**BEFORE THE STATE CORPORATION COMMISSION**
**OF THE STATE OF KANSAS**

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|---|---|---|
| **In the Matter of the Application of Kansas Gas** | **)** | |
| **Service, a Division of ONE Gas, Inc. for** | **)** | **Docket No. 24-KGSG-610-RTS** |
| **Adjustment of its Natural Gas Rates in the** | **)** | |
| **State of Kansas.** | **)** | |

**DIRECT TESTIMONY**

**PREPARED BY**

**ROBERT H. GLASS, Ph.D.**

**UTILITIES DIVISION**

**KANSAS CORPORATION COMMISSION**

**July 1, 2024**

## 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 performing 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 Weather Normalization and Customer Annualization.

**Organization**

**Q. How is your testimony organized?**

A. My testimony is organized in two major sections. First, I will discuss Weather Normalization. Then, I will discuss Customer Annualization. I will conclude by recommending the Commission adopt Staff's Weather Normalization and Customer Annualization adjustments.

## III. ANALYSIS: WEATHER NORMALIZATION

**Purpose**

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

A. A weather normalization adjustment is designed to minimize 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.[1]

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.

**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 counts are collected for the relevant customer classes. Weather data is also collected for each of the assigned 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 each customer class. In the third step, the WSFs are used to calculate volumetric adjustments. In the last step, these volumetric adjustments are used to calculate the revenue adjustments that correct for deviations from normal weather during the test year. Each of these steps is discussed in more detail below.

[1] 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.

***Data Collection***

**Q. Who provided the customer usage and customer count data?**

A. Kansas Gas Service (KGS) provided customer usage[2] and customer count data for its Sales classes.[3] KGS also assigned the members of the customer classes to their closest first-order weather station.[4] With this data, Staff was able to calculate the per capita usage for each customer class by weather station.

**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 KGS' Kansas customers (Wichita, Topeka, Dodge City, and Kansas City) for the period of October 1993 through September 2023. With this data, Staff calculated monthly Heating Degree Days (HDDs), Cooling Degree Days (CDDs), and precipitation. In addition, Staff calculated rolling 30-year normals for each of these weather variables.

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[2] Ideally, the data provided for weather normalization is 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 imperfections in the data are reduced in classes with many customers. In this regard, compensating errors are helpful.

[3] KGS provided data for Residential Sales, Small and Large Commercial Sales, and various classes of transportation customers from January 2012 to September 2023. For a few classes, Staff had data back to January 2011 from the previous rate case. However, at the beginning of 2013, KGS reorganized its commercial and transportation classes which made it impossible to link the previous data with the new customer classes. Since data continuity is necessary for sound statistical analysis, at best, most rate classes, only had data since 2013 that was consistent.

[4] 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. (https://www.weather.gov/top/office).

**Q. Please explain what HDDs and CDDs are.**

A. HDDs and CDDs are weather variables that measure deviations from an established base temperature (in this case, 65 degrees).[5] 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.[6] Figure 1 below shows the relationship between temperature (Fahrenheit) and HDDs. The relationship between temperature (Fahrenheit) and CDDs are the reverse image of Figure 1.

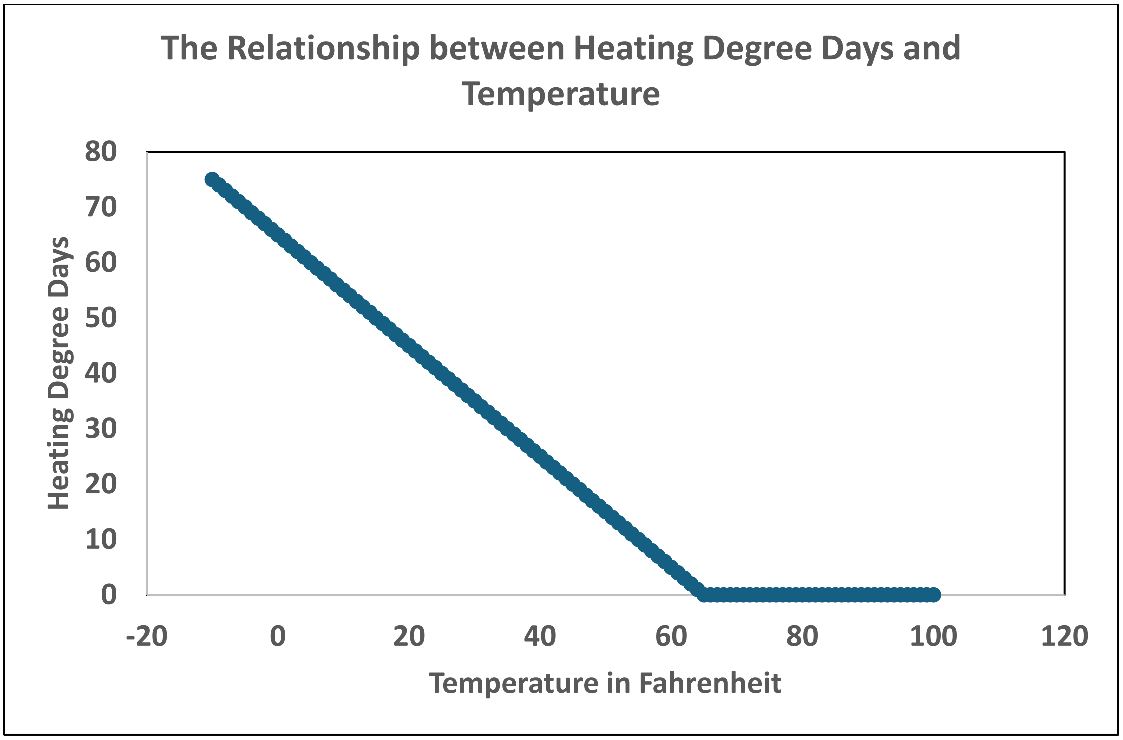
[5] Degree days are weather variables based on the assumption that when the outside temperature is 65 degrees Fahrenheit, an average person will not require heating or cooling to be comfortable. https://www.weather.gov/key/climate_heat_cool

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

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

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

**Figure 1**




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.

In terms of natural gas usage, HDDs indicate customer demand for gas space heating—the greater the number of HDDs, the cooler the weather, and thus, a greater demand for space heating. Similarly, HDDs, CDDs and precipitation indicate customer gas demand for irrigation.

***Regression Analysis***

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

A. The purpose of performing regression analysis is to derive statistically significant weather sensitivity factors, WSFs, for each weather-sensitive customer class. The WSFs measure the strength of the relationship between customer usage and weather for each of the customer classes—i.e., the WSFs are the estimated parameters for the weather variables in the regression equations.

**Q. What is Regression Analysis?**

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

**Q. How does Staff use Regression Analysis?**

A. Staff uses a linear equation to establish the relationship between weather and average customer usage. Regression analysis is used to estimate the values of the coefficients of the weather variables in the linear equation. The equation below is an example of a simple weather normalizing equation.

$$\boldsymbol{y = a + WSF_1 * HDD + WSF_2 * HDD(-1) + \varepsilon}$$ [7]

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

In the equation, $y$ represents average customer usage $a$ is the intercept term, $\varepsilon$ is an error term, $HDD$ and $HDD(-1)$ [8] are the independent weather variables, and $WSF_1$ and $WSF_2$ are the weather sensitive parameters to be estimated.[9]

**Q. How are the WSFs used by Staff?**

Staff uses the WSFs to calculate volumetric adjustments that correct for temperature deviations from the 30-year norms for each customer class.

**Q. Did Staff encounter any issues with the data?**

A. Yes. There were two types of data problems: occasional negative values for monthly customer usage, and a few cases where, for a short period of time, data obviously did not fit the data pattern of the whole time series.

First, there were several cases where data for a class had negative values. Staff checked with KGS to make sure these values were valid.[10] The negative numbers were due to billing corrections for billing errors in previous months. In most cases these negative numbers did not come into play because Staff's check for structural breaks in the data resulted in eliminating the data through the period that contained the negative numbers. However, in some cases Staff used the Chow method for interpolation to replace the negative numbers with data consistent with the time series.[11] In only one case was there a negative number in the test year data, and in

[8] 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.
[9] Attached to this testimony as Exhibit RHG-1 is a more detailed description of Staff's Regression Analysis approach.
[10] Staff Data Requests 146 and 149, and KGS responses.
[11] Gregory Chow and An-loh Lin, "Best Linear Unbiased Interpolation, Distribution, and Extrapolation of Time Series by Related Series," ***The Review of Economics and Statistics***, Vol. 53, No. 4 (November 1971), pp. 372-375.

that case the number was changed for estimation purposes but not for the calculation of test year billing determinants.

Second, there were several cases where data did not fit with the data pattern for the whole time series. Staff asked KGS about these instances of apparently aberrant data, and in some cases KGS was able to correct the data, and in a few other cases KGS was unable to correct the data.[12] Most of these situations occurred in January 2013 when KGS instituted new transportation classes and changed some of the sales classes. When an outlier could not be correct, Staff simply started the estimation process with February 2013 rather than use the January 2013 data. An example of this treatment of an outlier and what the effects of eliminating the outlier had on the regression results is provided in Exhibit RHG-1, which explains Staff's Regression Analysis approach.

