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Nicholas Bowden
Surrebuttal Testimony
File Nos. ER-2021-0240 & GR-2021-0241

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MISSOURI PUBLIC SERVICE COMMISSION

FILE NO. ER-2021-0240

SURREBUTTAL TESTIMONY

OF

NICHOLAS BOWDEN, PhD.

ON

BEHALF OF

UNION ELECTRIC COMPANY

d/b/a Ameren Missouri

St. Louis, Missouri
November, 2021

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SURREBUTTAL TESTIMONY

OF

NICHOLAS BOWDEN, PhD.

FILE NO. ER-2021-0240

Q. Please state your name and business address.

A. Nicholas Bowden, PhD., 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, PhD., that filed direct and rebuttal testimony in this proceeding?

A. Yes, I am.

I. PURPOSE OF TESTIMONY

Q. What is the purpose of your surrebuttal testimony in this proceeding?

A. First, I provide updated billing determinants through the true-up period for this case. Next, I respond to Staff witness Kim Cox's block normalization rebuttal testimony, and Staff witness Robin Kleithermes' Seasonal Proration and MEEIA margin rates rebuttal testimony.

Q. Do you have any schedules supporting your surrebuttal testimony?

A. Yes. I have three schedules supporting my surrebuttal testimony.

II. UPDATED BILLING DETERMINANTS THROUGH THE TRUE-UP PERIOD

Q. What is the effect of the true-up information through September 30, 2021 on billing determinants?

A. The billing unit analysis results in the normalized test year billing units, and when the current rates are applied, it provides the Company's normalized revenue. The normalized test year billing units are detailed in Schedule NSB-S1. The Company's normalized revenue in this case is $2,488,469,254. The Company's actual revenues, total revenue adjustments, and normalized revenues are shown by customer class in Table 1.

Table 1. Normalized Revenue By Class

Rate Class	Actual Revenues	Total Adjustments	Normalized Revenue
1M	1,290,296,460	-20,235,628	1,270,060,832
2M	268,550,404	3,429,838	271,980,242
3M	499,661,585	1,373,388	501,034,973
4M	219,136,388	-4,274,788	214,861,600
11M	187,858,151	5,803,552	193,661,703
Lighting	36,840,553	-45,615	36,794,938
MSD	74,966	0	74,966
Total	2,502,418,507	-13,949,253	2,488,469,254

Consistent with my direct testimony, the Company makes seven adjustments to normalize billing units and consequently revenues, and also makes two adjustments that do not impact billing units but result in direct adjustments to revenue.[1] The seven billing unit adjustments are as follows:

1. A weather normalization adjustment;
2. A days adjustment;
3. A seasonal proration adjustment
4. An energy efficiency adjustment;
5. A solar adjustment;
6. A growth adjustment; and
7. An initial pandemic shock adjustment.

The two direct revenue adjustments are as follows:

[1] In my direct testimony there were six adjustment. For clarity, we separated one adjustment, the seasonal days adjustment, into two separate adjustments, the days adjustment and the seasonal proration adjustment.

1. An economic development incentive adjustment; and

2. A community solar adjustment.

The revenue value of each billing unit adjustment through true-up is shown in Table 2 by customer class.

Table 2. Billing Unit Revenue Adjustments

Rate Class	Weather Adjustment	Days Adjustment	Seasonal Proration	EE Adjustment	Solar Adjustment	Growth Adjustment	Pandemic Shock Adjustment
1M	-8,423,940	-30,580	2,079,536	-15,474,994	-841,357	2,361,650	0
2M	-595,158	1,377,542	624,643	-2,609,064	-214,373	2,336,393	2,509,857
3M	-472,458	1,971,539	1,682,703	-5,433,647	-142,336	101,031	3,865,420
4M	-305,989	1,016,548	295,019	-1,207,354	0	-5,366,239	1,402,810
11M	-82,714	706,581	-40,923	-93,344	-26,943	4,862,154	478,742
Lighting	0	0	0	0	0	-45,615	0
MSD	0	0	0	0	0	0	0
Total	-9,880,259	5,041,629	4,640,979	-24,818,403	-1,225,010	4,249,373	8,256,829

The value of each non-billing unit revenue adjustment through the true-up period are shown in Table 3 by customer class.

