	**477.16**	192	379,969	**1,979.01**
Apr-23	73	24,702	**338.38**	193	269,307	**1,395.37**

Table 4

	Wichita					
	Small Commercial Transport			Small Volume Transportation		
	Cust Count	Usage	Avg Usage	Cust Count	Usage	Avg Usage
Apr-22	76	16,225	**213.49**	161	301,309	**1,871.48**
May-22	76	10,928	**143.79**	165	142,352	**862.74**
Jun-22	86	3,269	**38.01**	161	101,401	**629.82**
Jul-22	71	2,281	**32.13**	151	64,817	**429.25**
Aug-22	68	2,307	**33.93**	148	58,264	**393.68**
Sep-22	68	2,468	**36.29**	148	69,605	**470.30**
Oct-22	**11**	**2,518**	**228.91**	**65**	**92,907**	**1,429.34**
Nov-22	68	7,141	**105.01**	149	166,482	**1,117.33**
Dec-22	68	24,812	**364.88**	149	417,849	**2,804.36**
Jan-23	68	33,512	**492.82**	149	549,031	**3,684.77**
Feb-23	68	29,501	**433.84**	149	495,367	**3,324.61**
Mar-23	68	26,283	**386.51**	149	448,488	**3,009.99**
Apr-23	68	14,886	**218.91**	149	274,510	**1,842.35**

Goodland

For Goodland, only the Small Volume Transportation Class has curious numbers for October 2022. See Table 5 below.

Table 5

	Goodland		
	Small Volume Transportation		
	Cust Count	Usage	Avg Usage
Apr-22	23	28,882	**1,255.74**
May-22	21	12,275	**584.52**
Jun-22	22	9,113	**414.23**
Jul-22	22	3,102	**141.00**
Aug-22	20	5,860	**293.00**
Sep-22	26	2,687	**103.35**
Oct-22	**22**	**625**	**28.41**
Nov-22	26	7,107	**273.35**
Dec-22	26	20,574	**791.31**
Jan-23	26	32,377	**1,245.27**
Feb-23	26	28,392	**1,092.00**
Mar-23	26	28,348	**1,090.31**
Apr-23	26	23,344	**897.85**

Large Volume Transportation Class Unexpected Data

Dodge City, Topeka, and Wichita Large Volume Transport Class all had data problems at the same time: May and June 2021, November 2023, and August and September 2024. Table 6 below illustrates these problems.

Table 6

	Large Volume Transport								
	Dodge City			Topeka			Wichita		
	Cust Count	Therms	Avg Use	Cust Count	Therms	Avg Use	Cust Count	Therms	Avg Use
Jan-21	59	1,336,826	**22,658**	27	1,105,758	40,954.00	42	1,919,082	45,692.43
Feb-21	60	1,354,703	**22,578**	27	1,196,898	44,329.56	42	2,003,018	47,690.90
Mar-21	62	1,287,575	**20,767**	27	1,322,121	48,967.44	42	1,968,196	46,861.81
Apr-21	59	1,183,184	**20,054**	28	830,509	29,661.04	42	1,451,385	34,556.79
May-21	**34**	**1,094,296**	**32,185**	**17**	**342,937**	**20,172.76**	**28**	**1,172,982**	**41,892.21**
Jun-21	**37**	**1,482,954**	**40,080**	**17**	**859,611**	**50,565.35**	**21**	**1,222,255**	**58,202.62**
Jul-21	60	1,436,661	**23,944**	27	451,608	16,726.22	42	1,057,596	25,180.86
Aug-21	61	2,307,303	**37,825**	28	478,822	17,100.79	42	1,015,404	24,176.29
Sep-21	60	2,545,462	**42,424**	27	440,957	16,331.74	44	1,052,224	23,914.18
Oct-21	62	1,442,179	**23,261**	24	462,196	19,258.17	40	1,004,099	25,102.48
Nov-21	61	1,170,491	**19,188**	26	593,571	22,829.65	42	1,288,801	30,685.74
Dec-21	61	1,306,805	**21,423**	26	796,132	30,620.46	43	1,294,190	30,097.44
Sep-23	52	5,194,199	**99,888**	24	506,025	21,084.38	41	1,228,144	29,954.73
Oct-23	56	3,243,958	**57,928**	24	497,555	20,731.46	42	1,015,956	24,189.43
Nov-23	**92**	**5,527,340**	**60,080**	**43**	**847,688**	**19,713.67**	**76**	**2,755,794**	**36,260.45**
Dec-23	52	1,683,951	**32,384**	24	1,404,139	58,505.79	41	1,507,812	36,775.90
Jan-24	54	1,515,618	**28,067**	24	1,217,294	50,720.58	41	1,728,957	42,169.68
Feb-24	53	1,114,185	**21,022**	24	818,981	34,124.21	40	2,127,920	53,198.00
Mar-24	53	1,877,438	**35,423**	24	606,098	25,254.08	40	1,749,554	43,738.85
Apr-24	53	3,111,213	**58,702**	24	996,887	41,536.96	41	1,256,136	30,637.46
May-24	53	2,622,047	**49,473**	23	540,301	23,491.35	40	1,173,816	29,345.40
Jun-24	54	2,868,954	**53,129**	23	452,438	19,671.22	41	1,807,228	44,078.73
Jul-24	53	2,252,847	**42,507**	23	293,890	12,777.83	41	1,497,250	36,518.29
Aug-24	**53**	**5,865,139**	**110,663**	**22**	**641,903**	**29,177.41**	**41**	**2,656,869**	**64,801.68**
Sep-24	**10**	**149,124**	**14,912**	**4**	**64,286**	**16,071.50**	**5**	**300,690**	**60,138.00**

Unexpected Data for the Dodge City Large Volume Firm Class

Figure 1 below is Dodge City average use for the Large Volume Firm Class. The problem are the occasional spikes in the data, particularly in 2017 and 2018, are shown in Figure 1 below. The data for the huge spikes are below in Table 7.