**Q. Were there any other estimation problems related to the customer usage data?**

A. Yes. Because the data consists of weather-sensitive variables collected at regular intervals over an extended period of time, autocorrelation and seasonality were present in the data.[13] Autocorrelation and seasonality result in distortionary time series behavior—i.e. parameters such as the mean and variance of the time series change over time.

[12] See KGS response to Staff Data Requests Number 144 and 145.

[13] 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.

**Q. How did Staff correct for the autocorrelation and seasonality issues?**

A. To correct for autocorrelation and seasonality, Staff applied autoregressive, seasonal autoregressive, and moving average terms to the regression equations. How Staff decided when to add these terms and which terms to add is described in Exhibit RHG-1 attached to this testimony. Including these terms substantially improved the standard error and other metrics of the 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.[14] These calculated differences were multiplied by the WSFs and then multiplied by the class customer counts for each month because the WSFs were estimated using per capita customer usage. The result is the estimated change in usage attributable to deviations from normal weather.[15] This calculation is done for each customer class for each weather station, and the sum of all those adjustments is the total weather normalized volumetric adjustment.

[14] 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.

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

***Revenue Adjustment***

**Q. Please describe the process used for calculating the revenue adjustment.**

A. To calculate the revenue adjustment, the volumetric sales adjustments for each tariff class were multiplied by the appropriate rate for that customer class.[16] 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 weather normalization analysis indicates KGS sold approximately 13.4 million Mcfs less than it otherwise would have if weather conditions had been normal during the test year—weather was warmer than usual during the test year resulting in less customer usage of natural gas. Specifically, Staff's weather normalization analysis results in a volumetric adjustment of 3,438,397 Mcfs (1,000 cubic feet), resulting in a revenue increase of $7,307,300 as shown in Table 1.

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

**Table 1**

| Weather Normalization Adjustments | | |
|---|---|---|
| **Customer Class** | **Volumes** | **Revenue** |
| Residential | 2,246,354 | $ 5,275,563 |
| General Service - Small | 235,309 | $ 552,318 |
| General Service - Large | 299,883 | $ 544,138 |
| General Service - TE | 132,660 | $ 241,136 |
| Small Generator Service | 1,085 | $ 697 |
| Irrigation Sales | (7,963) | $ (13,450) |
| Sales for Resale | (28,147) | $ - |
| Small Transport k-System | 3,541 | $ 4,425 |
| Small Transport t-System | 230,426 | $ 336,376 |
| CNG k-System | 58,520 | $ 112,182 |
| CNG t-System | 0 | $ - |
| Irrigation Transport | 126 | $ 122 |
| Large Transport k - Tier 1 | 3,769 | $ 4,710 |
| Large Transport k - Tier 2 | 46,777 | $ 40,762 |
| Large Transport k - Tier 3 | 59,182 | $ 51,572 |
| Large Transport k - Tier 4 | 30,355 | $ 26,451 |
| Large Transport t - Tier 1 | 80,843 | $ 70,446 |
| Large Transport t - Tier 2 | 3,585 | $ 4,697 |
| Large Transport t - Tier 3 | 5,239 | $ 6,865 |
| Large Transport t - Tier 4 | 6,882 | $ 9,017 |
| Wholesale Transport | 29,972 | $ 39,272 |
| **Total** | **3,438,397** | **$ 7,307,300** |

For comparison, KGS' weather normalization volumetric adjustment was 3,070,414 Mcfs, resulting in a revenue increase of $6,403,185. Thus, Staff proposes a weather normalization adjustment of $904,115—the difference between Staff's and KGS' results. Staff's weather Sensitivity factors are presented in Exhibit RHG-1.

**Recommendation**

**Q. Do you have a recommendation?**

A. Yes. Since the weather experienced in KGS's service territory during the test year was warmer than normal weather for that area during the test year, an adjustment is necessary to ensure test year revenue reflects KGS's normal ongoing operations. Therefore, I recommend the Commission accept Staff's weather normalization revenue adjustment of $904,115—the difference between Staff's and KGS's weather normalization results.

## IV. ANALYSIS: CUSTOMER ANNUALIZATION

**Purpose**

**Q. What is the purpose of annualizing customer counts?**

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 counts, volumes, and revenues are adjusted to reflect the number of customers for each customer class KGS was serving at the end of the test year. Thus, the adjustment represents the revenue KGS would have received if the number of customers at year-end had received service throughout the entire test year. Hence, a customer annualization adjustment is applied to the test year so the test year customer counts, volumes, and revenue are reflective of the current customer counts.

**<u>Process</u>**

***Data Collection***

**Q. Who supplied Staff with the customer counts per customer class and weather station?**

A. As discussed above, KGS supplied monthly customer counts for its Sales rate classes by weather station.

***Customer Coefficient Calculation***

**Q. What is a 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 2022 customer counts from September 2023 customer counts for each rate class by weather station. This value was then divided by twelve to evenly spread the difference across the test-year months.[17]

***Customer Count Adjustment***

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

A. Beginning in October 2022 of the test year, the customer coefficient is multiplied by 11.5 (November 2022 by 10.5, and so on) and continues until the actual customer count and annualized customer count are equal.

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

**Q. Why did Staff annualize customer counts using this method?**

A. Staff annualized customer counts using this method for two reasons. First, it simulates the number of customers KGS 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 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 count times the monthly weather normalized volumes per customer across each rate class and corresponding weather station.

***Revenue Adjustment***

**Q. How did Staff calculate the revenue adjustment?**

A. In order to arrive at monthly adjusted revenues, Staff added the product of the annualized monthly volumes and the corresponding volumetric charge to the product of the annualized customer count 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 with the customer annualization according to customer class and weather station.

***Results***

**Q. What customer annualization adjustment is Staff recommending?**

A. Staff's calculation of the customer annualization results in negative values for changes in customer count, volumetric, and revenue adjustments: customer count adjustment is (910), volumetric adjustment is (1,189,023) Mcfs, and a total revenue decrease of ($1,622,635) as shown in Table 2.

**Table 2**

| Customer Annualization Adjustments | | | | |
|---|---|---|---|---|
| **Customer Class** | **Customer Counts** | **Volumes** | **Revenue** | |
| Residential | (820) | (87,404) | $ | (384,181) |
| General Service - Small | (50) | (7,935) | $ | (35,262) |
| General Service - Large | (11) | (6,906) | $ | (18,253) |
| General Service - TE | 1 | 29,230 | $ | 54,097 |
| Small Generator Service | 4 | 97 | $ | 2,718 |
| Irrigation Sales | (1) | (402) | $ | (1,133) |
| Sales for Resale | (4) | (5,809) | $ | (11,495) |
| Small Transport k-System | 0 | 0 | $ | - |
| Small Transport t-System | (20) | (39,532) | $ | (71,846) |
| CNG k-System | (4) | (7,388) | $ | (17,197) |
| CNG t-System | 0 | 0 | $ | 0 |
| Irrigation Transport | 0 | 0 | $ | - |
| Large Transport k - Tier 1 | 11 | 468,976 | $ | 597,767 |
| Large Transport k - Tier 2 | (6) | (34,144) | $ | (43,481) |
| Large Transport k - Tier 3 | (0) | (7,099) | $ | (7,572) |
| Large Transport k - Tier 4 | 2 | 76,730 | $ | 75,745 |
| Large Transport t - Tier 1 | (7) | (838,451) | $ | (765,122) |
| Large Transport t - Tier 2 | (1) | (8,826) | $ | (16,317) |
| Large Transport t - Tier 3 | (2) | (32,540) | $ | (50,711) |
| Large Transport t - Tier 4 | 1 | 40,564 | $ | 61,318 |
| Wholesale Transport | (5) | (728,184) | $ | (991,709) |
| **Total** | **(910)** | **(1,189,023)** | **$** | **(1,622,635)** |

KGS calculated a customer annualization revenue adjustment $(1,433,801). Thus, Staff is proposing a customer annualization adjustment of $(188,834), the difference between Staff's and KGS' filed positions.

**Recommendation**

**Q. Does Staff have a recommendation?**

A. Yes. Staff's methodology appropriately adjusts test year revenues to reflect the number of customers KGS was serving at the end of the test year. Thus, the adjustment represents the revenue KGS would have received if the number of customers at year-end had received service throughout the entire test year. Therefore, I recommend the Commission accept Staff's customer annualization adjustment of $(188,834), the difference between Staff's and KGS' filed positions.

## V. CONCLUSION

**Q. Please summarize your recommendation.**

A. I recommend the Commission accept Staff's proposed weather normalization revenue adjustment of $904,115 and customer annualization adjustment of $(188,834). The combined adjustment is $715,280.