Table 3. Non-Billing Unit Revenue Adjustments

Rate Class	EDI Adjustment	Community Solar Adjustment
1M	0	94,056
2M	0	0
3M	-198,864	0
4M	-109,583	0
11M	0	0
Lighting	0	0
MSD	0	0
Total	-308,447	94,056

III. BLOCK NORMALIZATION

Q. Does Staff agree with the Company's block normalization results?

A. No.

Q. What is the first reason Staff gives for disagreeing with Ameren Missouri's block normalization?

A. Staff claims that Ameren Missouri uses historical weather and usage data, while Staff uses actual billing data for the current test year.[2]

Q. What is the difference between the usage data used by Ameren Missouri and the actual billing data used by Staff?

A. Not as much as Staff seems to imply. The historical usage data used by the Company is also actual billing data. The actual billing data used by Staff is also historic usage data. Staff's attempt at a high-level distinction appears more semantic than substantive. The Company uses monthly weather and block usage data from the year 2007 to April 2021, while Staff only uses data from the 12 months ending April 2021. Generally speaking, using more data generates better estimates of statistical relationships. Staff will later admit that their attempt to estimate a regression model produces unreasonable results.[3] One reason their regression produces unreasonable results is their choice to use only the limited amount of data available from the test year. It is also unclear why Staff attempts to make this type of distinction here, because Staff uses two to three years of historical data when they are weather normalizing total kilowatt-hours ("kWh").

[2] File No. ER-2021-0240, Kim Cox Rebuttal Testimony, pp. 2-3.
[3] *Id.,* p. 7, ll. 5-6.

Q. Did Staff accurately describe the method used by the Company to determine the amount of kWh that should be billed at Block 1 prices under normal weather conditions?

A. Yes, the Company estimated the linear relationship between a measure of weather (Heating Degree Days or "HDD") and the actual percent of kWh billed at Block 1 rates using Ordinary Least Squares ("OLS").[4] The relationship was estimated separately for each month using monthly aggregate Block 1 usage and HDD for the years 2007 to 2020 (and 2021 when available).

Q. Does Staff believe the Company's regression accurately captures the relationship between weather and usage?

A. No. Staff claims that the Company's regression does not accurately capture the relationship between weather and usage.[5]

Q. What logic or evidence does Staff submit to support this position?

A. None. Instead, Staff makes ambiguous claims based on ill-founded logic, and illustrates a lack of understanding about the statistical methods used by the Company.

Q. Please explain why Staff's claims are ambiguous and ill-founded.

A. There are several separate, but related observations Staff makes in an attempt to support its position. In order to address the ill-founded nature of Staff's claim, it is necessary to provide some background information related to statistical theory and methods.

[4] Regression is used by Staff to refer to the model specified by the Company and the method used to estimate the model. These two things are related but distinct. The choice of variables and the relationship between the variables define the model, and OLS is a method for estimating the relationship.
[5] *Id.,* p. 5, ll. 3-10.

Q. Can you explain why Staff's observation about the January 2018 data point does not provide support for their position?

A. Yes. Staff observes that "January 2018 had a **higher** percentage of usage billed in the first rate block compared to January 2009, 2010, 2011 and 2014 … even though there were **fewer** HDDs" in those years than there were in 2018.[6]

An equivalent and clearer statement of this observation will aid understanding. January 2018 had **more** HDD and a **higher** percentage of usage billed in the first rate Block than January 2009, 2010, 2011, and 2014.

Generally speaking, **more** HDD means more total usage, and more total usage means a **lower** percentage of usage billed in the first rate Block. Staff claims that the Company's regression model "may not fully quantify the relationship" because January 2018 has **more** HDD and a **higher** percentage of usage billed in the first rate Block.[7]

This is an observation about the data, not a criticism of the Company's model or the application of OLS. In fact, this observation helps illustrate why it is appropriate to use OLS in this setting.[8]

Q. Why does Staff's observation about January 2018 support the use of OLS rather than undermine it?

A. OLS allows the identification or accurate estimation of the causal relationship between an independent variable, like the weather, and a dependent variable, like customer usage,

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[6] Id., p. 5, ll.5-7.

[7] Staff witness Kim Coxt footnote 6 on page 5 of her rebuttal testimony states: "Generally, the more HDDs in a winter month results in more overall kWh which produces an overall lower percentage billed in the first rate block since it is capped at 750 kWh per customer. Ameren Missouri's regression is dependent upon this relationship being true, so when one month with greater HDDs has less usage than a month with more HDDs, the regression may not be able to fully quantify the relationship."