Figure 1: Dodge City Large Volume Firm

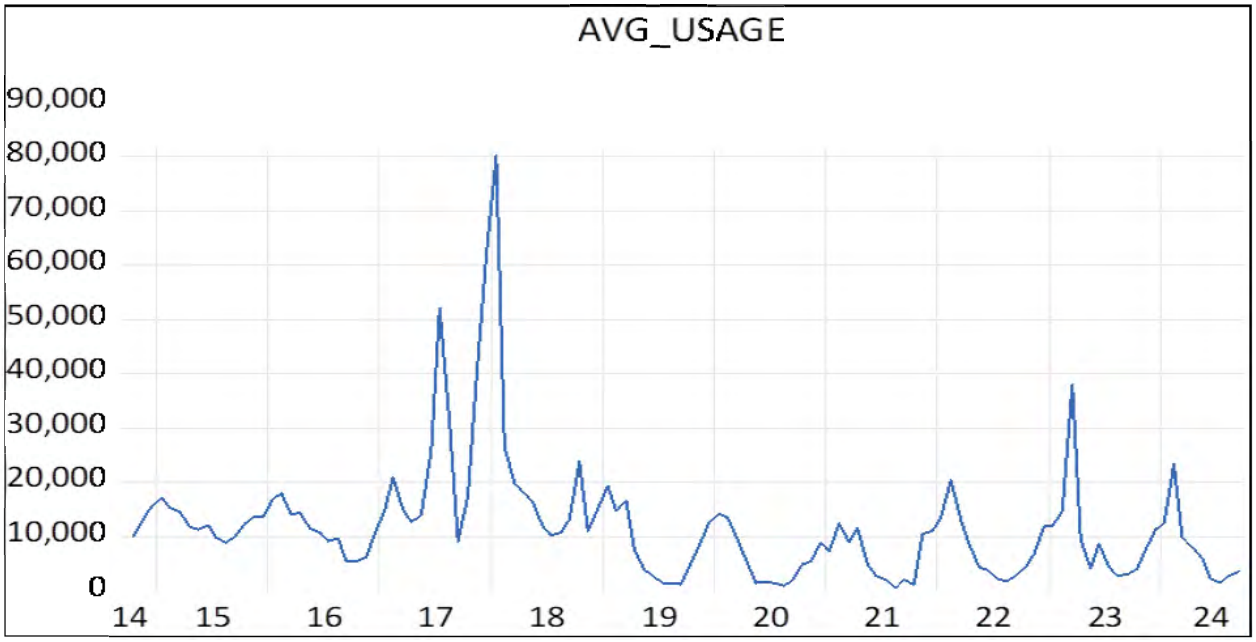


Table 7

	Dodge City						
	Large Volume Firm				Large Volume Firm		
	Cust Count	Therms	Avg Use		Cust Count	Therms	Avg Use
Apr-17	6	76,406	**12,734**	**Nov-22**	9	60,762	**6,751**
May-17	7	97,418	**13,917**	**Dec-22**	8	95,219	**11,902**
Jun-17	7	181,387	**25,912**	**Jan-23**	10	118,126	**11,813**
Jul-17	**6**	**312,893**	**52,149**	**Feb-23**	8	117,592	**14,699**
Aug-17	7	217,071	**31,010**	**Mar-23**	**7**	**264,754**	**37,822**
Sep-17	7	64,301	**9,186**	**Apr-23**	10	95,114	**9,511**
Oct-17	7	121,686	**17,384**	**May-23**	9	36,321	**4,036**
Nov-17	7	269,153	**38,450**	**Jun-23**	10	85,244	**8,524**
Dec-17	**7**	**432,322**	**61,760**	**Aug-23**	10	27,443	**2,744**
Jan-18	**7**	**560,704**	**80,101**	**Sep-23**	10	31,772	**3,177**
Feb-18	5	131,922	**26,384**	**Oct-23**	10	42,498	**4,250**
Mar-18	5	99,123	**19,825**	**Nov-23**	9	67,206	**7,467**
Apr-18	5	91,610	**18,322**	**Dec-23**	9	102,342	**11,371**

Concordia Irrigation Interruptible Class Data Problems

Below is Figure 2 for Concordia Irrigation Interruptible Class. There are two data problems in Figure 2: the negative number for December 2023 and the unusually low numbers for June 2019 and June 2023.

Figure 2: Concordia Irrigation Interruptible Class

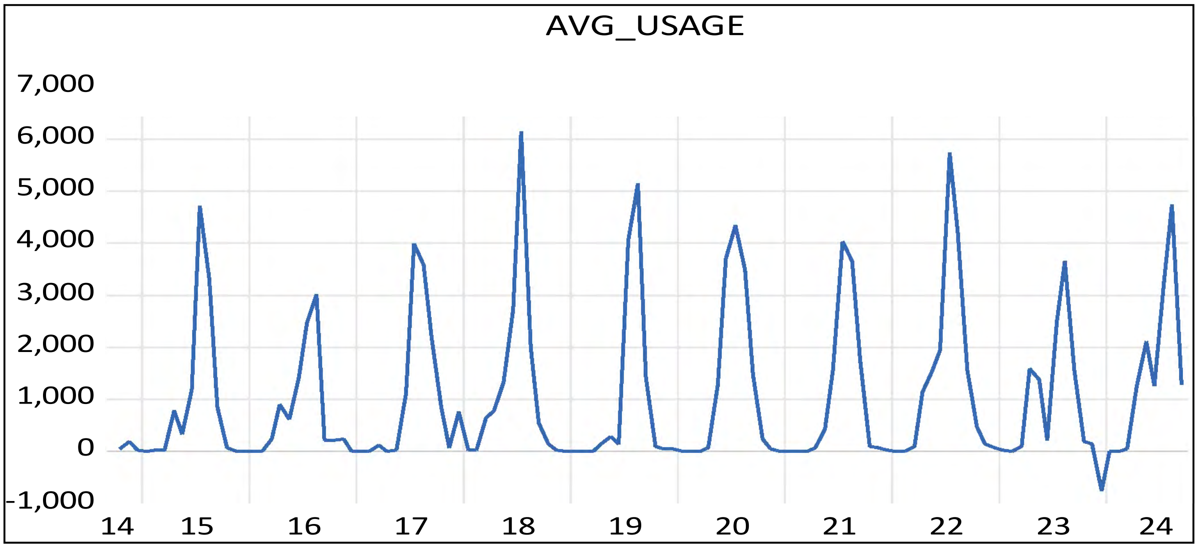


Table 8 below shows the negative usage for December 2023 and that the number of customers is smaller than the surrounding months.

Table 8

Concordia Irrigation Interruptible			
	No. Cust	**Therms**	**Avg Use**
Sep-23	39	60,642	1,554.92
Oct-23	38	7,411	195.03
Nov-23	39	6,048	155.08
Dec-23	**29**	**(21,513)**	**(741.83)**
Jan-24	35	94	2.69
Feb-24	38	174	4.58
Mar-24	38	1,622	42.68

Table 9 below shows that June 2019 and June 2023 are significantly different than other Junes during the 10-year period used for weather normalization. The 10-year average usage is 1,527.84 per customer while the 8-year average usage without 2019 and 2023 is 1,820.88 per customer.