**Q. Does this conclude your testimony?**

A. Yes. Thank you.

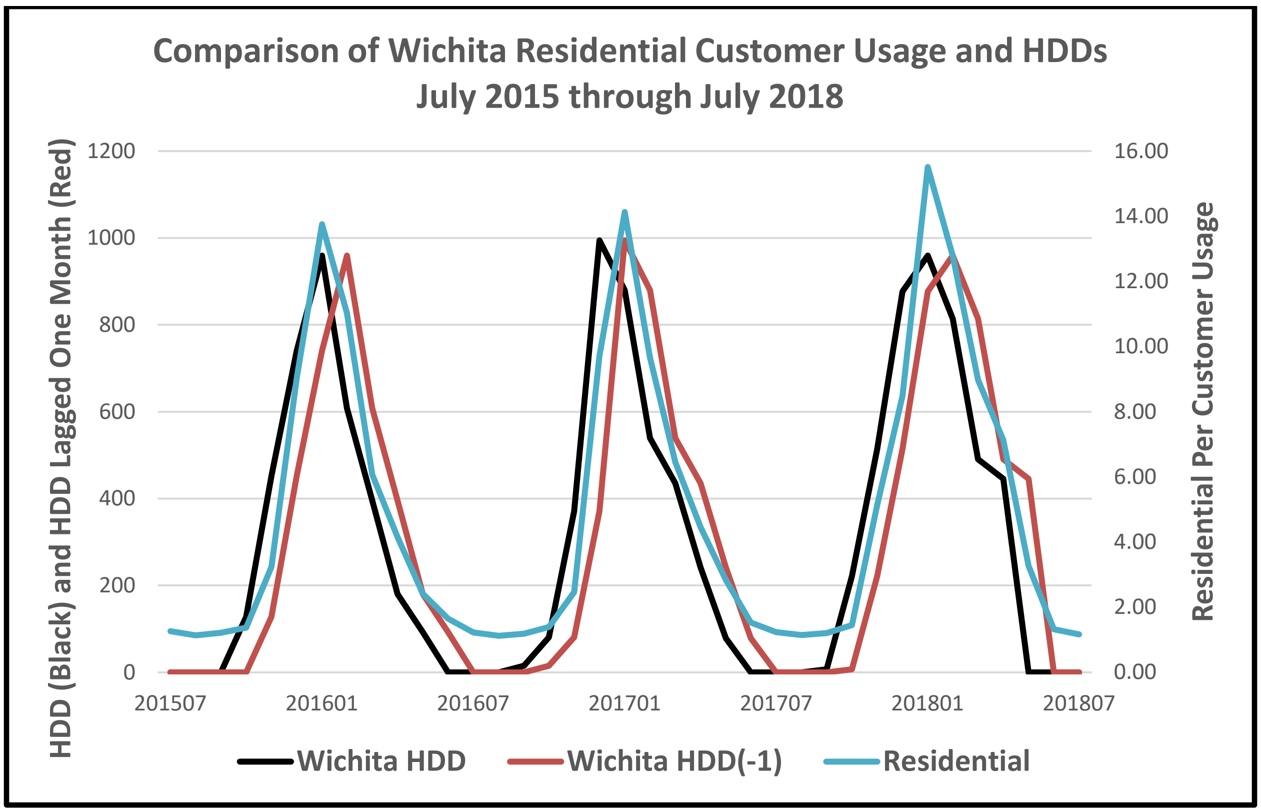
# Exhibit RHG-1: Staff's Approach to Weather Normalization

## Introduction

### Why Statistical Analysis Works for Weather Normalization

Below in Figure 1 is a comparison of Wichita Residential average customer usage and two weather variables that measure winter demand for space heating from July 2015 through July 2018. The weather variables do not match-up perfectly, but they look closely correlated. In fact, the weather variables explain 97% of the variation in the average usage variable.[1] It is the close correlation between Residential average customer usage and weather that makes statistically estimating weather normalization possible. For large, well-behaved classes such as the Wichita Residential Class, average customer usage and weather are tightly related. Unfortunately, this tight fit does not exist for all customer classes. As a result, our approach to weather normalization is not mechanical process.

**Figure 1**




[1] The 97% is the value of the adjusted $R^2$. $R^2$ is the coefficient of determination.
$R^2 = \frac{\text{Sum of Squares Explainded by the Regression}}{\text{Total Summ of Squares of the Dependent Variable}}$.
The adjusted $R^2$ is adjusted for the number of independent variables: $R^2 \geq$ Adjusted $R^2$. .

## Outline of Staff's Approach

Not only is our approach to weather normalization not mechanical, but our approach to statistical analysis is not mechanical. We approach all statistical problems by thinking through the issue or issues we are trying to understand.

Our first step is always to look at the data. If the data is bad, then no statistical technique is going to help understand the issue under investigation. After looking at the data and ensuring that the data can be used to investigate the issue, the next step is to decide on the appropriate statistical techniques to use.

For weather normalization, we use a combination of data investigation and regression estimation. 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. Then we run the simple equation below for each class and use the results to test for structural breaks in the data.

**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, $\varepsilon$ 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.

The elimination of the outliers and breakpoints, in most cases, makes the time series data stable and stationary.[4] Because the data is a time series and has seasonal effects, fitting the regression equations requires using autoregressive moving average (ARMA) terms. To use ARMA terms the data needs to be stationary. The addition of ARMA terms in the regression analysis is the final step. If, however, no good regression equation is found that includes the weather variables, then we return to the data analysis and try to identify why the regression equation does not include the weather variables. Without the weather variables in the regression equation, the equation is useless for weather normalization.

## 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

[2] In the irrigation equations, the CDD and perception variables are added and nearly always the parameters on the HDD variables indication the HDD variables are not statistically significant for estimating irrigation demand.
[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 is one in which the mean, variance, and autocorrelation structure are constant over time.

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 if the coefficient is smaller in absolute value than the standard deviation, I eliminate the variable.

## 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 data. If the data has outliers or structural breaks in it, then these need to either be eliminated or corrected. For example, if there is a structural break in the data midway through the time series, then using the whole time series for estimation will cause an incorrect estimation of the customer classes weather sensitivity.

### 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.

**Figure 2**

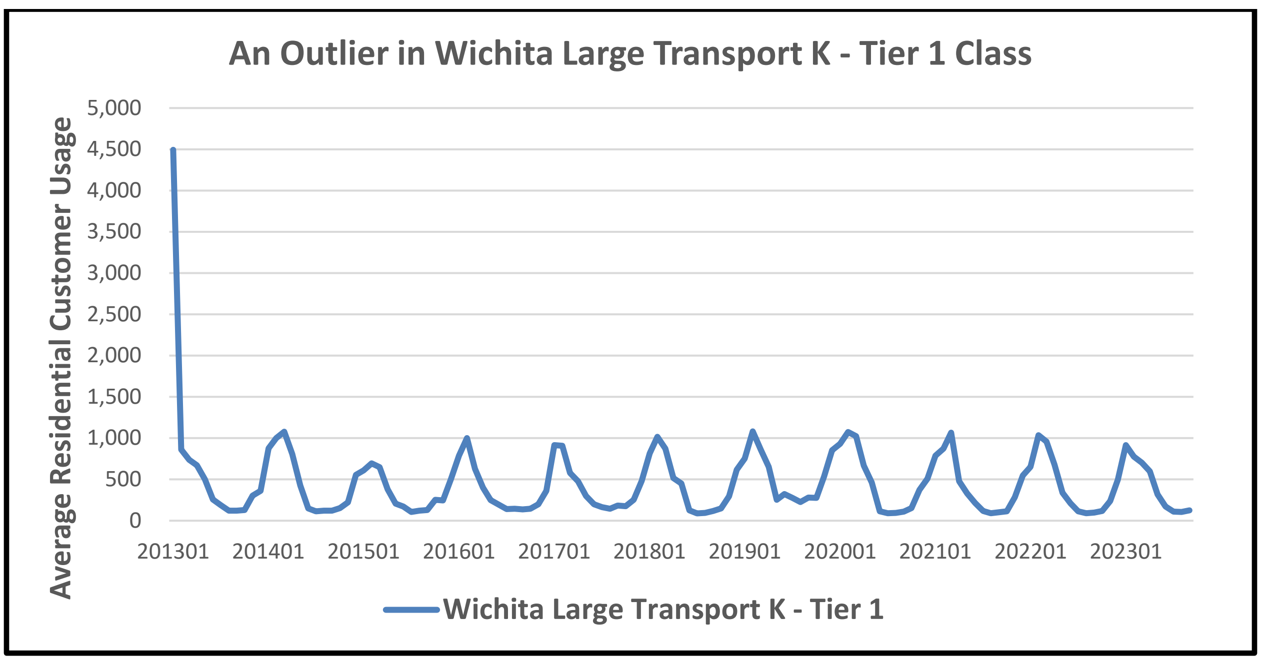
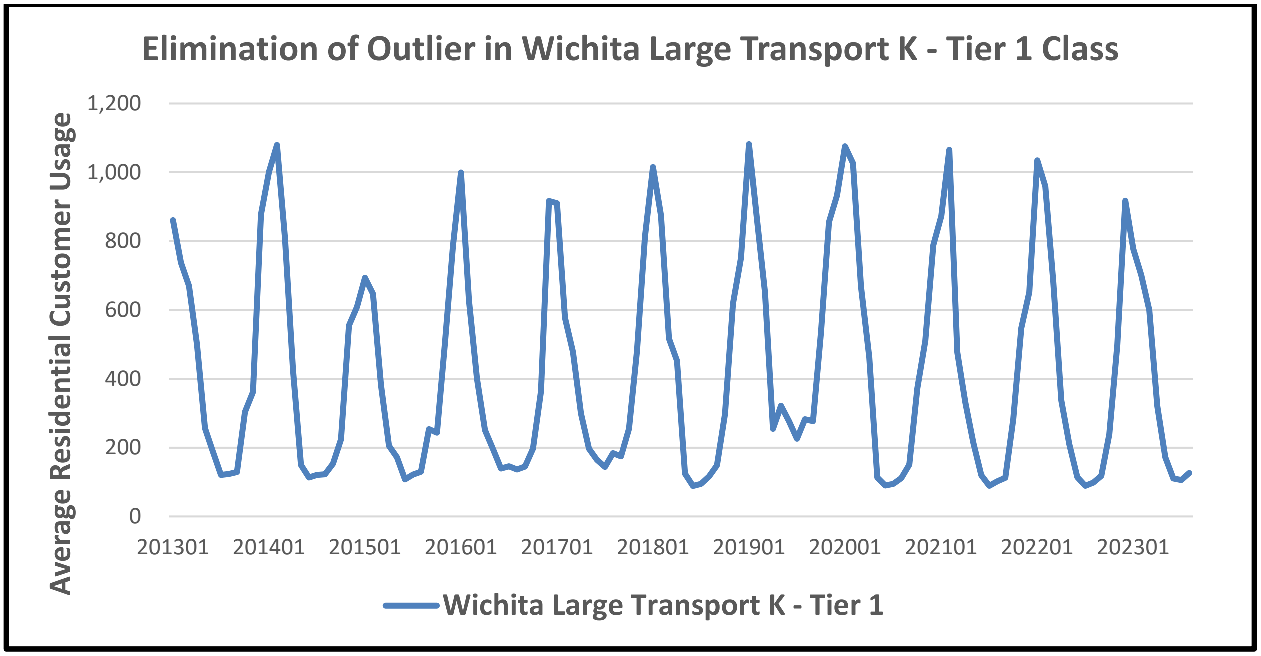