[8] The observation is that there are deviations in that data which do not fit a deterministic view of the relationship between the variables.

when observed values of the dependent variable include idiosyncratic deviations from the underlying causal relationship. That fact is a fundamental characteristic of OLS and can be understood by considering the simplest and most fundamental expression of an OLS model.

$$y = \boldsymbol{\alpha} + \boldsymbol{\beta} x + \varepsilon$$

More specifically, OLS allows the unbiased (accurate) estimate of β, the causal relationship between y and x, in the presence of unobserved sources of variation, ε.[9] Those unobserved sources of variation cause the dependent variable, y, to deviate from the value which would be predicted by a specific value of the independent variable, x, given the true relationship between the variables defined by α and β.[10]

In our specific context, the Company estimates the following linear regression model by OLS.

$$Block1 = \boldsymbol{\alpha} + \boldsymbol{\beta} HDD + \varepsilon$$

Where $Block\ 1$ is the percentage of total usage billed at Block 1 rates and HDD is heating degree days.[11] The OLS estimate of β is an estimate of the causal relationship between weather and Block 1 usage.[12]

It is critically important to understand that the Company's objective is to accurately estimate β, and not to explain all the reasons why Block 1 usage might vary. It is also important

[9] Unobservable sources of variations are real, but are not measured and often cannot be practically measured and represented numerically in a variable that could be used to estimate a regression model. For instance, aggregate residential electricity usage is affected by the daily idiosyncratic behaviors of more than one million households. The time each household wakes in the morning, the decisions they make about meal preparation, time spent watching television or charging cell phones all affect usage, but are not and could not practically be measured and used in estimation.

[10] In our specific context, y is the percentage of usage billed in Block 1 and x is HDD.

[11] HDD is an appropriate measure of weather to use in a monthly regression, because it is additive. HDD is the sum of deviations below a set temperature across the month. Deviations from above the set point are set to zero, and therefore do not cancel out the deviations below the set point. Average temperature is not additive, because positive and negative deviations from the average across the month cancel out in the calculation of the average, thereby negating the variation in weather which causes the variation in usage during the month.

[12] β is interpretated in the following way: $Block1$ increases by β percentages points when HDD increases by 1.

to understand that β can be accurately estimated by OLS without explaining all the reasons why Block 1 usage might vary. It is not clear that Staff understands the Company's objective and/or this fact about OLS.

Q. What conclusion does Staff draw from their observation about the deviation in the January 2018 data point?

A. Staff draws two related conclusions. First, Staff concludes that the Company's regression "may not be able to fully quantify the relationship" between weather and Block 1 usage.[13] The precise meaning of "may not be able to fully quantify the relationship" is unclear, and lacks identification of a specific deficiency in the Company's method or results. For example, Staff could have claimed that the Company's estimate of the relationship between of weather and usage is biased.[14] That is a concrete example of a potential deficiency in any OLS model. This specific claim would translate into something like, the Company's estimate of the causal relationship between weather and usage is systematically inaccurate. It is not clear that Staff believes the Company's method is systematically inaccurate and does not clearly articulate any conditions under which an estimate would or would not be systematically inaccurate, i.e. biased. Coefficients, like β, estimated by OLS are either biased or unbiased, systematically inaccurate or systematically accurate.

Second, Staff expands on this initial vague conclusion by incorporating an additional thought about why the Company's regression "may not fully quantify the relationship". Specifically, Staff concludes that "… the Company's regression fails to capture that variables other than weather may have impacted a customer's overall response to weather."[15] The words "may

[13] *Id*., p. 5, footnote 6.
[14] This is the same as saying the estimate of β is biased.
[15] *Id*., page 5, ll. 8-10.

have impacted" and "overall" suggest Staff lacks confidence in their understanding of the Company's analysis and OLS more generally. If additional variables, other than weather, are appropriate to include in a model of Block 1 usage and the model is estimated by OLS, then the result is additional coefficient estimates.[16] Those additional coefficient estimates would be estimates of the relationship between those additional variables and usage. It is not clear why Staff believes including additional variables would result in an estimate of β which "fully quantifies" the "overall" impact of weather on usage. The only independent variable that is necessary to include in an OLS regression to fully quantify the relationship between weather and usage is the weather, and the Company includes the weather.

Q. Is there any possible interpretation of Staff's criticisms which is supported by evidence?

A. No. Again, Staff's criticism of the Company's method is unclear, but the Company can imagine two possible interpretations of Staff's criticism, and neither are supported by evidence. One is not supported by Staff's evidence, because it is ill-founded, and therefore cannot be supported by any evidence. The other possibility, which is never clearly articulated, although it has a specific and well-known name, is not supported by evidence.

The first possibility, which Staff seems to attempt to support with evidence, both with the specific observation above related to January 2018, and a later discussion of R^2, is ill-founded.[17] The first possible criticism the Company can imagine Staff is attempting to make is as follows: variables other than weather impact the percentage of usage billed at Block 1 rates, and those

[16] If another variable, z, is added, the regression model would be $y = \boldsymbol{\alpha} + \boldsymbol{\beta}x + \boldsymbol{\gamma}z + \varepsilon$. The result of estimating the model by OLS would be estimates of $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$.

