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MISSOURI PUBLIC SERVICE COMMISSION

FILE NO. ER-2022-0337

REBUTTAL TESTIMONY

OF

NICHOLAS BOWDEN, Ph.D.

ON

BEHALF OF

UNION ELECTRIC COMPANY

D/B/A AMEREN MISSOURI

St. Louis, Missouri
February, 2023

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REBUTTAL TESTIMONY

OF

NICHOLAS BOWDEN, Ph.D.

FILE NO. ER-2022-0337

I. Introduction

Q. Please state your name and business address.

A. Nicholas Bowden, Ph.D., Union Electric Company d/b/a Ameren Missouri ("Ameren Missouri" or "Company"), One Ameren Plaza, 1901 Chouteau Avenue, St. Louis, Missouri 63103.

Q. Are you the same Nicholas Bowden, Ph.D. that submitted direct testimony in this case?

A. Yes, I am.

II. Purpose of Testimony

Q. To what testimony or issues are you responding?

A. My rebuttal testimony responds to MPSC Staff witnesses' direct testimony related to the determination of billing units and normalized revenues as well as MPSC Staff witnesses' direct testimony related to the analysis of the SB 564 rate cap. Billing unit and normalized revenue issues include:

1. MEEIA Adjustment
2. Solar Adjustment
3. Weather Normalization
4. Rider EDI Adjustment

5. Community Solar Adjustment

6. Lighting Municipal Discount Calculation

III. Staff's MEEIA Annualization Adjustment

IV. Q. Did you review MPSC Staff's calculation of the MEEIA Adjustment?

A. Yes, I did.

Q. Did you discover any issues related to Staff's calculation of the MEEIA Adjustment?

A. Yes, I did.

Q. Briefly describe the issues you discovered?

A. Generally speaking, I discovered two types of issues related to Staff's MEEIA adjustment. First, there were input data errors. Staff appeared to have selected some of the wrong raw MEEIA test year savings data for use in its calculation. Second, there were formula errors in Staff's MEEIA adjustment workpapers.

Q. Did you discuss and/or resolve any of the issues with Staff?

A. Yes, in a series of emails and meetings, the Company and Staff discussed and to the best of my understanding resolved all issues related to the calculation of the MEEIA adjustment to be reflected by Staff in their next round of testimony. I will respond to Staff's testimony via a future round of testimony if all of the issues are not resolved.

V. Staff's Solar Annualization Adjustment

Q. Did the Staff include a Solar Adjustment in its calculation of the Company's normalized revenue?

A. No.

Q. Should the Staff have included a Solar Adjustment?

A. Yes. The number and size of behind-the-meter solar generation facilities are known and measurable in the test year and will have a significant impact on billing units in the future. The Company knows this information because customer installations of behind-the-meter solar generation must be inspected by the Company as a condition for service, solar rebates, and net metering.

Between July 2021 and June of 2022, approximately 12,500 kW of behind-the-meter solar capacity was installed by the Company's retail customers. Estimated production for those facilities is over 17 million kWh annually. That production is more than the annual usage of 1,400 residential customers. The solar annualization adjustment provided in my Direct Testimony shows those installations result in a decrease of $887,000 in the Company's revenue annually. The size of this annual decrease will only increase through the true-up period.

Q. Has Staff included a Solar Adjustment in its calculation of the Company's normalized revenue in the past?

A. Yes, Staff included an adjustment for the impact of behind-the-meter solar generation installations in its Revenue Requirement and Cost of Service Report in File No. ER-2014-0258.[1] Specifically, Staff states that "there were an unusual amount of solar panel installations within the test year and update period that could affect projections of Ameren Missouri’s load." Staff goes on to say that it "expects that future rate cases are unlikely to have such a large amount of solar installations in the test year because of the reduction in solar panel installations due to the incentive reduction and other factors such as the cap on

[1] Staff Report Revenue Requirement Cost of Service Section 4. Regulatory Adjustment to Test Year Sales and Rate Revenue Subsection k. Solar Revenue Adjustment page 72.

payments." Staff is not wrong to say that the incentives and the cap on payments had an impact on installation rates. The Company did observe reduced levels of installations in the years which followed 2014, although those levels were still known and measurable and had an impact on customer's net usage, and therefore billing units. However, Staff would be wrong to say there was not a large amount of solar installations in the test year in this case. In the case when Staff supported the solar annualization adjustment, the Company's proposed adjustment was $1 million.[2] The adjustment in this case, $887,000, is not materially different from the one Staff previously supported based on the logic that it was large and, as I noted above, the $887,000 will grow through the true-up phase of this case.