Table 9

Concordia Irrigation Interruptible			
	No. Cust	Therms	Avg Use
Jun-15	30	35,923	1,197.43
Jun-16	37	53,145	1,436.35
Jun-17	36	39,982	1,110.61
Jun-18	31	84,678	2,731.55
Jun-19	**31**	**4,918**	**158.65**
Jun-20	29	107,526	3,707.79
Jun-21	35	55,173	1,576.37
Jun-22	39	75,992	1,948.51
Jun-23	**29**	**6,458**	**222.69**
Jun-24	37	46,503	1,256.84

Bad Data Mitigation Methods

Primary Method—Averaging Closest Months

In my Direct Testimony on pages 7 and 8, I discussed the extreme example of the Topeka Large Volume Transport Class negative volumes for October 2022. Clearly, a customer cannot consume a negative amount of gas in a month. Table 1 above has the Topeka Large Volume Transport Class negative value for October 2022 and some surrounding data.

The Large Volume Transport Class portion of Table 1 is shown below as Table 10, the same table as Table 1 in the Direct Testimony on page 7. In addition, Table 10 has our adjustment of the negative value for October 2022. All the October 2022 data is in red.

As noted in the testimony, we used a simple average of the month before and the month after to substitute for the initial negative value. This was the primary method used to adjust the data problems described above. However, this primary method did not always provide a realistic result. In cases where it did not provide a realistic result, we tried a second method.

Table 10

An Extreme Example & Staff Solution to October 2022 Data Problem						
	Topeka: Large Volume Firm Class					
	Unadjusted Data			Adjusted Data		
Month	Bill Count	Customer Gas Usage	Average Uasge	Bill Count	Customer Gas Usage	Average Uasge
Apr-22	13	127,301	**9,792**	13	127,301	**9,792**
May-22	14	80,441	**5,746**	14	80,441	**5,746**
Jun-22	15	44,150	**2,943**	15	44,150	**2,943**
Jul-22	14	25,485	**1,820**	14	25,485	**1,820**
Aug-22	13	21,738	**1,672**	13	21,738	**1,672**
Sep-22	12	29,548	**2,462**	12	29,548	**2,462**
Oct-22	**4**	**(14,319)**	**(3,580)**	**13**	**41,769**	**3,342**
Nov-22	13	53,990	**4,153**	13	53,990	**4,153**
Dec-22	12	127,034	**10,586**	12	127,034	**10,586**
Jan-23	13	183,331	**14,102**	13	183,331	**14,102**
Feb-23	13	158,694	**12,207**	13	158,694	**12,207**
Mar-23	12	161,969	**13,497**	12	161,969	**13,497**
Apr-23	13	114,044	**8,773**	13	114,044	**8,773**
NOTE: The numbers in parentheses are negative numbers.						
NOTE: The data for October 2022 was adjusted by averaging the bill count and customer usage data for September and November 2022.						

<u>Secondary Method—Using the Average of that Month in the Dataset</u>

Our secondary method was to calculate the average of all of that particular month's data in the dataset. As an example, consider October 2022. We took the average of October 2014 through October 2021 and included October 2023 in the average. The result of this adjustment method was 3,408 therms compared to 3,342 therms using the primary adjustment method. A comparison of how these two methods fit within the context of the immediate surrounding data is shown in Table 11 below.

Table 11

Comparison of Staff' Primary Method and Secondary Method for Solving October 2022 Data Problems						
	Topeka Large Volume Firm Class					
	Average of the 2015-2023*			Staff's Simple Interpolation		
	Customer Count	Customer Gas Usage	Average Uasge	Customer Count	Customer Gas Usage	Average Uasge
September	9	22,501	2,572	12	29,548	2,462
October	**9**	**30,670**	**3,408**	**13**	**41,769**	**3,342**
November	10	56,288	5,848	13	53,990	4,153
NOTE: September through November 2022 are excluded from the averaging.						

Why the Primary Adjustment Method Is Preferred to the Secondary Adjustment Method

Using the primary adjustment method is preferred because it only uses surrounding data. In many commercial and industrial classes, especially the transportation classes, there are large swings in the data. By using the previous and following months customer bills and customer usage, most of the effect of these swings can be avoided. For example, a class that at the beginning of the estimation period has only 9 customers, but by the test year, it has 14 customers, could have different average customer usage characteristics in in the two different part of the estimation period, which would distort the secondary adjustment process.

Other Methods of Adjustment Used

We ran into several cases where there had been one customer in a class, and then for one period there was customer usage but zero customers in the class. In these cases, we assumed that there was always one customer in the class.

When we ran into cases where there were breakpoints in the regression analysis, if changes in the regression analysis did not eliminate the breakpoints, then we would shorten the period of estimation to exclude the breakpoints from the estimation data.

In some cases, the final month of the test year looked out of place. Table 6 above has three examples of this phenomenon. In these cases, we excluded the last month and tried to find a regression model that would work. However, when the final month data looked out of place, there were also other data problems that prevented successfully estimation of a weather normalization model.