Figure 3 below shows the effect of eliminating the outlier.

**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 |

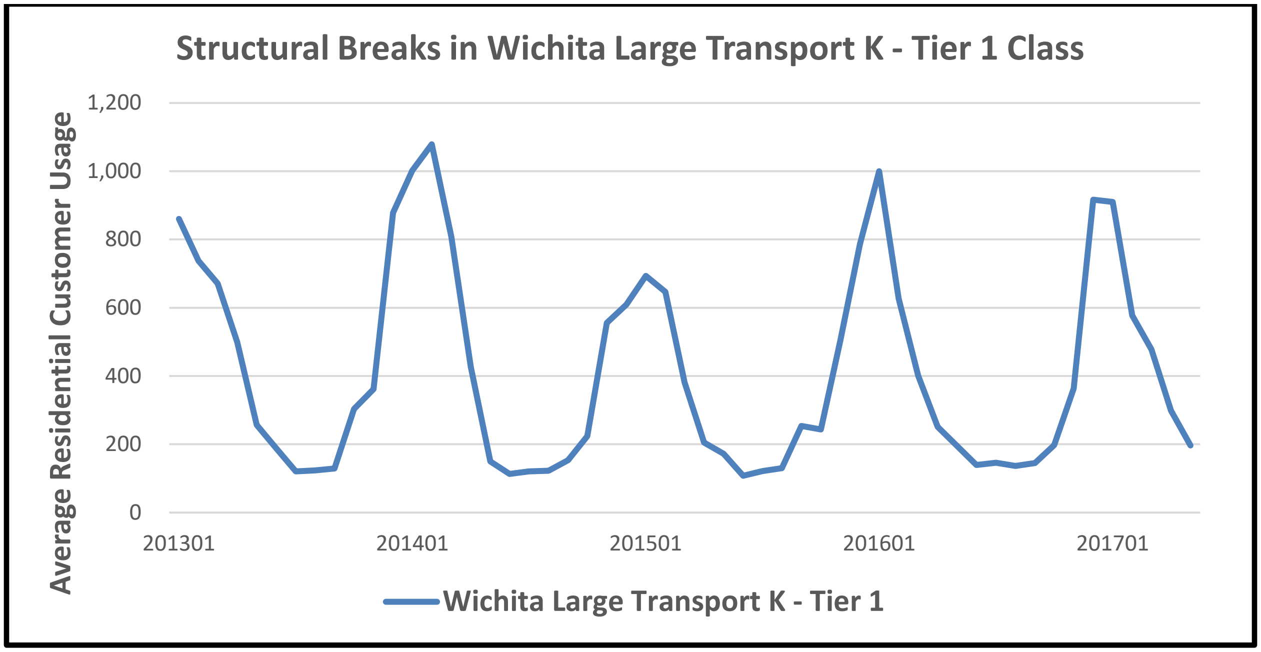
The results show a large difference for the HDD variable's coefficient, including a sign change, and a small difference for the HDD(-1) variable coefficient. However, the starker differences are in the criteria results. For example, the adjusted $R^2$ increases from 50% to 93% by dropping the outlier 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 all much more positive with the omission of the outlier. The reason the outlier has such a dramatic effect is that ordinary least squares method of estimation was used, the standard method of estimation. Each data point is squared, thus exacerbating the outlier effect.

## The Problem of Structural Breaks

### An Example of Structural Breaks

After eliminating the outlier in Figure 2, Figure 4 reveals an additional potential problem with the average customer usage data—there seem to be periods where the data do not follow the basic pattern of the whole data set. For example, notice the period from the summer of 2014 through the summer of 2015 which is shown in Figure 4 below. The different pattern from the summer of 2014 through the summer of 2015 becomes obvious in Figure 4.

**Figure 4**




There are three basic tests for structural breaks in a data series: the Chow Test, the Andrews-Quandt Test, and the Bai-Perron Test. To use the Chow Test, you must know the structural breakpoint, which is a problem. Looking at Figure 5, it could be any data point between the beginning of 2014 and the end of 2015.

The solution to this problem is to use the Quandt-Andrews Test which identifies the breakpoint with the greatest significance. That is more helpful because the test identifies the breakpoint but does not completely solve the problem we face—we want to know all the breakpoints or at least the last significant breakpoint, not the most significant breakpoint.

The Bai-Perron Test provides estimates of up to 5 breakpoints and provides the significance of each of them. This provides what we are looking for, and for that reason, we begin our analysis of structural stability of the data with the Bai-Perron Test.

The only problem with the Bai-Perron Test is the output in EViews only gives the location (data point) of the breakpoint if the significance level is below 5% probability. If the probability of the test result is something like 5.5%, then the location of the potential breakpoint is not provided. In case of a near significant breakpoint, we then go back to the Quandt-Andrews Test which will provide nearly the same significance level for the breakpoint and identify its location. The reason they might not have the identical significance level is that each test uses a different test to determine significance. We then run the basic Eq 01 equation for the data including the data before the potential breakpoint and after the potential breakpoint. We look at the difference in parameter values and make a judgement about whether the difference is important enough—how different in absolute value terms are the WSFs between the two estimated equations. We have in the past put in a dummy variable for the period before the potential breakpoint and used it in the equation by adding a term where the WSFs are multiplied by the dummy variable to check to see the estimate the significance of the breakpoint. But estimating the equation with the two different time periods is equally effective and much less troublesome.

## Application of the Breakpoint Tests

In the Large Transport K -Tier 1 Class case, Table 2 gives the results of the Bai-Perron Test.

**Table 2**

| Bai-Perron Multiple Breakpoint Tests | | | |
|---|---|---|---|
| Sample: 2013M02 2023M09 | | | |
| Included observations: 128 | | | |
| Breaking variables: C WICH_HDD WICH_HDD(-1) | | | |
| Break test options: Trimming 0.05, Max. breaks 5, Sig. level 0.05 | | | |
| **Sequential F-statistic determined breaks:** | | | **2** |
| | | **Scaled** | **Critical** |
| **Break Test** | **F-statistic** | **F-statistic** | **Value**** |
| 0 vs. 1 * | 7.79 | 23.37 | 15.37 |
| 1 vs. 2 * | 11.48 | 34.43 | 17.15 |
| 2 vs. 3 | 3.67 | 11.00 | 17.97 |
| * Significant at the 0.05 level. | | | |
| ** Bai-Perron (Econometric Journal, 2003) critical values. | | | |
| **Break dates:** | **Sequential** | **Repartition** | |
| **1** | **2015M06** | **2014M06** | |
| **2** | **2014M06** | **2015M12** | |

Notice that the test provides two breakpoints: one at the beginning of the pattern change in data and the second where the new data pattern develops. Also notice that the recommended repartition of the data takes place several months after the breakpoint. To illustrate the effect of the breakpoints, Table 3 below has the estimation of the basic equation for the period February 2013 to September 2023 and December 2015 to September 2023.