VI. Staff's Weather Normalization of Total Usage

Q. Did you review Staff's Weather Normalization of Total Usage?

A. Yes, I did.

Q. Did you identify any issues with Staff's Weather Normalization of Total Usage?

A. Yes, there are two general problems with the procedure Staff uses to weather normalize total usage:

(1) Staff's regression model specification inaccurately estimates the effect of weather; and

(2) Staff's normalization process does more than remove the effect of abnormal weather.

Both problems cause Staff's method of weather normalization to be inaccurate.

[2] File No. ER-2014-0258, *Direct Testimony of James Pozzo*, p. 5, filed July 3, 2014.

Q. Why does Staff's choice of regression model specification inaccurately estimate the effect of weather on electricity usage?

A. Staff's model inaccurately estimates the effect of weather because Staff includes a lag of the *dependent* variable, kWh usage, as an *independent* variable in its regression specification.

Q. What is regression specification, and how does it relate to weather normalization?

A. Specifying a regression means choosing the variables included in the estimation of a regression model, which is a statistical model used to estimate the relationship between one observable phenomenon (the dependent variable) and one or more other observable phenomenon (the independent variable(s)). In the basic textbook model, regression analysis is discussed in the terms of the following specification.

$$y = \alpha + \beta x + \varepsilon$$

Ordinary Least Squares (OLS) is the primary method used in regression analysis to estimate α and β, which define the relationship between the independent variable x and dependent variable y. The remaining ε is variation in the dependent variable y not explained by the independent variable x.

In the present setting, weather normalizing electricity usage, the goal is to accurately estimate the relationship between the weather and electricity usage. The relationship can be illustrated using the following specification.[3]

$$usage = \alpha + \beta\ temperature + \varepsilon$$

[3] The specification used here is a simplification of the models used by Staff and intended to aid the illustration of relevant issues. Nonetheless, the statistical problems illustrated using this simplified model apply equally to more complex specifications.

In the context of weather normalization, it is paramount to understand that the thing we need to do is accurately estimate β, the effect of temperature (weather) on electricity usage. This is true because weather normalization is defined in the following way.

$$normalUsage = usage - \beta(temperature - normalTemperature)$$

This is what it means to remove the effect of abnormal weather from usage.

Q. What is a lag of the dependent variable?

A. Recall our simple usage and weather regression model above.

$$usage = \alpha + \beta\ temperature + \varepsilon$$

In this model, $usage$ is the dependent variable and $temperature$ is the independent variable. In order to estimate a regression, we need many observations of $usage$ and $temperature$ in order to estimate the statistical relationship between the two variables. In order to illustrate this more explicitly, we should add subscripts to the regression specification. We choose subscript t since we observe usage and temperature across time and it is those observations across time that allow us to estimate the relationship of importance, β.

$$usage_t = \alpha + \beta\ temperature_t + \varepsilon_t$$

When we say that Staff includes a lag of the dependent variable, we mean the following.[4]

$$usage_t = \alpha + \beta\ temperature_t + \gamma\ usage_{t-1} + \varepsilon_t$$

[4] Staff uses the MetrixND statistical software's built in autoregressive moving average function rather than explicitly including the lag of the dependent variable as an independent variable. Nonetheless, the Staff specification of an autoregressive model of order 1 results in the inclusion of the lagged dependent variable in the model estimated by MetrixND.

If we think of $usage_t$ as the electricity usage that occurred on day t, then $usage_{t-1}$ is the electricity usage that occurred on the day before day t. Even more intuitive, we can think of it as today's usage and yesterday's usage.

Q. Please explain how the inclusion of a lag of the dependent variable causes an inaccurate estimate of the relationship between weather and usage in Staff's regression specification.

A. The lagged dependent variable, yesterday's usage, is itself a function of weather, and its inclusion in the regression "soaks up" some of the effect that would be captured by β, the coefficient on the explicit weather variable. It is the explicit weather variable and it's associated β that Staff uses to normalize usage. To be more specific, yesterday's usage is defined in the following way.

$$usage_{t-1} = \alpha + \beta\ temperature_{t-1} + \varepsilon_{t-1}$$

Now look at the specification for yesterday's usage which includes the lagged dependent variable.

$$usage_{t-1} = \alpha + \beta\ temperature_{t-1} + \gamma\ usage_{t-2} + \varepsilon_{t-1}$$

A statistical problem[5] will arise if today's weather and yesterday's weather are correlated, or if today's usage is specified to be a function of today's weather and yesterday's weather. The former is true empirically, and the latter is true because both the Company and Staff specify their regression models this way.

Return once more to the simplest usage and temperature model for an explanation.

$$usage_t = \alpha + \beta\ temperature_t + \varepsilon$$

[5] The specific problem is the inaccurate estimate of β, the thing we need to estimate accurately in order to accurately weather normalize.