[17] A discussion of Staff's ill-founded logic related to the interpretation of R^2 in this context will be discussed later.

variables are omitted from the regression model, so the Company's model fails to capture the relationship between weather and Block 1 usage.

First counterpoint: Staff's observation about January 2018 could be explained by unobservable sources of variations, ε. The fundamental purpose of OLS is to estimate β, the causal relationship between weather and usage, in the presence of ε. Staff has provided no evidence that the deviation it observes in January 2018 is not caused by ε.

Second counterpoint: If other observable variables do exist and help to explain the Block 1 usage, their omission from the regression **does not** mean the Company fails to estimate the causal relationship between weather and Block 1 usage. This is a fact about OLS.

This first possible interpretation of Staff's criticism appears to be the one Staff is attempting to support. Staff provides evidence that there is variation in Block 1 usage that is not explained by the Company's regression. Using this evidence alone, Staff concludes that the Company's estimate of β is inaccurate. For the reasons stated above, this conclusion **cannot** be drawn from that evidence.

The second possible criticism the Company can imagine Staff is attempting to make is as follows: the Company's regression model suffers from omitted variable bias. Omitted variable bias occurs when there is an observable independent variable which causes changes in dependent variable, is omitted from the regression model, and systematically varies with the independent variable of interest. In this case, the omitted variable would need to cause changes in Block 1 usage and systematically vary with the weather.[18] If this is the claim Staff is attempting to make, they provide no evidence that the Company's model suffers from omitted variable bias. Staff could have

[18] The variable cannot just be another measure of weather, because that is not a new variable. Also, the variable cannot be some measure of weather sensitive usage, like electric space heat, because that is a component of usage not an independent variable.

provided empirical evidence by identifying such a variable and showing it has the aforementioned properties. Staff could have provided anecdotal evidence by identifying such a variable and providing a logical explanation why that variable would have these properties. Staff does neither.

Q. Why is the Company's objective to produce an unbiased estimate of $\boldsymbol{\beta}$ and not to explain all of the variation in Block 1 usage?

A. The Company's objective is the weather normalization of Block 1 usage. The Company normalizes Block 1 usage using the following method.

$$NormalBlock1_i = Block1_i + \beta(NormalHDD - HDD_i)$$

In order for the Company to accurately weather normalize Block 1 usage, the Company only needs to produce an unbiased estimate of β.[19] OLS can produce an unbiased estimate of β without including all the variables that cause Block 1 usage to vary in the regression model. Therefore, it is not necessary for the Company to identify all the variables that cause Block 1 usage to vary.

Q. Has Staff made a clear argument that it believes the estimate of $\boldsymbol{\beta}$ is biased?

A. No. In order for an estimate of β to be unbiased, the specified model must satisfy the classical assumptions of OLS. The classical assumptions of OLS cannot be tested directly, because they are assumptions about the population and not the sample used to estimate a regression model. Satisfaction or violation of these assumptions must be argued in principle using reason. Staff has made no principled argument concerning the violation of the classical assumptions of OLS and therefore has made no clear argument that β is biased.

[19] In a statistical setting, the true relationship can never be known. The best achievable result is an unbiased estimate of the true relationship. The purpose of statistical analysis is the development of a model which returns an unbiased estimate.

While it is not possible to test the classical assumptions of OLS directly, the residuals of an OLS regression, the estimates of ε, can be inspected for patterns which suggest violations of the classical assumptions. Staff has provided no such analysis. The Company has conducted this analysis and found no obvious patterns in the residuals which suggest violations of the classical assumption of OLS.

Q. Has Staff provided any evidence that the estimate of $\boldsymbol{\beta}$ is biased?

A. No. Staff concludes β is inaccurate after making an observation about the data and later making an inference using a summary statistic, R^2. It is simply **not** possible to draw this conclusion by either of those methods.

Q. Do the values of R^2 support Staff's claim that the Company's regressions do not capture the relationship between weather and usage?

A. No. R^2 is probably the most misunderstood and misused summary statistic associated with an OLS. Practically speaking, R^2 alone is a relatively useless summary statistic. In a very specific circumstance, R^2 can be a useful guide for specifying a regression model, but it **cannot** be used alone to determine the appropriateness or validity of a model or estimates of a model.[20] Furthermore, R^2 **does not** provide any information about the biasedness (accuracy) of an estimate of β. Nonetheless, Staff attempts to do just that in this situation.

Staff states "the Company's individual monthly regressions for the months of May, October, November and December result in questionably low R^2 values."[21] Staff does not provide a value of R^2 which would be high enough to make the regression results unquestionable. There is a very good reason why Staff does not do this: it **cannot** be done. R^2 is not that kind of statistic.