EXHIBIT RHG-2

DOCKET NO. 25-BHCG-298-RTS

Staff's Weather Normalization Regression Analysis

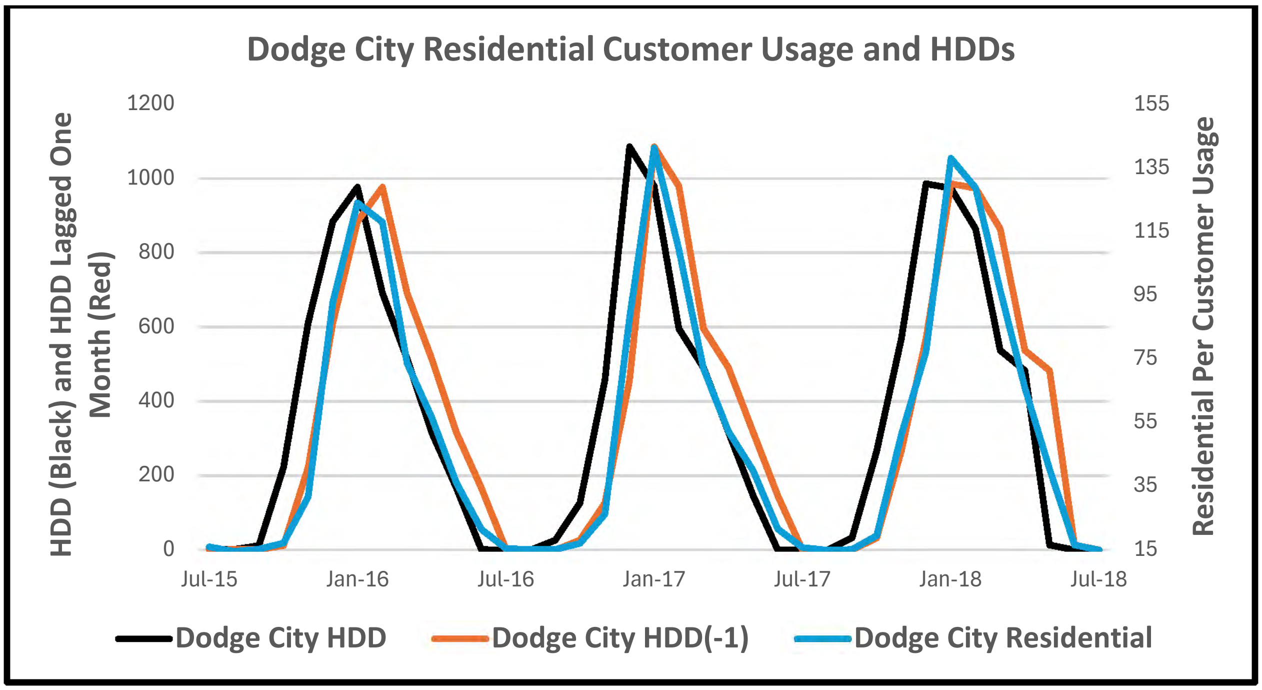
Staff's Weather Normalization Regression Analysis

Introduction

Why Statistical Analysis Works for Weather Normalization

Linear regression analysis works as well as it does for weather normalizing gas utilities customer usage because of the close relationship between the movements of average customer usage and heating degree days (HDD). Below in Figure 1 is a comparison of Dodge City Residential average customer usage and current period HDDs and previous period HDDs [HDD(-1)].

Figure 1



The data is from July 2015 through July 2018. The reason a complete dataset of 10 years is not shown is because the seasonal cycles would fill the graph and result in the graph looking like three curves layered on top of each other. The weather variables do not match-up perfectly, but they look closely correlated. In fact, the weather variables explain 97.6% of the variation in the average usage variable.[1] It is the close correlation between Residential

[1] The 97.6% is the value of the adjusted R^2. R^2 is the coefficient of determination.
$R^2 = \frac{\textit{Sum of Squares Explainded by the Regression}}{\textit{Total Summ of Squares of the Dependent Variable}}$.
The adjusted R^2 is adjusted for the number of independent variables: $R^2 \geq$ Adjusted R^2. .

average customer usage and weather that makes statistically estimating weather normalization successful. For large, well-behaved classes such as the Dodge City Residential Class, average customer usage and weather are tightly correlated. Unfortunately, this tight fit does not exist for all customer classes. As a result, a mechanical approach to weather normalization will run into problems at some point.

Outline of Staff's Approach

Preliminary Data Analysis

Our first step is always to look at the data. We begin with preliminary data investigation by graphing and looking at the average usage data for each class to check for outliers in the data. If the data is bad, then no statistical technique is going to save weather normalization.

Preliminary Statistic Analysis

For weather normalization, we use regression estimation. First, we run the Augmented Dickey-Fuller unit root test on average customer usage to see if it has a unit root. Then we run the simple equation below for each class and use the results to test for structural breaks in the estimation.

Eq 01 $$\boldsymbol{y = a + WSF_1 * HDD + WSF_2 * HDD(-1) + \varepsilon}$$ [2]

In the equation, y represents average customer usage a is the intercept term, ε is an error term, HDD and HDD(-1) [3] are the independent weather variables, and WSF_1 and WSF_2 are the weather sensitive parameters to be estimated.

Serial Correlation

The elimination of the outliers and the identification of breakpoints, in most cases, still leaves serial correlation in the error term, which means the time series data is not stationary.[4] This could be because the data still has seasonal effects. We start by inserting lagged variables of average customer usage. If that does not work, then we move to using autoregressive moving average (ARMA) terms.

---

[2] In the irrigation equations, the CDD and perception variables are added and nearly always the HDD variables add nothing to the explanatory value of the equation and are eliminated.
[3] A lagged variable (-1) is the previous month's value when looking at the current month. For example, if the month is October, September HDDs would be the lagged HDDs.
[4] A stationary time series has mean, variance, and autocorrelation structure that is constant over time.

Structural Breakpoints

We continually check for structural breakpoints because if we change our regression equation, we can sometimes add breakpoints or eliminate breakpoints. No regression equation is finalized until it is checked for breakpoints. The exception is when there are ARMA terms in the equation. If an equation has ARMA terms, then most breakpoint tests will not work.

Staff's Philosophy for Significance, Rejecting Variables, and Equation Building

It has been my experience that in statistics and econometrics classes, teachers point out that the 5% significance level for rejecting the null hypothesis is an arbitrary, ad hoc criteria developed by Ronald Fisher in the 1920s. Fisher recognized that the 5% significance level was arbitrary and ad hoc, but needed some criteria, and so he used it. Fisher did not intend the 5% significance level to be treated as rule by other researchers.

We treat the 5% significance level as a guide. If a coefficient is insignificant, but eliminating it noticeably affects the results of the regression for the worse, then we reconsider including the variable, but only after further analysis, experimentation, and testing. The only rule that we follow is that the coefficient needs to be larger in absolute value than the standard deviation. If the coefficient fails this fundamental test, it is eliminated.

Preliminary Data Analysis

Looking at the average customer usage graph and testing for structural breaks in the data are designed to identify data problems that would make statistical estimation meaningless. The most important part of statistical estimation is the data. If the data has outliers or does not follow any pattern, then regression analysis will be worthless.

The Problem of Outliers

An Example of the Effect of an Outlier

An outlier is a data point in a dataset that lies beyond the rest of the data. Below in Figure 2, the data point for March 2013 is well above the rest of the dataset as the graph shows. The effect of such a data point on the results of a regression equation can be overwhelming. This example is taken from the 24-KGSG-610-RTS docket.