Both the Company and Staff define $temperature_t$ as the mean two-day temperature outlined in the publication cited by Staff witness Poudel in Direct Testimony. In order to make the importance of that point clear, we can first rewrite the simple model as follows.

$$usage_t = \alpha + \beta W(temp_t, temp_{t-1}) + \varepsilon_t$$

Where W represents weather more generally, and $W(temp_t, temp_{t-1})$ reads, weather is a function of today's temperature and yesterday's temperature.[6] Due to the fact that Staff defines weather this way and includes the lagged dependent variable, Staff explicitly includes yesterday's temperature in two places. Once in the definition of today's weather and again because the lagged dependent variable is a function of yesterday's temperature. We can see it explicitly by doing the algebra.

$$usage_t = \alpha + \beta W(temp_t, temp_{t-1}) + \gamma\, usage_{t-1} + \varepsilon_t$$

$$usage_{t-1} = \alpha + \beta W(temp_{t-1}, temp_{t-2}) + \gamma\, usage_{t-2} + \varepsilon_{t-1}$$

And then by substitution.

$$usage_t = \alpha + \beta W(temp_t, temp_{t-1})$$

$$+ \gamma\,(\alpha + \beta W(temp_{t-1}, temp_{t-2}) + \gamma\, usage_{t-2} + \varepsilon_{t-1}) + \varepsilon_t$$

This causes some of the effect of yesterday's weather which needs to be accurately captured in β to be captured in γ, i.e., β is not accurately estimated by Staff.

Q. Can you provide any empirical support for the claims above?

A. Yes, I conducted a simple experiment which illustrates the issue empirically. First, I estimate Staff's model including the lagged dependent variable as Staff

[6] The explicit function is $W(temp_t, temp_{t-1}) = \frac{2}{3} * temp_t + \frac{1}{3} * temp_{t-1}$. Weather today is a weighted average of today's temperature and yesterday's temperature where today's temperature gets more weight than yesterdays.

did, and then I re-estimate the model excluding the lagged dependent variable. The empirical support is slightly complicated by the fact that Staff uses a linear spline of temperature variables in their regression. The Company also includes a linear spline, which is discussed in some detail in my Direct Testimony. All this means is that there are several estimated coefficients which represent the different effects of weather across the range of realized temperatures, i.e., there are several temperature βs. Actually, this fact helps illustrate the impact of including the lagged dependent variable more clearly, because all of the βs are attenuated (closer to 0) when the lagged dependent variable is included, i.e., the lagged dependent variable "soaks up" some of the effect of weather. Table 1 shows the attenuation (a specific form of inaccuracy) of temperature βs associated with the inclusion of the lagged dependent variable. The table also includes the difference in the absolute values of the βs and the difference as a percent. The positive difference in the absolute values shows that the estimates of βs are always "bigger" in the model without the lagged dependent variable, whether they are bigger negatives or bigger positives. The percent difference provides an intuitive representation of just how big.

Table 1

Temperature (T) Variable	Model with Lag usage	Model without Lag usage	Difference in Absolute Values	Percent Difference
ResSplines.AvgT	-955,810	-1,012,552	56,741	5.9%
ResSplines.MILDAvgT	1,018,023	1,054,771	36,747	3.6%
ResSplines.HotAvgT	1,162,775	1,168,059	5,284	0.5%
ResSplines.CoolAvgT	291,042	332,674	41,632	14.3%

Q. Why might Staff include a lag of the dependent variable in the regression model specification?

A. If there is autocorrelation in the error term, meaning that the usage that is unexplained by the model for one day exhibits a correlation with the unexplained usage from the prior day, then including a lag of the dependent variable may correct that autocorrelation. The classic assumptions of OLS include the assumption of no autocorrelation in the error term.

Q. Is autocorrelation correction a good reason to include a lag of the dependent variable in Staff's regression specification?

A. No. First, autocorrelation does not impact the estimation of β, the thing we really care about.[7] Autocorrelation only impacts the estimate of the standard error of β. The standard error of β is used in the calculation of the t-statistic[8], a measure of the statistical significance of β. If there is autocorrelation in the errors, then the estimates of the standard error of β will be too small, and therefore, the t-statistic will be too large. In this context, no one is trying to debate the significance of the effect of weather on usage. The generally accepted truth about the significant effect of weather on usage is obvious and is the underlying reason weather normalization of usage is done in the context of ratemaking. Again, it is paramount to understand that autocorrelation does nothing to affect the accuracy of our estimate of β, the thing we need for weather normalization.

[7] Wooldridge, Jeffrey M., "Introductory Econometrics: A Modern Approach," page 413, 3rd edition. "It follows that, as long as the explanatory variables are strictly exogenous, the β are unbiased, regardless of the degree of serial correlation in the errors." Explanatory variable is another term for independent variable and serial correlation is another term for autocorrelation. There is an overwhelming case for the strict exogeneity of daily temperature in this setting.