[20] R^2 or adjusted R^2 can be used to aid an analyst in determining if a specific additional independent variable should be added to a model when the analyst has a good theoretical reason to believe that independent variable plays a part in determining the outcome of the dependent variable.
[21] *Id.*, p. 5, l. 10 through p. 6, l. 1.

There is no theoretical basis on which to judge if the value of R^2 is high enough. In the context of Staff's claim, R^2 is useless.

Q. Can you explain the theoretical reasons why R^2 cannot be used in the manner Staff attempts to use it?

A. Yes. OLS is used in situations where unobservable variation, ε, exists, e.g. situations involving aggregate human behavior. One of the classical assumptions of OLS is that ε is distributed with zero mean and constant variance.[22] The value of the variance is situationally dependent and will determine the highest possible value of R^2 that can be achieved in a specific situation.[23] That is why there is no level of R^2 which is high enough to qualify a regression as correct. It depends on the situation. If there is truly a large amount of unobservable variation in y, than the model can be correctly specified (include all of the correct x variables) and have a relatively low R^2. There is no level of R^2 which proves or even suggests the model is correct or incorrect.

Staff also states "The closer the R^2 value is to 1.0 the more reasonable it is to assume that the variance of weather explains the variance of usage."[24],[25] This statement is the clearest reflection of Staff's lack of understanding about OLS and the objective of the Company's analysis. Let us correct Staff's statement here to make the error easier to understand: "The closer the R^2 value

[22] The zero mean assumption is perhaps the most critical assumption of OLS, because it is the hardest to interrogate through ex-post methods. It is the hardest to interrogate because OLS necessarily results in residuals, estimates of ε, that sum to zero.

[23] This is true because $R^2 = 1 - \frac{SS_e}{SS_t}$, where $SS_e = \sum e^2$ and $SS_t = \sum(y - \bar{y})$. And e is the sample estimate of ε.

[24] *Id.*, p. 6, ll. 1-3.

[25] Staff's statement leverages the most common, but misunderstood and misleading, interpretations of R^2. The common interpretation of R^2 is as follows: R^2 is the amount of variation in the dependent variable (y) that is **explained** by the independent variable(s) (one of more x). The unfortunate and misleading part of this interpretation is the inclusion of the word **explained**. R^2 is really a measure of the correlation between y and x, and does not have anything to do with the variation of y **caused** by x. In many situations, and in this one in particular, we are trying to identify the variation in y **caused** by x. R^2 is not able to tell us anything about the model's ability to identify the causal relationship we are interested in.

is to 1.0 the more ~~reasonable it is to assume that~~ the variance of weather explains the variance of usage." This is the definition of R^2. There is nothing about reasonableness in the definition, because R^2 is simply a calculation of the correlation between y and x, and does not imply anything about the reasonableness of the regression model.[26]

By inserting the words "reasonable … to assume," Staff appears to be expressing their belief about how R^2 should be used to make inference about the regression model. Staff appears to be saying, the higher the R^2, the more we all should believe the regression model is correct and has identified the causal relationship of interest. R^2 simply **cannot** be used to make this kind of inference.

Q. Is there any evidence which contradicts Staff's claim that the Company's regression "may not be able to fully quantify the relationship" between weather and usage?

A. Yes. In order to illustrate how this evidence contradicts Staff's claim, we need to translate "may not be able to fully quantify the relationship" into yet another potential concrete criticism of an OLS estimate: The Company failed to identify a statistically significant relationship between weather and Block 1 usage.

Standard OLS regression results include several statistics that aid the determination of the quality of an OLS estimate. Those statistics include the standard error of the regression coefficient(s), t-statistics, and p-values. Staff chooses to ignore all of these regression results. It is also worth noting that these statistics are more useful than R^2.

[26] There are several types of examples which can illustrate this point. For instance, R^2 always increases when additional variables are added to the model, even if those variables are unreasonable to include in the model. The same is not necessarily true for adjusted R^2, a modified version of R^2 and the statistic actually reported by Staff. Nonetheless, adjusted R^2 will often increase when unreasonable variables are added to a model. To illustrate this point, we re-estimated the Company's model for January and included the population of the Atlanta, GA as another independent variable. Adjusted R^2 increased. Staff's logic would suggest that including the population of Atlanta, GA in the model would make the model more reasonable. It is also true that R^2 remains the same if you switch the dependent and independent variables. Staff's logic would support the idea that a model which assumes Block 1 usage explains the weather is just as reasonable as a model which assumes the weather explains Block 1 usage.