Figure 2

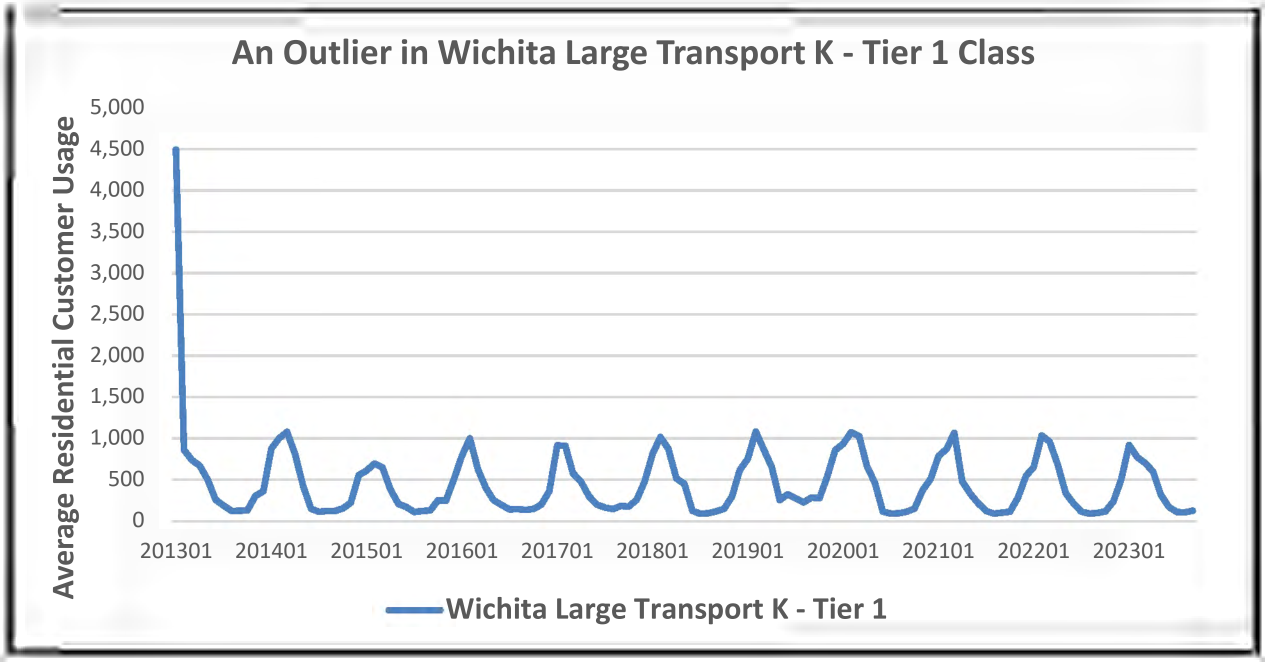
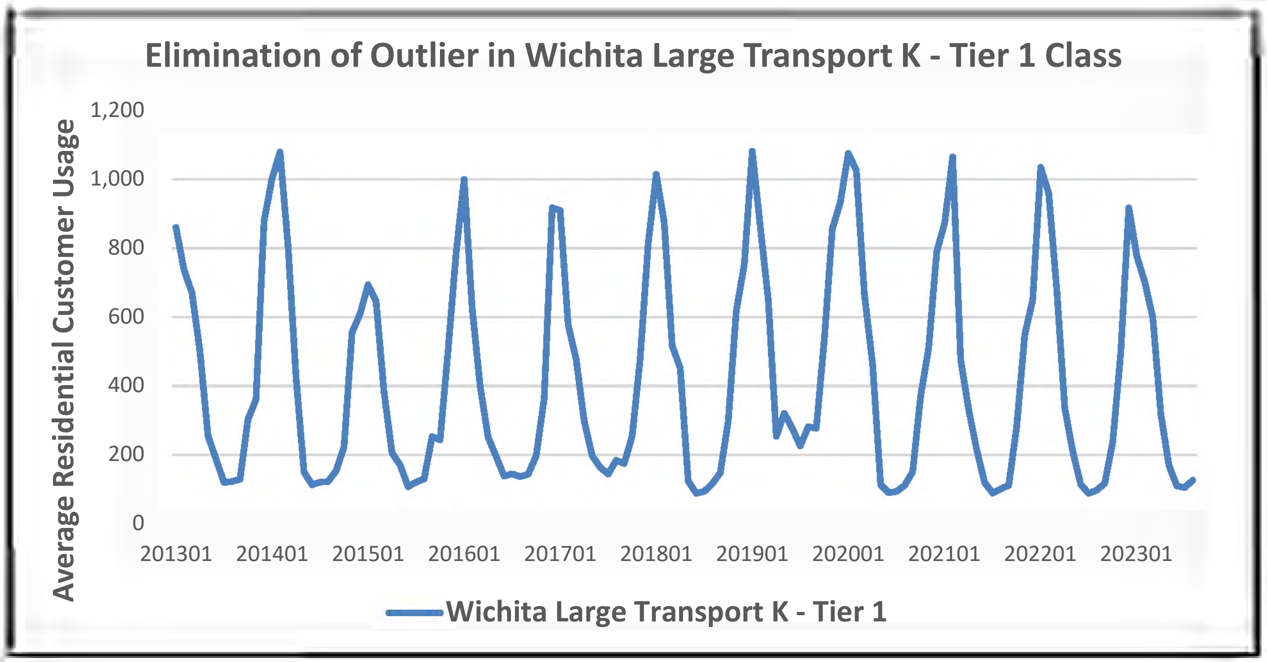


Figure 3 below shows the effect of eliminating the outlier. Note the difference in the left axis values in Figure 2 and 3.

Figure 3



The Statistical Effect of Eliminating an Outlier

To show the effect of the outlier on the regression analysis, we estimated Eq 01 for the Wichita Large Transport K -Tier 1 Class with and without the outlier. The results are provided in Table 1 below.