[8] The $t - statistic = \frac{\beta}{se(\beta)}$, where $se(\beta)$ is the standard error of β.

Second, there are other ways to correct for autocorrelation in the error term. These corrections do not impact the estimate of β itself, but they do correct the issue with t-statistics. The original correction method is referred to as the Newey-West estimator, but there are also later variants which fall under the label of heteroskedastic and autocorrelation consistent estimators. If Staff is interested in correcting the problems associated with autocorrelation in the error term, then Staff should use a heteroskedastic and autocorrelation consistent estimator for the calculation of the standard error of β. Staff should not include a lag of the dependent variable which confounds the estimate of β, the thing we actually care about because it is the only thing we need to weather normalize.

Q. Please explain how Staff's weather normalization procedure does more than remove the effect of abnormal weather.

A. The purpose of weather normalization is to remove the effect of abnormal weather on test year usage. The process of removing the effect of abnormal weather from test year usage requires two steps.

1. Accurately identify the causal relationship between weather and usage.
2. Use the relationship identified in step 1 to remove the effect of abnormal weather from the observed usage, i.e., estimate normal usage.

Assume we are using the following regression model to identify the causal relationship between weather and usage.

$$usage_t = \alpha + \beta\ temperature_t + \varepsilon_t$$

OLS is used to estimate α and β, the coefficients (or parameters) of the model. Given the estimates of α and β and the actual values of $usage_t$ and $temperature_t$, OLS also produces estimates of ε_t.[9] The only value needed to properly implement weather normalization is the estimate of the parameter β, typically referred to as $\hat{\beta}$ (beta hat).[10] In order to understand why this is true, we must understand how to interpret β mathematically. The true relationship β and our estimate of it, $\hat{\beta}$, have the same mathematical interpretation. The parameter estimate $\hat{\beta}$ tells us how much the dependent variable, $usage_t$, changes when the independent variable, $temperature_t$, changes by $\mathbf{1}$.[11] For illustration, if $\hat{\beta} = 10{,}439$, then usage increases by 10,439 kWh when the temperature increases by one degree. Similarly, it means that usage decreases by 10,439 kWh when the temperature decreases by one degree. It also means that usage increases by 10,439 × 2 = 20,878 kWh when temperature increases by two degrees, 10,439 × 3 = 31,317 kWh when temperature increases by three degrees, and so on and so forth.

Now that we know how $\hat{\beta}$ is interpretated, we can outline how it is used to weather normalize usage. Weather normalization was defined above using the following equation.

$$normalUsage = usage - \hat{\beta}(temperature - normalTemperature)$$

In order to understand, it's helpful to break down the second term on the right-hand side of the equation. First, $(temperature - normalTemperature)$. This term is the difference between actual test year temperature and normal temperature for a given day.

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[9] The estimate of ε_t are important later in the explanation, so we will define them here. The term ε_t is often referred to simply as the error term. The values of the estimated ε_t are not errors in the sense of the common usage of the term error. The error terms are more accurately understood to be variation in the dependent variable (usage here) caused by other actual variables in nature that are unobserved.

[10] The hat is used to distinguish between the true relationship and the estimate of the true relationship. The idea is that there is a true relationship between the two variables and all we can do is estimate it statistically. We never know it exactly.

[11] In the case of the linear spline specification utilized by both the Company and Staff, there will be a separate $\hat{\beta}$ for each section of the spline. Each $\hat{\beta}$ will be a different value, but have the same interpretation, and that interpretation will apply only to the range of temperatures which define the corresponding section of the spline.

Said another way, this is the number of degrees of test year temperature must change to get to normal temperature for a given day. Now, $\hat{\beta}(temperature - normalTemperature)$. This is the number of kWh usage would change if test year temperature changed by the number of degrees necessary to get to normal temperature for that given day. In other words, this is the amount of usage caused by abnormal weather. Finally, the amount of usage caused by abnormal weather is removed from actual test year usage to get normal usage. That is weather normalization.

There is one more piece of information related to weather normalization needed to illustrate how Staff does more than remove the effect of abnormal weather. After estimation of the regression, actual usage is defined as a function of the parameter estimate, $\hat{\alpha}$ and $\hat{\beta}$, and the unexplained variation or estimate of the error term, $\widehat{\varepsilon_t}$.

$$usage_t = \hat{\alpha} + \hat{\beta}\ temperature_t + \widehat{\varepsilon_t}$$

If this definition of actual usage is used in the definition of weather normalization, then we have the following expression of weather normalization.

$$normalUsage_t = \hat{\alpha} + \hat{\beta}\ temperature_t + \widehat{\varepsilon_t} - \hat{\beta}(temperature - normalTemperature)$$

Simplify the expression to see the true definition of weather normalized the usage.