In our context, the regression coefficient of interest is β. The standard error of the estimate of β is a measure of the precision in the estimate of β. The smaller the standard error, the more precise the estimate. Again, this piece of information helps illustrate why Staff's claim is difficult to understand. If Staff would have claimed that the estimate of the causal relationship is imprecise, then it would be possible to evaluate the claim. Staff did not make this claim, and Staff did not present an evaluation of the standard error that shows the estimate of β is imprecise. The Company evaluated the standard error of the estimates and concludes that the estimates of β are precise.

The t-statistic is probably the most common statistic used to appropriately judge the statistical significance of an OLS coefficient estimate.[27] The t-statistic tells us how unlikely it is that β is zero.[28] Generally speaking, the larger the t-statistic, the more unlikely it is that β is zero. Therefore, the larger the t-statistic, the more evidence there is that a relationship between weather and usage exists. The t-statistic can be large for two reasons: 1) The estimate of β is large, i.e. the relationship between the variables is strong; and 2) The standard error of the estimate of β is small, i.e. β is estimated precisely. The t-statistic encapsulates the interaction between these two statistical properties.[29]

T-statistics are compared to threshold values which come from a t-distribution. The comparison allows one to draw a specific conclusion about the significance of a relationship between an independent variable and dependent variable. For instance, the threshold value

[27] The definition of the t-statistic: $t = \frac{\hat{\beta}}{s.e.(\hat{\beta})}$, where $\hat{\beta}$ is the estimate of β. Recall, we estimate β. The true value of β is never known.

[28] Statistical analysis generally uses the following logic. First, you hypothesize something, and then reject or fail to reject the hypothesis based on how unlikely it was to get the outcome you did. In the context of OLS, the basic hypothesis is that $\beta = 0$, i.e. there is no relationship between weather and usage.

[29] It is worth noting that the standard error of the estimate of β, and therefore the t-statistic includes the same measure of the unexplained variation that is included in R^2. However, the t-statistic compares that level of unexplained variation to the strength of the relationship between a specific independent variable and the dependent variable. For this and other reasons, a t-statistic is a superior means by which to judge if a regression quantifies the relationship between an independent and dependent variable.

associated with the 95th percentile of the t-distribution is 1.96. If a t-statistic is greater than 1.96, then we can say that there is only a 5 percent chance that $\beta = 0$, i.e. there only a 5 percent chance that there is no relationship between weather and usage. It is true that there is not a specific level of significance that is "good enough," but it is also true that the higher t-statistic the more significant the relationship. The t-statistics for the weather variable in all of the regressions used by the Company exceed the value of 1.96, and many are far greater.

The p-value provides similar information as the t-statistic, but gives the precise level of statistical significance associated with an independent variable. Specifically, the p-value communicates the probability that $\beta = 0$. For example, the t-statistic associated with HDD in January regression for the Residential class is 13.29, well beyond the 1.96 threshold. The p-value associated with HDD in January is 0.00000001525. That means that there is a 0.00001525% chance of obtaining the β we did if there is no relationship between HDD and Block 1 usage. Recall, Staff expressed doubt about the ability of the Company's model of the Residential class in January to capture the relationship between weather and usage given an observation about unexplained variation. This example and many more like it are evidence that Staff's claims are misguided.

Q. Does Staff express concern about the Company's application of the weather normalized Block 1 percentage calculations discussed above?

A. Yes.

Q. Did Staff correctly characterize the Company's calculation of the normalized Block 1 percentages?

A. Not exactly. Staff states that the Company calculated its weather normalized Block 1 percentage in a regression. The Company does not calculate its weather normalized Block 1 percentage in a regression. The Company uses the estimate of the causal relationship between weather and Block 1 usage from a regression to calculate normalized Block 1 percentages. There are two distinct steps in the calculation of the weather normalized Block 1 percentage. There is a third distinct step in the process of weather normalizing the kWh in Blocks 1 and 2, which we will discuss below to address Staff's expressed concern.

It is also helpful to note that weather normalization of Residential and Small General Service kWh consists of two distinct parts.[30] The first part is the normalization of total kWh. The second part is the normalization of Block 1 and Block 2 kWh, which we just noted has three steps. The discussion below will address Staff's concern by outlining additional logic the Company uses to ensure that the normalization of Block 1 and Block 2 kWh is consistent with the normalization of total kWh.

Q. What is Staff's specific concern about the Company's application of the weather normalized Block 1 percentage calculation calculated using the output of its regression?

A. Staff is concerned, because they do not believe the Company applies the weather normalized percentage it calculated in the second step of its block normalization process in the third step of the process. The third step of the process is the normalization of Block 1 kWh, and by consequence the normalization of Block 2 kWh.