**Table 3**

| The Effect of an Breakpoints on Regression Estimation | | | | |
|---|---|---|---|---|
| Dependent Variable: Wichita Large Transport K - Tier 1 | | | | |
| Method: Least Squares | | | | |
| **Sample: 2013M02 2023M09** | | | | |
| | | | | |
| **Variable** | **Coefficient** | **Std. Error** | **t-Statistic** | **Probabilty** |
| | | | | |
| 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 |
| | | | | |
| **Sample: 2015M12 2023M09** | | | | |
| | | | | |
| C | 129.909 | 10.650 | 12.198 | 0.000 |
| WICH_HDD | (0.052) | 0.035 | (1.495) | 0.138 |
| WICH_HDD(-1) | 0.902 | 0.035 | 25.632 | 0.000 |
| | | | | |
| R-squared | 0.950 | Mean dependent var | | 432.76 |
| Adjusted R-squared | 0.949 | S.D. dependent var | | 313.97 |
| S.E. of regression | 71.230 | Akaike info criterion | | 11.40 |
| Sum squared resid | 461,712 | Schwarz criterion | | 11.48 |
| Log likelihood | (533) | Hannan-Quinn criter. | | 11.43 |
| F-statistic | 858 | Durbin-Watson stat | | 0.74 |

The effect of eliminating the data prior to the last breakpoint is important. The coefficient on the current month HDDs becomes smaller and its significance level falls to insignificance even at probability 10%. This result is encouraging because the coefficient has the wrong sign. In addition, the lagged HDD coefficient is larger with the elimination of the breakpoints. Also, the basic criteria elements improve. Eliminating the bad data in the time series improved the estimation of the basic equation.

## Regression Analysis

### Testing for Serial Correlation

After doing the preliminary data analysis, we estimate EQ 01 with the dataset cleared of outliers and structural breaks. Because the data used for the regression is a time series, we expect serial correlation—a correlation between a variable and a lagged version of itself. Serial correlation does not affect the biasedness or the consistency of an estimate, but it does affect the efficiency of the estimate—the variance of the estimator is larger or smaller than it should be.[5] Because the variance is different, that means that significance testing that uses the variance, for example the t-test, is going to be in error. If the serial correlation is positive, then the variance will be larger than estimated and the t-test will overestimate the significance of the statistical result.

To mitigate serial correlation, we use autoregressive moving average (ARMA) terms. To get a better idea of what the serial correlation looks like, we use correlograms and Q-statistics, which are provided by most statistical packages. The correlograms we use are visual presentations of the autocorrelation and partial autocorrelation functions of the residuals and the square of the residuals.[6] In almost any time series textbook there is a chapter that explains how to interpret the correlograms. Usually, they have examples with simulated data from an autocorrelation equation, so the results are easy to interpret. That is not the case in the real world. In general, if you have a large majority of the terms on the positive side of the chart, then start with autocorrelation. If the large majority are on the negative side, then start with moving average. After that, I suggest experimenting and trying to get some intuition for what works. Below is a more technical description if that helps.

The Q-Test is a check to see if the autocorrelation coefficients are all 0 (jointly not significant) where the residual autocorrelation coefficients are $\boldsymbol{r(i) = corr(\hat{\varepsilon}_t, \hat{\varepsilon}_{t-i}), 1, \ldots, m}$ 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:

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

[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.

[6] Residuals are the difference between the actual value of the dependent variable and the estimated value of the dependent variable. The correlogram of the residuals describes serial correlation. The correlogram of the squared residuals is to determine if the variance suffers from heteroscedasticity—the variance is not constant.

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

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

## Using ARMA Terms to Mitigate Serial Correlation

The four ARMA terms that I used in modifying the initial regression equation are: autoregressive, moving average, seasonal autoregressive, and seasonal moving average. These are briefly described below.

### The Autoregressive Model

The simplest autoregressive model is called the ar(1). In other words, the error term at time $t$ is correlated with the error term at time $t-1$ because $y_t$ is correlated with $y_{t-1}$. Thus, an ar(1) model starts with an error term is $\mu_t = \rho\,\mu_{t-1} + \varepsilon_t$. Assuming one exogenous variable, the basic equation is $y_t = \beta_0 + \beta_1 x_{1t} + \mu_t$. Then substituting for $\mu_t$ into the basic equation gives: $y_t = \beta_0 + \beta_1 x_{1t} + \rho\,(y_{t-1} - \beta_0 + \beta_1 x_{1t-1}) + \varepsilon_t$. The substitution shows the effect of having the current period's error term dependent on the previous period's error term.

To give some intuition of what is happening, if you want to estimate an equation with an ar(1) term in Excel, which does not have functions for autoregression in its regression tools, you can simply lag the two variables and estimate the equation with the extra lagged variables. The coefficient on the $y_{t-1}$ term will be the $\rho$ in the autoregressive error equation or at least very close to it.

Higher order autoregressive terms such as ar(3) represent only an ar(3) term, $\mu_t = \rho\,\mu_{t-3} + \varepsilon_t$, in Eviews. The conventional representation of ar(3) is ***ar(3) ≡ ar(1) + ar(2) + ar(3) or*** $\mu_t = \rho_1\,\mu_{t-1} + \rho_2\,\mu_{t-2} + \rho_3\,\mu_{t-3} + \varepsilon_t$.

### The Moving Average Model

Like the simplest autoregressive model, the simplest moving average model is a ma(1). With a ma(1) last periods error term is correlated with periods error term. Thus, $y_t = \mu_t + \theta\,\varepsilon_{t-1} + \varepsilon_t$. If the mean ($\mu_t = 0$), then the substitution of the moving average error term gives $y_t = \beta_0 + \beta_1 x_{1t} + \theta\,\varepsilon_{t-1} + \varepsilon_t$.

The substitution illustrates the difference between autoregressive and moving average error terms: autoregressive error terms are concerned with the effect of last period's variables correlation with current period's variables while moving average is concerned with the effect of last period's error term on this period's error term.

Like higher order autoregressive terms, higher order moving average terms do not include the lower order terms.

### Seasonal Autoregressive Model

The best way to understand the seasonal autoregressive model is through an example. Start with an ar(1) autoregressive process and a sar(12) seasonal autoregressive process: $\boldsymbol{y_t = \rho_1\, y_{t-1} + \varepsilon_t\; and\; y_t = \varphi_{12}\, y_{t-12} + \varepsilon_t.}$ The combined the result is $\boldsymbol{y_t = \rho_1\, y_{t-1} + \varphi_{12}\, y_{t-12} - \rho_1\varphi_{12} y_{t-13} + \varepsilon_t.}$ The multiplication of the regular ($\boldsymbol{\rho}$) and the seasonal ($\boldsymbol{\varphi}$) autoregressive terms for the parameter on the $\boldsymbol{y_{t-13}}$ term provides a non-linear effect. Also note that the process now has an ar(13).

### Seasonal Moving Average Model

Using a similar example to the seasonal autoregressive model, the ma(1) term and the sma(12) term are $\boldsymbol{y_t = \mu_t + \theta\, \varepsilon_{t-1} + \varepsilon_t\;\; and\; y_t = \mu_{t-12} + \omega_{12}\, \varepsilon_{t-12} + \varepsilon_t.}$ Assuming the means are zero, the combined the result $\boldsymbol{y_t = \theta_1\, \varepsilon_{t-1} + \omega_{12}\, \epsilon_{t-12} + \theta_1\omega_{12}\epsilon_{t-13} + \varepsilon_t.}$ The non-linearity is the same as for the autoregressive process except for the change in sign from minus to plus. And there is also a ma(13) term.

### Using Examples to Illustrate the Use of ARMA Terms in Weather Normalization

We will go through two examples: the Wichita Large Transport K – Tier 1 Class that was used for the bad data examples, and the Wichita Residential Class that does not have bad data problems and is well-behaved.

## Wichita Large Transport k – Tier 1—A Problematic Customer Class

The initial estimate of the regression equation for the Wichita Large Transport k Tier-1 is at the bottom of Table 3 above, but is reproduced below at Table 4

**Table 4**

| The Initial Estimation for Wichita Large Transport k Tier-1 | | | | |
|---|---|---|---|---|
| Method: Least Squares | | | | |
| Sample: 2015M12 2023M09 | | | | |
| Included observations: 94 | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C | 129.909 | 10.650 | 12.198 | 0.000 |
| WICH_HDD | (0.052) | 0.035 | (1.495) | 0.138 |
| WICH_HDD(-1) | 0.902 | 0.035 | 25.632 | 0.000 |
| R-squared | 0.950 | Mean dependent var | | 432.76 |
| Adjusted R-squared | 0.949 | S.D. dependent var | | 313.97 |
| S.E. of regression | 71.230 | Akaike info criterion | | 11.40 |
| Sum squared resid | 461,712 | Schwarz criterion | | 11.48 |
| Log likelihood | (533) | Hannan-Quinn criter. | | 11.43 |
| F-statistic | 858 | Durbin-Watson stat | | 0.74 |
| Prob(F-statistic) | 0 | | | |

Figures 5 below shows the correlogram for the residuals and Figure 6 shows the correlogram for the squared residuals. The dashed lines in each figure indicate the critical values to reject the hypothesis of no serial correlation (Figure 5) and no heteroskedasticity (Figure 6). If the bars are outside of the dashed lines, then the hypothesis of no serial correlation and no heteroskedasticity cannot be rejected. The correlograms show that both serial correlation and heteroskedasticity cannot be rejected. In this case, it seems that inserting both an ar(1) and ma(1) into the equation should mitigate the serial correlation.