Table 1

The Effect of an Outlier on Regression Estimation				
Dependent Variable: Wichita Large Transport K - Tier 1				
Method: Least Squares				
Sample: 2013M01 2023M09				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Probabilty**
C	119.224	42.348	2.815	0.006
WICH_HDD	0.017	0.140	0.122	0.903
WICH_HDD(-1)	0.909	0.140	6.500	0.000
R-squared	0.509	Mean dependent var		454.45
Adjusted R-squared	0.501	S.D. dependent var		472.35
S.E. of regression	333.748	Akaike info criterion		14.48
Sum squared resid	14,034,860	Schwarz criterion		14.55
Log likelihood	(931)	Hannan-Quinn criter.		14.51
F-statistic	65	Durbin-Watson stat		1.01
Sample: 2013M02 2023M09				
C	134.757	10.460	12.884	0.000
WICH_HDD	(0.077)	0.035	(2.217)	0.028
WICH_HDD(-1)	0.880	0.035	25.478	0.000
R-squared	0.930	Mean dependent var		422.89
Adjusted R-squared	0.929	S.D. dependent var		308.82
S.E. of regression	82.387	Akaike info criterion		11.68
Sum squared resid	848,446	Schwarz criterion		11.75
Log likelihood	(745)	Hannan-Quinn criter.		11.71
F-statistic	830	Durbin-Watson stat		0.67

The results show a large difference for the HDD variable's coefficient, including a sign change, and a small difference for the HDD(-1) variable coefficient. However, the starker differences are in the criteria results. For example, the adjusted R^2 increases from 50% to 93% by dropping the outlier from the estimation. The Standard Error of the Regression falls from 334 to 82. In addition, the Log Likelihood increases substantially, and the information indexes are superior with the omission of the outlier. The reason the outlier has such a dramatic effect is that ordinary least squares (OLS) method of estimation was used. With OLS estimation, each data point is squared, thus exacerbating the outlier effect.

Regression Analysis

<u>Serial Correlation</u>

What Serial Correlation is

After running the simple regression model (eq. 01) with the two HDD variables, there is usually still seasonality in the data that will result in serial correlation in the error term. In particular, we have found that at lags of six and twelve months, there was serial correlation. Intuitively, this just means that last February is a good place to start when estimating average customer usage this February. Or last October can help explain customer usage in April. If this type of serial correlation is not treated, it does not bias the coefficients, but it does bias the variance of the coefficients, which results in biasing test statistics like t-tests and F-tests or any other test which is dependent on the variance of individual coefficient estimations.[5] With positive serial correlation, which is the usual case with seasonality, the coefficient variances are estimated as too small, resulting in the t-tests and F-tests overestimating the significance of the coefficients. Sometimes we have also found first order serial correlation in the error term. This just means that next period average customer usage is the best forecast using this period's average customer usage.

Q-Statistics: Test for Serial Correlation

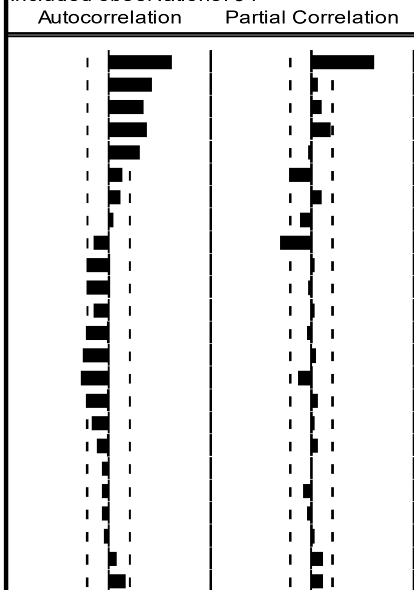
We use the Q-statistics to test for serial correlation. In particular, graphs of the autocorrelation function (ACF) and the partial autocorrelation function (PCF) make it easy to identify where the serial correlation occurs. We usually find that either one month, two month, six month, or twelve month lags of average customer usage will mitigate the serial correlation. If lags of the average customer usage do not sufficiently mitigate serial correlation, then we will try autocorrection and moving average functions. Eviews has a nice

[5] An unbiased estimator does not under or overestimate the parameter in the population. A consistent estimator converges in probability to the parameter value as more and more data are added to the estimation. Efficiency means having the smallest possible variance.

graphical presentation of the ACF and PCF functions that aid in choosing lags. Figure 4 below shows an example of the ACF and PCF functions. Almost any time series textbook will have a section on how to read the graph.

Figure 4

Date: 06/12/24 Time: 13:27
Sample: 2015M12 2023M09
Included observations: 94



	AC	PAC	Q-Stat	Prob
1	0.632	0.632	38.698	0.000
2	0.436	0.061	57.321	0.000
3	0.352	0.092	69.623	0.000
4	0.373	0.178	83.603	0.000
5	0.311	-0.020	93.387	0.000
6	0.120	-0.218	94.874	0.000
7	0.100	0.086	95.909	0.000
8	0.039	-0.110	96.068	0.000
9	-0.141	-0.314	98.170	0.000
10	-0.212	0.012	103.01	0.000
11	-0.224	-0.009	108.46	0.000
12	-0.152	0.024	111.02	0.000
13	-0.219	-0.039	116.36	0.000
14	-0.255	0.035	123.71	0.000
15	-0.267	-0.118	131.87	0.000
16	-0.205	0.065	136.74	0.000
17	-0.169	0.018	140.10	0.000
18	-0.109	0.058	141.51	0.000
19	-0.057	0.002	141.90	0.000
20	-0.062	-0.082	142.38	0.000
21	-0.065	-0.032	142.90	0.000
22	-0.030	0.019	143.01	0.000
23	0.072	0.100	143.67	0.000
24	0.170	0.101	147.41	0.000

Technical Description of the Q-Statistic

The Q-Test is a check to see if the autocorrelation coefficients are all 0 (jointly not significant) where the residual autocorrelation coefficients are $\boldsymbol{r(i) = corr(\hat{\varepsilon}_t, \hat{\varepsilon}_{t-i}), 1, \dots, m}$ where $\boldsymbol{r(i)}$ is the residual at time t. In other words, if r(1) = 0, r(2) = 0, ... , r(m) = 0, then there is no autocorrelation up to order m.

The test statistic is:

$$\boldsymbol{Q(m) = T(T+2)\sum_{i=1}^{m}\frac{r_i^2}{T-i} \sim Chi\ Squared(m)}$$

The intuition is that if $\boldsymbol{\hat{\varepsilon}_t s}$ are autocorrelated, then the r(i)s should be "large" $\Rightarrow$ Q(m) is "large." If Q(m) is larger than a "critical value"—Q(m) > Q_{CV}(m) $\Rightarrow$ H_0: r(1) = 0, r(2) = 0, ... , r(m) = 0 is rejected. And therefore the $\boldsymbol{\hat{\varepsilon}_t s}$ are autocorrelated.

A second Q-Test can be used to check for heteroscedasticity. The Q-Test is the same as the Q-Test before except this time the $\boldsymbol{r(i)}$ is the squared residuals $\boldsymbol{r(i) = corr(\hat{\varepsilon}_t^2, \hat{\varepsilon}_{t-1}^2\,)}$, $\mathbf{1}, \dots, \boldsymbol{m}.$ If the r(1) = 0, r(2) = 0, ... , r(m) = 0 then there is no heteroscedasticity up to order m.