[30] Both the Company and Staff use a distinct two-part process to normalize Residential and Small General Service kWh. Total kWh are normalized in one part and blocks in another. The sub-processes used to do the block part are at issue here.

Q. Does the Company use its calculation of weather normalized Block 1 percentages to normalize Block 1 kWh all months?

A. Yes and no. Yes, the weather normalized Block 1 percentage is used in the computational logic of the normalization of kWh in every month. But the normalization of kWh includes if-else logic, which results in the use of a substitute percentage when specific conditions are met. Those conditions implicitly recognize the fact that variables other than weather, including unobservable ones, play a role in determining Block 1 kWh.

Q. Can you provide an explanation of the additional logic involved in the application of the weather normalized Block 1 percentages?

A. Yes. The logic follows by extension from a relationship we discussed earlier and Staff has also explicitly acknowledged. Discussed above is how **more** total kWh means a **lower** percentage of total kWh billed in the first rate block. Similarly, **less** total kWh means a **higher** percentage of total kWh billed in the first rate block.

There is an important intermediate piece of logic in these statements, and that piece of logic is included in our process of weather normalizing kWh. If **total kWh increases** (more kWh), then **kWh in the first block will increase** and **kWh in the second block will increase**. However, we expect the increase in kWh in the second block to be greater than the increase in the first block, which causes the percentage of total kWh in the first block to be **lower** than it was prior to normalization. This intermediate logic is included in the Company's normalization of Blocks 1 and 2 kWh. Similar logic exists for decreases in total kWh.

Q. Please provide an example of the additional logic involved in the application of the weather normalized Block 1 percentages.

A. In January of 2020, the Residential Basic customers used 1,334,639,792 kWh in total, 649,764,076 kWh in the first block, and 684,875,716 kWh in the second block. Therefore, 48.7% of kWh were in the first block.

The process of weather normalizing total kWh indicated a 6.88% increase in total kWh for the class. Therefore, the weather normalized total kWh for the class is 1,426,434,524 kWh. The Company's regression and normalized Block 1 percentage calculation indicated that 44.3% of the total normalized kWh should fall into Block 1. However, 44.3% of the weather normalized total kWh is 631,794,758 kWh. This number is less than the original kWh in the first block. This violates the logical conditions outlined above, when the total kWh increases both blocks need to increase (or at least not decrease).

The additional logic results in a weather normalized Block 1 kWh equal to the original Block 1 kWh, 649,764,076 kWh, and all of the increase in total kWh is allocated to the second block.

Q. Does the inclusion of this additional logic mean the Company's Block 1 normalization percentage calculation is unreasonable?

A. No. The inclusion of this logic improves the consistency of the outcome of the weather normalization process. It does not mean the regression analysis and normalized Block 1 percentage calculation are unreasonable.

For example, let's look at what happens in January because the additional logic is included in the process. Because the normalized Block 1 percentage would have decreased the Block 1 kWh, the additional logic kept Block 1 kWh constant, and all of the kWh were allocated to Block 2.

The percentage of kWh in Blocks 1 still changed, which is consistent with the logic the Company shares with Staff. The normalized Block 1 percentage implied by the additional logic is (649,764,076/1,426,434,524) × 100 = 45.6%. This result does not make the 44.3% estimated by the normalized Block 1 percentage calculation look unreasonable. In fact, it does just the opposite, it makes it look reasonable.

Q. Is the additional logic biased to the Company's benefit?

A. No. In fact, Staff illustrates that the Company's application of the additional logic in the normalization of Block 1 kWh is symmetric. Specifically, Staff states "Ameren Missouri did not use its regression results for the months of January and May and instead used the actual kWh billed in the first rate block. However, for October, Ameren Missouri again did not use its regression results and instead applied the entire weather adjustment for the month to only the first rate block."[31]

Staff's statement illustrates how this consistency is imposed on both Block 1 and Block 2 equally. In January and May, the additional logic allocated the total change in kWh to Block 2 (kWh billed in the first block did not change), and in October the additional logic allocated the total change in kWh to Block 1 (kWh billed in Block 2 did not change).[32]

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[31] *Id*., p. 4, ll. 2-6.

[32] For completeness there are four pieces of logic. Two for the case when total kWh increase and two for the case where total kWh decreases. In each of those two cases, there are two cases, one that prevents the first block from moving in the opposite direction and one that prevents the second block from moving in the opposite direction. This is what is meant by symmetric treatment.