$$normalUsage_t = \hat{\alpha} + \hat{\beta} normalTemperature_t + \widehat{\varepsilon_t}$$

This expression makes sense. Normal usage is determined by the same model as the actual observed usage, but with normal temperature instead of the actual temperature. Nothing else should be changed. Specifically, variation in usage caused by variables that are not in the model and are not weather, $\widehat{\varepsilon_t}$, should be included in the definition normal usage.[12]

Staff's weather normalization procedure does more than remove the effect of abnormal weather because Staff removes the variation in usage caused by unobserved variables that are not weather, $\widehat{\varepsilon_t}$. Staff estimates the weather regression model, then takes the parameter estimates, $\hat{\alpha}$ and $\hat{\beta}$, to produce an estimate of usage based on normal weather and the exclusion of other variation in usage not explained by the model, $\widehat{\varepsilon_t}$.

$$normal\widehat{Usage}_t = \hat{\alpha} + \hat{\beta} normalTemperature_t$$

Therefore, Staff's weather normalization procedure does more than remove the effect of abnormal weather. Staff's method removes the effect of abnormal weather and also removes the effect of all unobserved variables that are NOT weather.

Q. Are you able to estimate the effect of Staff's choice to normalize for more than just weather in their weather normalization?

A. Yes. Using Staff's regression model outputs, I estimate the effect of Staff's choice to be 9,565,780 kWh for the Residential class. In this instance, Staff's weather normalization procedure produces 9,565,780 less kWh than its regression model would have produced if Staff included the error term in the procedure. Staff's procedure does not systematically produce less normalized usage. The result is determined by the idiosyncratic nature of the error terms in the period used to fit the model and the test year period. It could have just as likely gone the other direction. The issue is one of principle. Staff's procedure does more than weather normalize. It normalizes out all variation in

[12] The error term, $\widehat{\varepsilon_t}$, could be capturing the effect of economic conditions, consumer preferences, and any number of other real factors that are affecting customers usage behavior. The most important thing to understand is that the variation in usage captured in the error term is NOT related to weather. That is why a proper weather normalization leaves the error term in the calculation of normal usage.

usage not explained by the regression specification. This is not the goal of weather normalization, nor should it be.

VI. Staff's Weather Normalization of Residential and SGS Block Usage

Q. Did you review Staff's Weather Normalization Residential and SGS Block Usage?

A. Yes, I did.

Q. Did you identify any problems with Staff's weather normalization of block usage?

A. Yes, I identified two issues. They are as follows:

(1) Staff's regression model relies on an invalid assumption.

(2) Staff's discretionary application of regression model results produces unreasonable billing unit results.

Q. How does Staff weather normalize Residential and SGS Block usage?

A. Staff uses OLS to estimate the relationship between average usage per customer and Block 1 usage percentage.[13]

$$blockOneUsage = \alpha + \beta \, averageUsage + \varepsilon$$

Staff uses the estimate of the relationship between average usage per customer and Block 1 usage percentage, β, to normalize Block 1 percentages using weather normalized average total usage per customer.

$$normalBlockOneUsage = blockOneUsage + \beta(normalAverageUsage - AverageUsage)$$

[13] The Block 1 usage percentage is the percentage of monthly customer usage for the rate class which occurs below the block 1 kWh threshold. The kWh threshold is important, because different rates apply to kWh of usage above and below the threshold. For residential customers, the threshold is 750, and different rates apply to kWh above and below the threshold.

The weather normalized average usage per customer needed for this block weather normalization is a result of Staff's total kWh weather normalization. Staff's procedure for that total kWh weather normalization and its problems are outlined above.

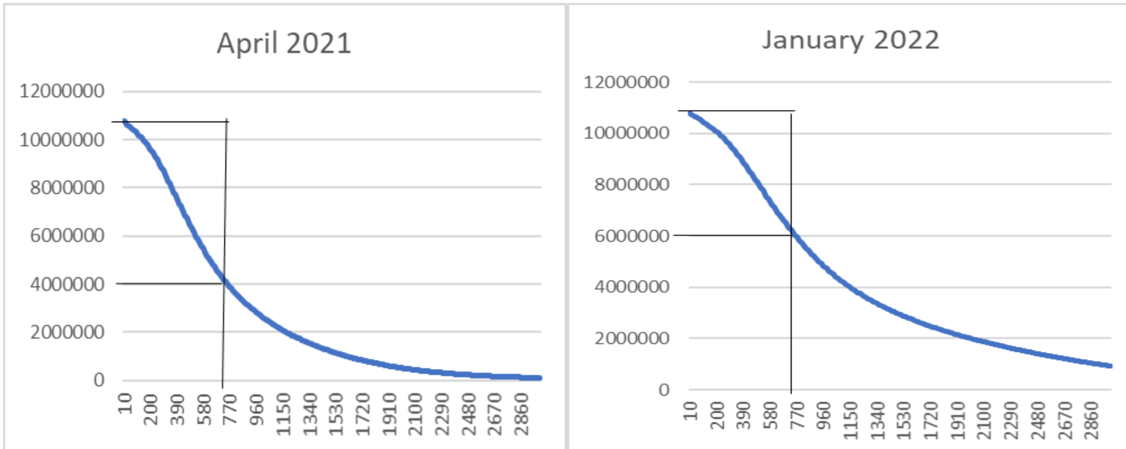
Q. What is your assessment of Staff's regression model?