**Figure 5**

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 |

**Figure 6**

Date: 06/24/24 Time: 11:19
Sample: 2015M12 2023M09
Included observations: 94

| | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|
| 1 | 0.605 | 0.605 | 35.544 | 0.000 |
| 2 | 0.618 | 0.396 | 72.947 | 0.000 |
| 3 | 0.507 | 0.077 | 98.401 | 0.000 |
| 4 | 0.378 | -0.124 | 112.73 | 0.000 |
| 5 | 0.356 | 0.034 | 125.57 | 0.000 |
| 6 | 0.264 | -0.009 | 132.72 | 0.000 |
| 7 | 0.185 | -0.083 | 136.26 | 0.000 |
| 8 | 0.171 | 0.025 | 139.33 | 0.000 |
| 9 | 0.098 | -0.017 | 140.36 | 0.000 |
| 10 | 0.039 | -0.087 | 140.52 | 0.000 |
| 11 | -0.004 | -0.061 | 140.52 | 0.000 |
| 12 | -0.017 | 0.052 | 140.55 | 0.000 |
| 13 | -0.006 | 0.079 | 140.56 | 0.000 |
| 14 | 0.009 | 0.049 | 140.57 | 0.000 |
| 15 | -0.063 | -0.138 | 141.02 | 0.000 |
| 16 | -0.114 | -0.168 | 142.51 | 0.000 |
| 17 | -0.147 | -0.062 | 145.06 | 0.000 |
| 18 | -0.187 | -0.015 | 149.23 | 0.000 |
| 19 | -0.144 | 0.110 | 151.72 | 0.000 |
| 20 | -0.180 | -0.010 | 155.66 | 0.000 |
| 21 | -0.167 | -0.043 | 159.11 | 0.000 |
| 22 | -0.157 | -0.038 | 162.20 | 0.000 |
| 23 | -0.150 | 0.026 | 165.07 | 0.000 |
| 24 | -0.172 | -0.038 | 168.89 | 0.000 |

The second estimation included an ar(1) term and a ma(1) term. The results are below in Table 5 below. The result show improvement in the standard error of the regression, the Log Likelihood function, the F-statistic, and the information criteria. However, notice that the ma(1) term is not significant with a probability of 20% and the HDD coefficient is larger in absolute value and more significant.

**Table 5**

| The Second Estimation for Wichita Large Transport k Tier-1 | | | | |
|---|---|---|---|---|
| Method: ARMA Maximum Likelihood (OPG - BHHH) | | | | |
| Date: 06/24/24 Time: 11:25 | | | | |
| Sample: 2015M12 2023M09 | | | | |
| Included observations: 94 | | | | |
| Convergence achieved after 38 iterations | | | | |
| | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| | | | | |
| C | 132.363 | 22.708 | 5.829 | 0.000 |
| WICH_HDD | (0.061) | 0.037 | (1.650) | 0.102 |
| WICH_HDD(-1) | 0.905 | 0.036 | 24.872 | 0.000 |
| AR(1) | 0.721 | 0.084 | 8.549 | 0.000 |
| MA(1) | (0.162) | 0.127 | (1.278) | 0.205 |
| SIGMASQ | 2,931.911 | 337.616 | 8.684 | 0.000 |
| | | | | |
| R-squared | 0.970 | Mean dependent var | | 432.76 |
| Adjusted R-squared | 0.968 | S.D. dependent var | | 313.97 |
| S.E. of regression | 55.963 | Akaike info criterion | | 10.95 |
| Sum squared resid | 275,600 | Schwarz criterion | | 11.12 |
| Log likelihood | (509) | Hannan-Quinn criter. | | 11.02 |
| F-statistic | 568 | Durbin-Watson stat | | 1.96 |
| Prob(F-statistic) | 0 | | | |
| | | | | |
| Inverted AR Roots | 0.72 | | | |
| Inverted MA Roots | 0.16 | | | |

Figures 7 and 8 show the new correlograms. They both have improved. However, note that in Figure 8 at the 12th period, there is a point of heteroskedasticity. Also, note that the standard error the regression, the Log Likelihood function, the F-statistic, and the information criteria all improved.

**Figure 7**

Date: 06/24/24 Time: 11:32
Sample: 2015M12 2023M09
Q-statistic probabilities adjusted for 2 ARMA terms

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | 0.021 | 0.021 | 0.0410 | |
| | | 2 | -0.078 | -0.078 | 0.6330 | |
| | | 3 | -0.065 | -0.062 | 1.0542 | 0.305 |
| | | 4 | 0.169 | 0.168 | 3.9298 | 0.140 |
| | | 5 | 0.190 | 0.180 | 7.6046 | 0.055 |
| | | 6 | -0.151 | -0.146 | 9.9327 | 0.042 |
| | | 7 | 0.055 | 0.112 | 10.250 | 0.068 |
| | | 8 | 0.129 | 0.117 | 11.992 | 0.062 |
| | | 9 | -0.142 | -0.250 | 14.140 | 0.049 |
| | | 10 | -0.132 | -0.097 | 16.016 | 0.042 |
| | | 11 | -0.131 | -0.093 | 17.888 | 0.036 |
| | | 12 | 0.112 | -0.022 | 19.279 | 0.037 |
| | | 13 | -0.061 | -0.068 | 19.697 | 0.050 |
| | | 14 | -0.082 | 0.059 | 20.463 | 0.059 |
| | | 15 | -0.138 | -0.141 | 22.636 | 0.046 |
| | | 16 | -0.024 | -0.021 | 22.701 | 0.065 |
| | | 17 | -0.058 | -0.040 | 23.090 | 0.082 |
| | | 18 | -0.007 | 0.029 | 23.095 | 0.111 |
| | | 19 | 0.050 | 0.058 | 23.393 | 0.137 |
| | | 20 | -0.014 | -0.025 | 23.417 | 0.175 |
| | | 21 | -0.069 | -0.065 | 24.002 | 0.196 |
| | | 22 | -0.087 | -0.080 | 24.955 | 0.203 |
| | | 23 | 0.028 | 0.009 | 25.052 | 0.245 |
| | | 24 | 0.165 | 0.101 | 28.570 | 0.158 |

*Probabilities may not be valid for this equation specification.

**Figure 8**

Date: 06/24/24 Time: 11:32
Sample: 2015M12 2023M09
Included observations: 94

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.041 | 0.041 | 0.1660 | 0.684 |
| | | 2 | 0.075 | 0.073 | 0.7128 | 0.700 |
| | | 3 | 0.082 | 0.077 | 1.3872 | 0.709 |
| | | 4 | 0.196 | 0.188 | 5.2535 | 0.262 |
| | | 5 | 0.010 | -0.012 | 5.2643 | 0.384 |
| | | 6 | 0.098 | 0.071 | 6.2585 | 0.395 |
| | | 7 | 0.015 | -0.018 | 6.2827 | 0.507 |
| | | 8 | 0.027 | -0.020 | 6.3570 | 0.607 |
| | | 9 | 0.019 | 0.008 | 6.3970 | 0.700 |
| | | 10 | 0.073 | 0.043 | 6.9695 | 0.728 |
| | | 11 | -0.007 | -0.011 | 6.9747 | 0.801 |
| | | 12 | 0.311 | 0.314 | 17.625 | 0.128 |
| | | 13 | -0.008 | -0.039 | 17.631 | 0.172 |
| | | 14 | -0.053 | -0.113 | 17.952 | 0.209 |
| | | 15 | 0.017 | -0.019 | 17.984 | 0.263 |
| | | 16 | 0.221 | 0.128 | 23.621 | 0.098 |
| | | 17 | -0.055 | -0.051 | 23.975 | 0.120 |
| | | 18 | -0.058 | -0.101 | 24.374 | 0.143 |
| | | 19 | -0.052 | -0.073 | 24.698 | 0.171 |
| | | 20 | -0.096 | -0.134 | 25.824 | 0.172 |
| | | 21 | -0.123 | -0.103 | 27.696 | 0.149 |
| | | 22 | -0.076 | -0.100 | 28.429 | 0.162 |
| | | 23 | -0.049 | 0.022 | 28.738 | 0.189 |
| | | 24 | -0.068 | -0.088 | 29.336 | 0.208 |

The last step is to eliminate the ma(1) term and the HDD term and see how much they hurt the regression statistics. I did this one at a time starting with the ma(1) term.