Using Lags of Average Customer Usage as a First Step to Mitigate Serial Correlation

There are two reasons for trying lagged average customer usage first. First, the lagged variable is more backward looking than the autocorrection and moving average functions which are better for forecasting. With weather normalization we are not forecasting, instead we are trying to estimate the impact of previous weather on previous customer usage. Second, the lagged variables are more intuitive than autocorrelation and moving average functions: (1) because the algebraic representation is simpler than for autocorrection and moving average functions, and (2) by using lags rather than autocorrelation and moving average functions, the estimation process remains least squares rather than maximum likelihood or some other more complicated process, and for example, Bai-Perron breakpoint tests only work with least squares estimation.

Algebraic Difference between Lags of the Dependent Variable and ARMA Terms

One of the common misconceptions is that adding a first order autoregressive term, AR(1), is about the same as using the first lag of the dependent variable. The problem comes in the fact that in most textbooks AR(1) is defined as

$$y_t = c + \ y_{t-1}.$$

But, when an equation follows an AR process, it is the error term that follows an AR process, not the dependent variable. So,

$$y_t = c + \ u_t \ and \ u_t = \rho u_{t-1} + \varepsilon_t$$

With some substitution,

$$y_t = c + \ \rho u_{t-1} + \varepsilon_t \ and \ u_{t-1} = y_{t-1} - c$$

$$y_t = c + \ \rho(y_{t-1} - c) + \varepsilon_t$$

$$y_t = (1 - \rho)c + \ \rho(y_{t-1}) + \varepsilon_t$$

Now compare the above equation to just adding a lag of the dependent variable.

$$y_t = c + \ \rho(y_{t-1}) + \varepsilon_t$$

The coefficient on y_t, ρ is the same, but the constant becomes more complex with the AR(1) term.

Assuming an independent variable in the equation reveals the complexity of the difference between lagging the dependent variable and using an AR process. For an AR(1) process it is:

$$y_t = c + \beta x_t + u_t \text{ } and \text{ } u_t = \rho u_{t-1} + \varepsilon_t$$

$$y_t = c + \beta x_t + \rho u_{t-1} + \varepsilon_t$$

$$y_t = c + \beta x_t + \rho(y_{t-1} - c - \beta x_{t-1}) + \varepsilon_t$$

$$y_t = (1 - \rho)c + \rho y_{t-1} + \beta x_t - \rho\beta x_{t-1} + \varepsilon_t$$

For a lag of the dependent variable the equation becomes:

$$y_t = c + \beta x_t + \rho(y_{t-1}) + \varepsilon_t$$

Unit Roots

A unit root creates a time series that is non-stationary: the time series' statistical properties change over time. There are three types of unit roots: unit roots that are random walks, unit roots with a drift but no trend, and unit roots with a drift and trend.[6]

A unit root can create serious problems for regression estimation. Granger and Newbold wrote a paper about the effects of unit roots on equation estimation titled "Spurious Regressions in Econometrics."[7] Autocorrelation usually leads to an underestimation of the variance. Unit roots are an extreme case of autocorrelation. Granger and Newbolt state "a high value of R^2 should not ... be regarded as evidence of a significant relationship between autocorrelated series. "[8]

The simplest and easiest method of mitigating a unit root is to difference the variables,[9] which eliminates the unit root. But because the WSFs also are used for the weather normalization

---

[6] The random walk is a time series without a drift or trend, but the data fluctuates randomly around a zero mean. This type of time series is not predictable. The unit root with a drift has a non-zero mean that the data fluctuates around but the mean does not change over time which causes the time series to drift upward or downward. The unit root with a drift and a trend has data that tends to fluctuate around a non-zero mean, and the mean itself changes over time either upwards or downwards.

[7] Granger, C. W. J.; Newbold, P. (1974). "Spurious regressions in econometrics". Journal of Econometrics. 2 (2): 111–120

[8] Ibid. p. 114.

[9] The first difference of a variable is: $\Delta \boldsymbol{y_t} = \boldsymbol{y_t} - \boldsymbol{y_{t-1}}$. Multiple differencing is possible if needed.

adjustment of the gas cost adjustment, differencing is not a feasible adjustment. This leaves one exception to the problems created by unit roots.

Cointegration

The one exception is if the different time series variables are cointegrated. Cointegration is when a linear combination of two or more non-stationary time series has a long-run equilibrium. In other words, the left-hand variable has a unit root, the right-hand independent variables have a unit roots, but the linear combination among the variables creates a long run equilibrium resulting in the error term not having a unit root. In the case of cointegration, a shock to the equilibrium is mitigated by a mean reverting process returning the variables to the long-run equilibrium.[10] If there is no cointegration, then a shock to system means a permanent change to the time series path of the system. Something common in customer count and customer usage time series.

The implications of cointegration for weather normalization are nice. As already noted, average customer usage has a unit root for most customer classes and weather stations, and HDD, and HDD(-1) also have a unit root for all weather stations. Then if average customer usage and the HDD and HDD(-1) are cointegrated, then estimation in levels is appropriate rather than using differencing. To put it simply, when average customer usage, HDD, and HDD(-1) are cointegrated, standard weather normalization procedures are statistically appropriate.

Breakpoints in the Regression Estimation of Coefficients

What a Structural Break Is

A structural break is an abrupt change in regression parameters that results in the regression model failing to adequately describe the situation either in the period before or after the structural break: structural breaks are both data and model based, not just data based.