A. The basic assumption of Staff's regression model conflicts with empirical facts. Staff estimates one relationship between average usage and Block 1 usage using data from all or some of the months in the test year and then applies this one relationship to all months in the normalization process.[14] By doing this, Staff assumes the relationship between average usage and Block 1 usage is the same in every month. The existence of a single relationship between these two variables, which are actually two properties on the monthly distributions of the underlying kWh billing data, is not supported by the kWh usage billing data. We can show this using the same data provided to Staff, which Staff also uses to construct variable values used in these regressions.

There would be a single relationship between average usage and Block 1 usage across the months, and Staff's assumption would be reasonable, if the distribution of usage in each month had the same "shape." The shapes of the distribution of kWh usage in April 2021 and January 2022 for the Residential class are shown below in Figure 1 with total billed kWh on the vertical axis and individual customer level billed kWh thresholds on the horizontal axis.

[14] For the Residential model Staff uses the fifteen months starting April 2021 and ending June 2022. Therefore, staff uses data from all twelve months with two data points from three of the months, April, May and June. For the SGS model staff uses nine months of data, June 2021 and November 2021 through June 2022.

Figure 1. Distribution of Residential kWh



The two graphical representations shown in Figure 1 do not have the same shape and therefore show that the primary assumption that Staff makes is not supported by the data.

More explanation of the meaning of the "shape" of the distribution is warranted. It is true that both distributions are decreasing, but that is not the important part. The important part is *the height of the distribution at any point along the distribution* relative to *the height of the distribution at the origin*. The heights of the two distributions are roughly equal at the origin, since there are roughly the same number of customers in each month and roughly speaking each customer consumes at least 10 kWh.[15] Therefore, we can focus on the heights of the two distributions at any point along the distribution, and most importantly, the height of the distributions at 750 kWh.

[15] The data used to generate the distributions is the cumulative frequency distribution data used by Staff. The data contains kWh usage in 10 kWh bins. If 1 million residential customers used at least 10 kWh, then the height of the first bin would be 10,000,000. The distribution necessarily decreases, because a customer must consume the first kWh before they can consume the second, and so on. The height of the distribution drops for each customer whose monthly usage was lower than the value on the horizontal axis. The graphs shows that approximately 600,000 and 400,000 customers consumed more than 750 kWh in January and April respectively.

The interpretation of the height of the distribution can be illustrated by imaging the addition one kWh of usage anywhere along the distribution. Regardless of where it is added this additional kWh will have the same impact on average usage per customer. The question is: Where is that one additional kWh most likely to appear? One additional kWh of usage could appear at any point along the distribution that is lower than the height of the distribution at the origin. The lower the height of the distribution at any given kWh level, the higher the probability that an additional one kWh will occur to the left of that given kWh level. The lower the height of the distribution at 750, the higher the probability the additional one kWh will be a block 1 kWh.

In this illustration, it is more likely that an additional kWh will occur below the threshold in April than it will in January. That means that an increase in average usage is more likely to increase Block 1 usage in April than in January.[16] Staff's model does not allow this to be true, and instead requires that an increase in average usage in every month have the same probability of increasing Block 1 usage. This conflicts with the underlying billing data and is therefore unreasonable.

Q. What unreasonable results does Staff's discretionary application of its weather normalization procedure produce?

A. First, Staff uses a regression to estimate the relationship between average usage and the percentage of total usage that is Block 1 usage. Second, Staff uses the estimated relationship and normalized average usage to estimate normalized percentage of total usage in Block 1. Third, Staff uses the estimated normalized percentage to allocate normalized total usage to Block 1 usage and Block 2 usage. However, in several months,

[16] This is equivalent to saying β for April should be larger than β for January. Staff uses the same β for all months.