**Table 6**

| The Final Estimation for Wichita Large Transport k Tier-1 | | | | |
|---|---|---|---|---|
| Method: ARMA Maximum Likelihood (OPG - BHHH) | | | | |
| Sample: 2015M12 2023M09 | | | | |
| Included observations: 94 | | | | |
| Convergence achieved after 12 iterations | | | | |
| | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| | | | | |
| C | 124.627 | 23.301 | 5.349 | 0.000 |
| WICH_HDD(-1) | 0.865 | 0.026 | 32.905 | 0.000 |
| AR(1) | 0.621 | 0.072 | 8.673 | 0.000 |
| SIGMASQ | 3,051.022 | 339.819 | 8.978 | 0.000 |
| | | | | |
| R-squared | 0.969 | Mean dependent var | | 432.76 |
| Adjusted R-squared | 0.968 | S.D. dependent var | | 313.97 |
| S.E. of regression | 56.450 | Akaike info criterion | | 10.95 |
| Sum squared resid | 286796 | Schwarz criterion | | 11.06 |
| Log likelihood | (511) | Hannan-Quinn criter. | | 11.00 |
| F-statistic | 929 | Durbin-Watson stat | | 2.02 |
| Prob(F-statistic) | 0 | | | |
| | | | | |
| Inverted AR Roots | 0.62 | | | |

Eliminating the ma(1) improved all the criteria. But eliminating the HDD term hurt the standard error of the regression, the Log Likelihood function, and the F-statistic, but only slightly. The effect on the information criteria was mixed. Also, the correlograms remained basically as before. Thus, we went with the simpler equation, the one without the HDD term for three reasons: it was not significant, it was negative, which is counter-intuitive, and eliminating it did not meaningfully damage the equation's estimation criteria.

## Wichita Residential Class—A Well-Behaved Customer Class

The second example is the well-behaved Wichita Residential Class that was first used in Figure 1 at the beginning of this attachment. The initial estimate of the basic equation (Eq 01) is provided in Table 7 below.

**Table 7**

| Withita Residential Class Initial Estimate | | | | |
|---|---|---|---|---|
| Method: Least Squares | | | | |
| **Sample (adjusted): 2011M01 2023M09** | | | | |
| Included observations: 153 after adjustments | | | | |
| **Variable** | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.** |
| C | 0.698 | 0.092 | 7.590 | 0.000 |
| WICH_HDD | 0.006 | 0.000 | 18.990 | 0.000 |
| WICH_HDD(-1) | 0.008 | 0.000 | 24.608 | 0.000 |
| R-squared | 0.972 | Mean dependent var | | 5.46 |
| Adjusted R-squared | 0.972 | S.D. dependent var | | 4.71 |
| S.E. of regression | 0.793 | Akaike info criterion | | 2.39 |
| Sum squared resid | 94 | Schwarz criterion | | 2.45 |
| Log likelihood | (180) | Hannan-Quinn criter. | | 2.42 |
| F-statistic | 2,611 | Durbin-Watson stat | | 1.87 |
| Prob(F-statistic) | 0 | | | |

There are no outliers in the data for average customer usage and below is the check for stability.

**Table 8**

| Wichita Residential Customer Class: Bai-Perron Test | | | |
|---|---|---|---|
| Multiple breakpoint tests | | | |
| Bai-Perron tests of L+1 vs. L sequentially determined breaks | | | |
| Date: 06/24/24 Time: 09:22 | | | |
| **Sample: 2010M12 2023M09** | | | |
| Included observations: 153 | | | |
| Breaking variables: C WICH_HDD WICH_HDD(-1) | | | |
| Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05 | | | |
| **Sequential F-statistic determined breaks:** | | | **0** |
| **Break Test** | **F-statistic** | **Scaled F-statistic** | **Critical Value**** |
| 0 vs. 1 | 2.163022 | 6.489065 | 13.98 |
| * Significant at the 0.05 level. | | | |
| ** Bai-Perron (Econometric Journal, 2003) critical values. | | | |

With no data problems, we move on to checking for serial correlation and heteroskedasticity. Figure 9 shows the correlogram for the residuals and Figure 10 shows the correlogram for the residuals squared. Figure 9 shows some serial correlation, but much milder than in the case of the Wichita Large Transport k Tier-1 Class. Also, there is no serial correlation in the first period, but the bars are swinging left to right and back again much like the initial correlogram for the Wichita Large Transport k Tier -1 Class.

**Figure 9**

Date: 06/24/24 Time: 09:56
Sample (adjusted): 2011M01 2023M09
Included observations: 153 after adjustments

| | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|
| 1 | 0.059 | 0.059 | 0.5498 | 0.458 |
| 2 | -0.252 | -0.256 | 10.489 | 0.005 |
| 3 | -0.312 | -0.299 | 25.925 | 0.000 |
| 4 | -0.179 | -0.260 | 31.028 | 0.000 |
| 5 | 0.140 | -0.034 | 34.149 | 0.000 |
| 6 | 0.247 | 0.056 | 44.019 | 0.000 |
| 7 | 0.090 | 0.016 | 45.343 | 0.000 |
| 8 | -0.095 | -0.016 | 46.825 | 0.000 |
| 9 | -0.277 | -0.175 | 59.481 | 0.000 |
| 10 | -0.303 | -0.349 | 74.696 | 0.000 |
| 11 | 0.218 | 0.036 | 82.640 | 0.000 |
| 12 | 0.489 | 0.304 | 122.82 | 0.000 |
| 13 | 0.241 | 0.263 | 132.63 | 0.000 |
| 14 | -0.266 | -0.082 | 144.69 | 0.000 |
| 15 | -0.340 | -0.060 | 164.53 | 0.000 |
| 16 | -0.081 | 0.097 | 165.66 | 0.000 |
| 17 | 0.091 | -0.034 | 167.09 | 0.000 |
| 18 | 0.238 | 0.000 | 177.08 | 0.000 |
| 19 | 0.110 | -0.002 | 179.24 | 0.000 |
| 20 | -0.059 | 0.060 | 179.87 | 0.000 |
| 21 | -0.276 | -0.023 | 193.54 | 0.000 |
| 22 | -0.252 | -0.084 | 205.00 | 0.000 |
| 23 | 0.077 | -0.106 | 206.09 | 0.000 |
| 24 | 0.497 | 0.144 | 251.50 | 0.000 |

Figure 10 shows almost no heteroskedasticity and this result does not change throughout the rest of the statistical analysis.

**Figure 10**

Date: 06/24/24 Time: 10:44
Sample (adjusted): 2011M01 2023M09
Included observations: 153 after adjustments

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.078 | 0.078 | 0.9416 | 0.332 |
| | | 2 | 0.006 | 0.000 | 0.9475 | 0.623 |
| | | 3 | -0.023 | -0.024 | 1.0304 | 0.794 |
| | | 4 | -0.032 | -0.029 | 1.1970 | 0.879 |
| | | 5 | -0.068 | -0.063 | 1.9285 | 0.859 |
| | | 6 | -0.146 | -0.138 | 5.3872 | 0.495 |
| | | 7 | -0.112 | -0.096 | 7.4253 | 0.386 |
| | | 8 | -0.128 | -0.124 | 10.120 | 0.257 |
| | | 9 | 0.018 | 0.020 | 10.174 | 0.337 |
| | | 10 | 0.123 | 0.106 | 12.670 | 0.243 |
| | | 11 | 0.067 | 0.030 | 13.421 | 0.267 |
| | | 12 | 0.186 | 0.158 | 19.268 | 0.082 |
| | | 13 | -0.014 | -0.067 | 19.301 | 0.114 |
| | | 14 | 0.278 | 0.277 | 32.453 | 0.003 |
| | | 15 | 0.053 | 0.028 | 32.929 | 0.005 |
| | | 16 | -0.117 | -0.089 | 35.288 | 0.004 |
| | | 17 | -0.125 | -0.056 | 38.020 | 0.002 |
| | | 18 | -0.137 | -0.069 | 41.300 | 0.001 |
| | | 19 | -0.060 | -0.011 | 41.929 | 0.002 |
| | | 20 | -0.146 | -0.097 | 45.738 | 0.001 |
| | | 21 | -0.009 | 0.010 | 45.753 | 0.001 |
| | | 22 | 0.050 | 0.048 | 46.213 | 0.002 |
| | | 23 | 0.005 | -0.060 | 46.218 | 0.003 |
| | | 24 | 0.245 | 0.143 | 57.258 | 0.000 |

Even though there is no autocorrelation in the first period, we start by estimating the basic equation with an ar(1) and ma(1) term. Below in Table 9 is the second estimate of the equation and Figure 11 shows the correlogram for the residuals. At the three digit level, there is no change in the estimated coefficients of the HDD terms, although with the addition of one more digit there is a slight change in the coefficients. Adding the ar(1) and ma(1) terms creates a small improvement in the estimation. In particular, the standard error of the regression improves as does the Log Likelihood function. However, the information criteria has not improved.

**Table 9**

| Withita Residential Class Second Estimate | | | | |
|---|---|---|---|---|
| Method: ARMA Maximum Likelihood (OPG - BHHH) | | | | |
| **Sample: 2011M01 2023M09** | | | | |
| Included observations: 153 | | | | |
| Convergence achieved after 17 iterations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C | 0.719 | 0.088 | 8.212 | 0.000 |
| WICH_HDD | 0.006 | 0.000 | 21.174 | 0.000 |
| WICH_HDD(-1) | 0.008 | 0.000 | 29.962 | 0.000 |
| AR(1) | 0.609 | 0.165 | 3.689 | 0.000 |
| MA(1) | (0.850) | 0.109 | (7.778) | 0.000 |
| SIGMASQ | 0.564 | 0.067 | 8.411 | 0.000 |
| R-squared | 0.974 | Mean dependent var | | 5.46 |
| Adjusted R-squared | 0.974 | S.D. dependent var | | 4.71 |
| S.E. of regression | 0.766 | Akaike info criterion | | 2.34 |
| Sum squared resid | 86 | Schwarz criterion | | 2.46 |
| Log likelihood | (173) | Hannan-Quinn criter. | | 2.39 |
| F-statistic | 1,121 | Durbin-Watson stat | | 1.63 |
| Prob(F-statistic) | 0 | | | |
| Inverted AR Roots | 0.61 | | | |
| Inverted MA Roots | 0.85 | | | |

Figure 11 shows that adding the ar(1) and ma(1) terms did not eliminate the serial correlation, but it did change it. The first period now has a positive bar. The other change in the serial correlation is that it looks seasonal now. The bars seem to swing with the seasons from left to right and back.