Why a Structural Break Creates Estimation Problems

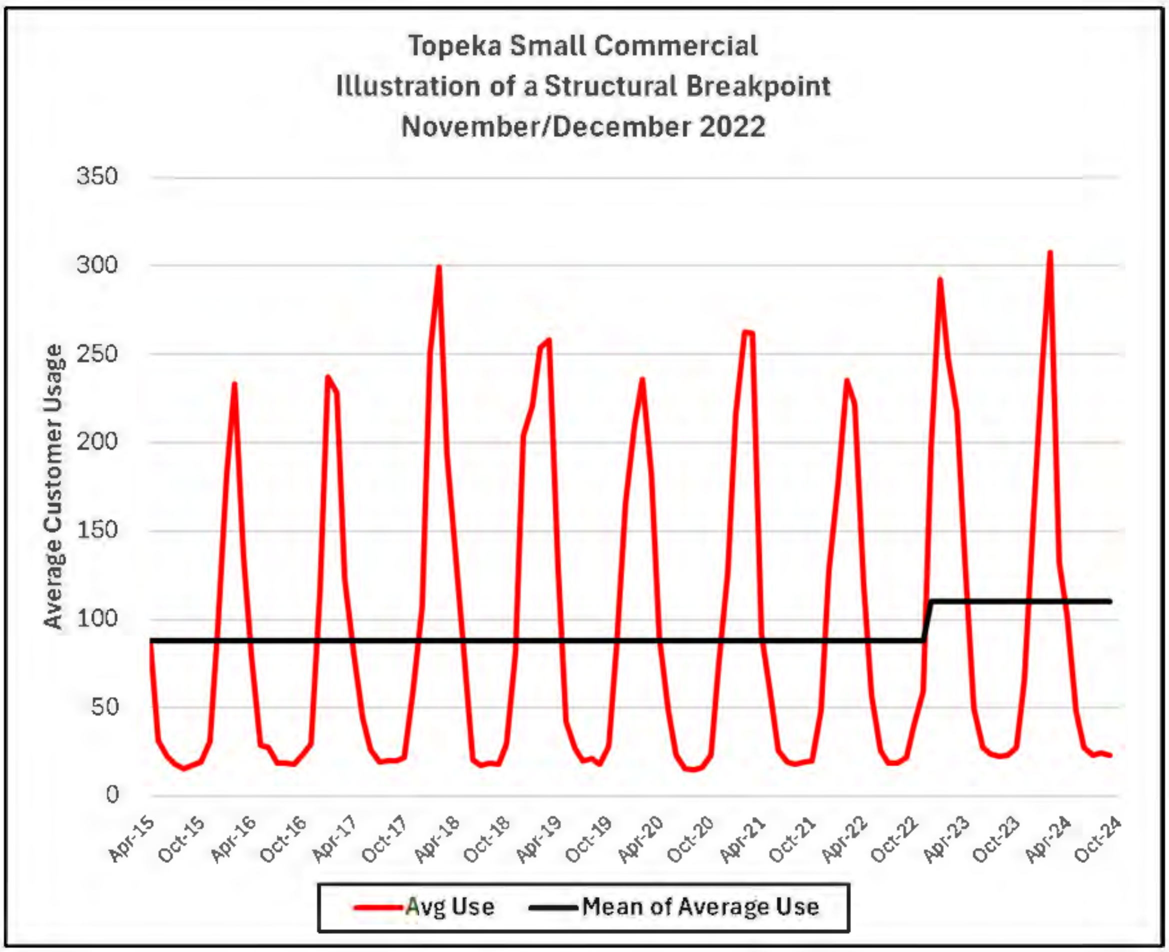
Structural stability—the assumption that regression coefficients do not change over time—is vital to applied regression analysis. However, economic and political events, or just the way a variable is measured, can create structural breaks.[11] For example, in March 1951, after years of conflict, the Federal Reserve and U.S. Treasury ended the agreement

[10] A cointegrated system can be estimated and then an error correction model can be used to estimate the short-run and long-run mean reverting processes.
[11] Ahmed, Mumtaz; Haider, Gulfam; Zaman, Asad (October 2016). "Detecting structural change with heteroskedasticity". Communications in Statistics – Theory and Methods. 46 (21): 10446–10455.

that the Federal Reserve would keep interest rates artificially low to reduce the cost of paying for World War II.[12]

Structural breaks in billing data can be caused by changes in the requirements for a class, or a sudden increase or reduction in a class due to a policy change, or the loss of a couple of customers in a small class. As an example of a structural break, the Topeka Small Commercial Class has a structural break in the period November/December 2022, which is illustrated in Figure 5 below.

Figure 5



The mean of the average usage variable increased from 87.9 in the first period to 110.0 in the second period—an increase of slightly more than 25%. Over the same periods, the standard

[12] https://www.federalreservehistory.org/essays/treasury-fed-accord. Another example is the "Volcker shock" of October 1979 when Paul Volcker announced that the Federal Reserve would restrict the growth in the money to control inflation. https://www.federalreservehistory.org/essays/anti-inflation-measures

deviation increased almost 20%. Table 2 below illustrates the effect of the structural break on coefficient values and standard errors. It also includes the mean and standard deviation of average usage for both periods.[13]

Table 2

Example of a Breakpoint Topeka Small Commercial Class		
The Breakpoint is November/December 2022	April 2015 to November 2022 (a)	December 2022 to September 2024 (b)
HDD		
Coefficient	0.04524	0.06310
Standard Error	0.00661	0.01201
HDD(-1)		
Coefficient	0.21443	0.23515
Standard Error	0.00712	0.01392
Averge Usage		
Mean	87.9	110.0
Standard Deviation	83.4	99.2

Eliminating the Problem of Structural Breaks

We eliminate the problem of estimating regression equations with structural breaks by only estimating the regression equation with data after the last structural break. The purpose of weather normalization is to adjust customer usage so that it reflects average weather. If there is a structural break, then the model parameters are going to be significantly different during the two periods. Since the later period is closer to the present, we use the estimate from the later period.

[13] The data for October 2022 was adjusted for the dataset used for the final estimation (see Exhibit RHG-1 for an explanation.) Staff ran several different regression models on the two different dataset—one dataset with October 2022 adjusted and a second dataset with October 2022 not adjusted. In both cases, a breakpoint was identified between June 2022 and July 2023, which is the confidence 90% confidence interval. With the unadjusted dataset, the break point was identified as July 2022 while with the adjusted dataset the breakpoint was December 2022.

STATE OF KANSAS)
) ss.
COUNTY OF SHAWNEE)

VERIFICATION

Bob Glass, being duly sworn upon his oath deposes and states that he is Chief of Economic Policy and Planning for the Utilities Division of the Kansas Corporation Commission of the State of Kansas, that he has read and is familiar with the foregoing *Direct Testimony*, and attests that the statements contained therein are true and correct to the best of his knowledge, information and belief.

Robert H. Glass
Bob Glass
Chief of Economic Policy and Planning
State Corporation Commission of the
State of Kansas

Subscribed and sworn to before me this 30 day of April, 2025.

Ann M. Murphy
Notary Public

My Appointment Expires: 4/28/29

NOTARY PUBLIC - State of Kansas
ANN M. MURPHY
My Appt. Expires 4/28/29

CERTIFICATE OF SERVICE

25-BHCG-298-RTS

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