Staff replaces its estimate of normalized percentages with 100%. The unreasonable nature of this discretionary choice to replace the estimated percentage with 100% is self-evident if we look at the result. Table 2 displays the effect of the choice on residential primary month July 2021 billing units.[17]

Table 2

	With 100% Choice	With Estimated Percentage
Total kWh	1,238,669,031	1,238,669,031
Summer kWh	1,211,747,321	1,211,747,321
Winter Block 1 kWh	14,352,572	14,352,572
Winter Block 2 kWh	12,569,138	12,569,138
Weather Normalization Factor	95.93%	95.93%
Block 1 Factor	100.00%	57.21%
Total kWh	1,188,283,371	1,188,283,371
Summer kWh	1,162,456,762	1,162,456,762
Winter Block 1 kWh	25,826,609	14,775,403
Winter Block 2 kWh	0	11,051,206

Staff's choice to replace its estimated Block 1 percentage, 57.21%, with 100%, causes Staff to allocate all 25.8 million kWh of winter usage in that primary month to Block 1. The Block 1 percentage Staff estimated would have allocated 14.7 and 11 million kWh to Block 1 and Block 2 usage types, respectively. There is no reasonable logic which supports this choice. This unreasonable choice improperly increases Staff's calculation of the Company's normalized revenue by more than $320,000.

[17] The definition and purpose of the primary month variables is explained in my Direct Testimony. Prior to the seasonal proration billing improvements, primary month data would contain only summer or winter usage, never both. Seasonally prorated billing procedures results in primary month data which may contain both summer and winter usage. Strict primary month billing did not necessarily bill kWh usage based on the calendar month in which the usage occurred. Seasonally prorated primary month billing does. In this instance illustrated above, the primary month is July, but the meter read start date for some billing cycle in that primary month was before June 1, 2021.

VII. Staff's Rider EDI Adjustment

Q. Did you review Staff's Rider EDI Adjustment?

A. Yes, I did.

Q. Were there any differences between the Company's and Staff's Rider EDI Adjustment?

A. Yes. The difference between the Company's and Staff's Rider EDI Adjustment is a result of differences in the Rider EDI discount values each used to calculate the adjustment. The Company uses the values of actual Rider EDI discounts observed in the test year to calculate its Rider EDI discount. Staff adjusts Rider EDI discounts in months of the test year prior to the effective date of current rates to reflect current rates.[18]

Q. Which approach do you recommend?

A. I recommend the use of Staff's approach to the calculation of the Rider EDI revenue adjustment at the time of true-up. Staff's approach annualizes Rider EDI revenues to current rates. The annualization of base rate revenues at historic rates to base rates revenues at current rates is standard procedure in the calculation of total normal revenues. Staff's decision to annualize Rider EDI revenues is logically consistent with that base rate annualization. Therefore, I recommend adoption of Staff's procedure for Rider EDI revenues and intend to implement the procedure at the time of true-up.

VIII. Staff's Community Solar Adjustment

Q. Did you review Staff's Community Solar Adjustment?

A. Yes, I did.

[18] Current rates became effective on February 28, 2022.

Q. Did you discover any errors in Staff's Community Solar Adjustment?

A. Yes, I did. Staff used the Community Solar Pilot Program Total Solar Block Charge effective after July 16, 2022, $11.92 per block, to calculate Community Solar Pilot Program revenue for the residential class in primary months July 2021 through February 2022. If Staff intended to calculate the actual test year revenues collected through the Community Solar Pilot, then Staff should have used the rate that was effective during those months of the test year, $13.91 per block. That rate, $13.91 per block, became effective on June 8, 2020 and remained in effect until February 28, 2022.

Staff did use the rate which became effective on February 28, 2022, $14.19 per block, to calculate Community Solar Pilot Program revenues for the remaining months of the test year, March 2022 to June 2022. If Staff used $13.91 per block rather than $11.92 for July 2021 through February 2022, then Staff would have calculated the actual Community Solar Pilot Program revenue collected in the test year, i.e., revenue at historic test year rates.

Q. How did the Company calculate the Community Solar Adjustment?

A. The Company calculated the total Community Solar Pilot Program revenue using Residential and SGS Total Solar Block Charges that were current until two weeks before the Company's filing in every month of the test year. Those rates were $14.19 and $13.26 per Solar Block for Residential and SGS customers, respectively. By doing so, the Company annualized Community Solar Pilot Program revenue to the level effective two weeks prior to the filing of Company direct.

Q. How do you recommend the Community Solar Adjustment be calculated for the true-up period?

A. I recommend that the Company and Staff calculate the Community Solar Adjustment using the Residential and SGS Total Solar Block Charges that are currently effective for every month of the test year. Those rates, which became effective on July 16, 2022 are $11.92 and $10.99 for the Residential and SGS customers respectively. This practice is consistent with the calculation of total base billing unit revenue calculations, i.e., those revenues are calculated at current rates, and not at the historic rates.

IX. Staff's Calculation of Lighting Class Municipal Discounts

Q. Did you review Staff's calculation of Lighting class revenues, including their calculation of the discounts municipal lighting facilities receive?