## Figure 11

Date: 06/24/24 Time: 09:55
Sample (adjusted): 2011M01 2023M09
Q-statistic probabilities adjusted for 2 ARMA terms

| | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|
| 1 | 0.176 | 0.176 | 4.8165 | |
| 2 | -0.163 | -0.200 | 9.0064 | |
| 3 | -0.256 | -0.200 | 19.348 | 0.000 |
| 4 | -0.134 | -0.091 | 22.222 | 0.000 |
| 5 | 0.166 | 0.145 | 26.661 | 0.000 |
| 6 | 0.273 | 0.163 | 38.710 | 0.000 |
| 7 | 0.121 | 0.063 | 41.100 | 0.000 |
| 8 | -0.075 | 0.003 | 42.015 | 0.000 |
| 9 | -0.251 | -0.131 | 52.370 | 0.000 |
| 10 | -0.248 | -0.189 | 62.541 | 0.000 |
| 11 | 0.244 | 0.246 | 72.450 | 0.000 |
| 12 | 0.499 | 0.361 | 114.25 | 0.000 |
| 13 | 0.260 | 0.174 | 125.72 | 0.000 |
| 14 | -0.223 | -0.185 | 134.18 | 0.000 |
| 15 | -0.317 | -0.089 | 151.43 | 0.000 |
| 16 | -0.084 | 0.069 | 152.66 | 0.000 |
| 17 | 0.096 | -0.068 | 154.28 | 0.000 |
| 18 | 0.237 | -0.018 | 164.14 | 0.000 |
| 19 | 0.112 | -0.021 | 166.37 | 0.000 |
| 20 | -0.070 | 0.027 | 167.24 | 0.000 |
| 21 | -0.279 | -0.064 | 181.21 | 0.000 |
| 22 | -0.244 | -0.098 | 192.01 | 0.000 |
| 23 | 0.077 | -0.080 | 193.10 | 0.000 |
| 24 | 0.456 | 0.144 | 231.39 | 0.000 |

*Probabilities may not be valid for this equation specification.

Because of the seasonal appearance of the correlogram for residuals, we next added seasonal autocorrelation and moving average terms to the equation. The seasonal ARMA terms were too much for the data, and the equation failed to estimate. Next, we backed down to just adding ar(12) and ma(12) terms because there does seem to be a seasonal serial correlation. When there is seasonal serial correlation, then the best initial predictor of this month's average usage is the same month's usage a year ago. The result of the estimation is presented in Table 10 below.

**Table 10**

| Withita Residential Class Third Estimate | | | | |
|---|---|---|---|---|
| Method: Least Squares | | | | |
| Sample: 2011M01 2023M09 | | | | |
| Included observations: 153 | | | | |
| Failure to improve objective (non-zero gradients) after 60 iterations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C | 0.443 | 0.450 | 0.984 | 0.327 |
| WICH_HDD | 0.006 | 0.000 | 13.937 | 0.000 |
| WICH_HDD(-1) | 0.008 | 0.001 | 13.169 | 0.000 |
| AR(1) | 0.000 | 0.000 | 0.114 | 0.910 |
| AR(12) | 1.000 | 0.000 | 14,651.860 | 0.000 |
| MA(1) | 0.006 | 0.007 | 0.895 | 0.372 |
| MA(12) | (0.989) | 0.005 | (186.591) | 0.000 |
| SIGMASQ | 0.282 | 0.025 | 11.312 | 0.000 |
| R-squared | 0.987 | Mean dependent var | | 5.46 |
| Adjusted R-squared | 0.987 | S.D. dependent var | | 4.71 |
| S.E. of regression | 0.545 | Akaike info criterion | | 1.87 |
| Sum squared resid | 43 | Schwarz criterion | | 2.03 |
| Log likelihood | (135) | Hannan-Quinn criter. | | 1.94 |
| F-statistic | 1,601 | Durbin-Watson stat | | 2.43 |
| Prob(F-statistic) | 0 | | | |

The equation failed to converge to a solution as the statement "Failure to improve objective (non-zero gradients) after 60 iterations" indicates. Having the four ARMA terms overwhelmed the data. Still, looking at Figure 11 it seems there is seasonal serial correlation in the residuals. What we tried next was the equation with ar(1) and ma(2) and then either an ar(12) or a ma(12) term. Tables 11 and 12 below have the estimation results. Table 11 uses the ar(12) term and Table 12 uses the ma(12) term.

**Table 11**

| Withita Residential Class Fourth Estimate—AR(12) | | | | |
|---|---|---|---|---|
| Method: ARMA Maximum Likelihood (OPG - BHHH) | | | | |
| Sample: 2011M01 2023M09 | | | | |
| Included observations: 153 | | | | |
| Convergence achieved after 23 iterations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C | 0.578 | 0.205 | 2.815 | 0.006 |
| WICH_HDD | 0.00617 | 0.000 | 16.884 | 0.000 |
| WICH_HDD(-1) | 0.00745 | 0.000 | 18.715 | 0.000 |
| AR(1) | 0.206 | 0.084 | 2.464 | 0.015 |
| AR(12) | 0.613 | 0.058 | 10.638 | 0.000 |
| MA(1) | (0.556) | 0.100 | (5.581) | 0.000 |
| SIGMASQ | 0.378 | 0.037 | 10.095 | 0.000 |
| R-squared | 0.983 | Mean dependent var | | 5.46 |
| Adjusted R-squared | 0.982 | S.D. dependent var | | 4.71 |
| S.E. of regression | 0.630 | Akaike info criterion | | 2.00 |
| Sum squared resid | 58 | Schwarz criterion | | 2.14 |
| Log likelihood | (146) | Hannan-Quinn criter. | | 2.06 |
| F-statistic | 1,395 | Durbin-Watson stat | | 1.94 |
| Prob(F-statistic) | 0 | | | |
| Inverted AR Roots | 0.98 | .85-.48i | .85+.48i | .50-.83i |
| | .50+.83i | .02+.96i | .02-.96i | -.46+.83i |
| | -.46-.83i | -.82+.48i | -.82-.48i | -0.94 |
| Inverted MA Roots | 0.56 | | | |

**Table 12**

| Withita Residential Class Fourth Estimate—MA(12) | | | | |
|---|---|---|---|---|
| Method: ARMA Maximum Likelihood (OPG - BHHH) | | | | |
| Sample: 2011M01 2023M09 | | | | |
| Included observations: 153 | | | | |
| Convergence achieved after 35 iterations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C | 0.690 | 0.167 | 4.140 | 0.000 |
| WICH_HDD | 0.00598 | 0.000 | 18.752 | 0.000 |
| WICH_HDD(-1) | 0.00741 | 0.000 | 21.588 | 0.000 |
| AR(1) | 0.278 | 0.146 | 1.900 | 0.059 |
| MA(1) | (0.494) | 0.122 | (4.059) | 0.000 |
| MA(12) | 0.448 | 0.080 | 5.601 | 0.000 |
| SIGMASQ | 0.460 | 0.054 | 8.496 | 0.000 |
| R-squared | 0.979 | Mean dependent var | | 5.46 |
| Adjusted R-squared | 0.978 | S.D. dependent var | | 4.71 |
| S.E. of regression | 0.695 | Akaike info criterion | | 2.18 |
| Sum squared resid | 70 | Schwarz criterion | | 2.32 |
| Log likelihood | (160) | Hannan-Quinn criter. | | 2.24 |
| F-statistic | 1,142 | Durbin-Watson stat | | 1.91 |
| Prob(F-statistic) | 0 | | | |
| Inverted AR Roots | 0.28 | | | |
| Inverted MA Roots | .96+.24i | .96-.24i | .71-.65i | .71+.65i |
| | .28+.89i | .28-.89i | -.21+.90i | -.21-.90i |
| | -.63-.66i | -.63+.66i | -.87-.24i | -.87+.24i |

The estimation model with the ar(12) term is obviously better than the model with the ma(12) term. The $R^2$, standard error of the regression, the Log Likelihood function, and the information criteria are all better with the ar(12) term rather than the ma(12) term. Finally, the coefficients on the HDD and HDD(-1) variables are similar but slightly different. For the Residential Class, these small differences actually make a difference where they don't make much difference in some of the smaller classes.

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 26 day of June, 2024.

Notary Public

My Appointment Expires: 4/28/25

<u>**CERTIFICATE OF SERVICE**</u>

24-KGSG-610-RTS

I, the undersigned, certify that a true and correct copy of the above and foregoing Testimony was served via electronic service on the 1st day of July, 2024, to the following:

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