A. Yes, I did.

Q. Did you find any errors in Staff's calculation of Lighting revenues?

A. Yes, Staff made an error in its calculation of discounts received by municipal lighting customers at current rates. Specifically, Staff failed to increase lighting discounts. Increased discounts are implied by increases in rates. Staff's rate change annualization models an increase in rates and therefore requires an increase in municipal discounts.

Q. What discounts are received by municipal lighting customers?

A. Sheet No. 58.2 and Sheet No. 59 of the Company's tariff for electric service outline the Discount for Franchised Municipal Customers. Municipal customers who have a historic ordinance granting the Company franchise to provide lighting facilities receive a 10% discount on their total bill.

Q. How did Staff err in their calculation of lighting discounts at current rates?

A. Staff annualizes lighting revenues for a rate increase which happened during the test year period, i.e., Staff calculates lighting revenues at current rates. In this case, Staff annualized revenues by increasing rates in months preceding March 2022. This is appropriate. However, Staff failed to increase discounts proportionately with the increased rates. This is inappropriate since the discounts are calculated as a percentage of total bills. If rates go up, then total bills go up, and so discounts should also go up.

Q. Does the Company increase discounts to reflect accurate discounts at current rates?

A. Yes. The Company achieves an accurate increase in discounts by calculating a realized discount rate for the entire class given historic undiscounted revenues and historic discounts observed in the test year.

$$RealizedDiscountRate = \frac{HistoricDiscounts}{HistoricUndiscountedRevenues}$$

Then the Company calculates undiscounted revenues at current rates and applies the realized discount rate to those revenues to determine the total discounts at current rates.

$$CurrentDiscounts = RealizedDiscountRate \times CurrentUndiscountedRevenues$$

Q. Does this realized rate method generate accurate discounts at current rates?

A. Yes.

X. Staff's Analysis of the SB 564 Rate Cap

Q. Did you review Staff's analysis of the SB 564 Rate Cap?

A. Yes, I did.

Q. Please describe the procedure used to test for an exceedance of the SB 564 Rate Cap?

A. Two values are needed to test for an exceedance of the SB 564 Rate Cap, the rate cap itself and the Company's all-in average kWh rate. If the Company's all-in rate exceeds the rate cap, then the rate cap is exceeded.

The rate cap itself is calculated by applying the annual 2.85% compound growth rate to the baseline rate outlined in SB 564 and established for the Company in XYZ. The Company's all-in kWh rate is defined as follows.

$$AllInRate = \frac{TotalRevenueRequirement + averageFAC + RESRAM}{TotalkWhBillingUnits}$$

Where $TotalRevenueRequirement$ is the total revenue requirement approved by the MPSC in a rate proceeding and $TotalkWhBillingUnits$ are the total kWh billing units established by the Commission's approval of rates. When the Commission approves a revenue requirement and rates, the Commission necessarily approves the billing units required to calculate those rates. The $averageFAC$ is a load weighted average of currently effective class specific FAC rates and $RESRAM$ is the currently effective RESRAM rate.

Q. Did you find any errors in Staff's analysis of the SB 564 Rate Cap?

A. Yes. At this juncture in the rate preceding, the MPSC has not approved a revenue requirement or kwh billing units. However, if the MPSC decides not to rule on the Company's filing, then the revenue requirement and kWh billing units filed in direct become effective. Therefore, any prospective evaluation of the compliance with or exceedance of the SB 564 rate cap should use the Company's requested revenue requirement and associated billing units required to generate the proposed change in rates.

These two values are the values used in the Company's prospective evaluation of compliance with or exceedance of the SB 564 rate cap.

On the other hand, Staff submitted a prospective evaluation of the rate cap based on an alternative kWh value. Specifically, Staff proposed the evaluation of the rate cap based on the Estimated Recovery Period Sales associated with RESRAM rate which became effective on February 1, 2023. It is not appropriate to use the RESRAM Estimated Recovery Period Sales value of kWh in the evaluation of the SB 564 rate cap. The use of this value of kWh inappropriately overestimates the average electricity rate of the Company.

Q. Does this conclude your rebuttal testimony?

A. Yes, it does.

BEFORE THE PUBLIC SERVICE COMMISSION
OF THE STATE OF MISSOURI

In the Matter of Union Electric Company d/b/a Ameren Missouri's Tariffs to Adjust Its Revenues for Electric Service.	)))	Case No. ER-2022-0337

AFFIDAVIT OF NICHOLAS BOWDEN

STATE OF MISSOURI)
) ss
CITY OF ST. LOUIS)

Nicholas Bowden, being first duly sworn states:

My name is Nicholas Bowden, and on my oath declare that I am of sound mind and lawful age; that I have prepared the foregoing *Rebuttal Testimony*; and further, under the penalty of perjury, that the same is true and correct to the best of my knowledge and belief.

/s/ Nicholas Bowden
Nicholas Bowden

Sworn to me this 15th day of February, 2023.