Q. Does Staff use OLS to weather normalize Block 1 usage?

A. Yes and no. Staff uses OLS to estimate the relationship between average usage per customer and Block 1 percentages. Staff uses this estimated relationship to normalize Block 1 percentages using weather normalized average usage per customer. Staff uses the results of this weather normalization process for the Small General Service class, but chooses to uses a cumulative frequency analysis instead of the regression based normalization for the Residential class. Staff states that the results were unreasonable for the Residential class, so the cumulative frequency distribution is preferred.

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

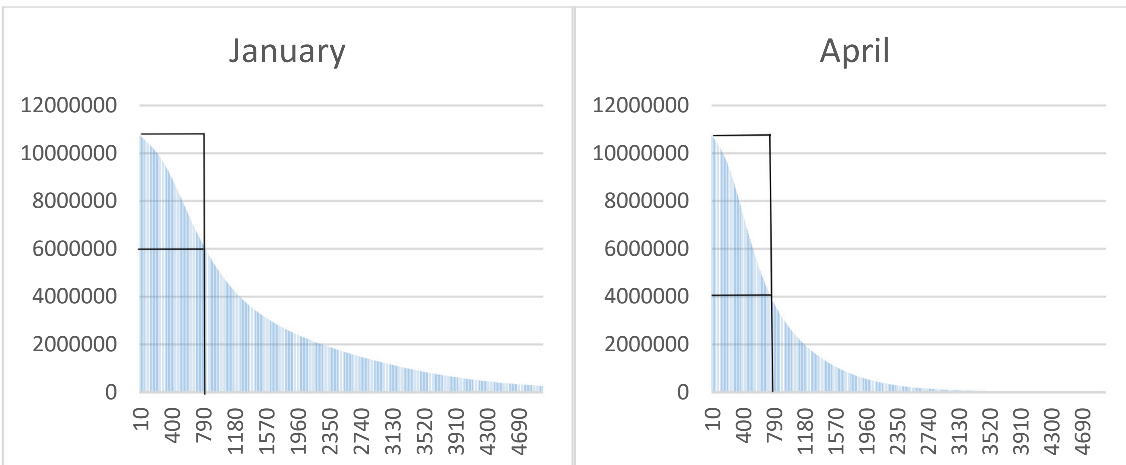
A. The basic assumption of Staff's regression model is overly restrictive. Staff does not estimate the relationship between weather and Block 1 usage. Instead, Staff estimates the relationship between average usage and Block 1 usage, and then uses normalized average usage to normalize Block 1 usage.[33] This approach is not flawed inherently, but it is flawed empirically in Staff's application of the approach.

Staff estimates the relationship between average usage and Block 1 usage using only the eight months of data from the test year. This is equivalent to assuming the eight months are eight randomly selected observations from a single population. It is more appropriate to assume the eight months are single observations selected from eight different populations. The practical problem with Staff's assumption is that it is forces the relationship between the average usage and Block 1 usage to be the same in all months.[34],[35]

[33] Using our notation from above, the estimate of β represents the relationship between average usage and normalized Block 1 usage.
[34] This is equivalent to saying there is only one β for all months not one β for each month.
[35] Practically speaking, Staff cannot estimate eight different relationships, because they have chosen to restrict themselves to only eight observations. It is not mathematically possible to estimate eight models with one observation each, nor is it mathematically possible to estimate eight different relationships in a single model with only eight observations.

There would be a single relationship between average usage and Block 1 usage, 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 in January and April for the Residential class are shown below in Figure 1 with actual billed kWh on the vertical axis and kWh thresholds on the horizontal axis.[36]

Figure 1. Distribution of Residential kWh



The shape of both distributions is necessarily decreasing, but that is not the important part. The important part is *the height of the distribution at any point along the distribution* to *the height of the distribution at the origin*.[37] Given the definition of these distributions, an additional kWh

[36] This data comes from Staff's cumulative frequency analysis. Staff's regression is focused on the relationship between the total kWh and the probability that an increase in the total will land on either side of the Block 1 threshold. We are able to characterize the average by characterizing the total, because the average is the total divided by the number of customers and the number of customers is fixed. Therefore, an increase in the total necessarily increases the average. Furthermore, the same kWh increase increases the average by the same amount regardless of the starting point of the total or average.

[37] The height of the distributions at the origin are equal. 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, the then height of the first bin would be 10,000,000. The distribution necessarily decreases, because a customer must consume the first kWh before the 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.

can occur at any point along the distribution that is lower than the height of the distribution at the origin. Also, an additional kWh anywhere along the distribution will increase the average usage per customer by the same amount in any month assuming the number of customers is constant.[38] The number of customers does change slightly across the year, but the change is negligible relative to the total number of customers. The greater the difference between the height of the distribution at the origin and the height of the distribution at any given kWh value, the higher the probability that an increase will occur there.

In this illustration, it is more likely that an increase in total kWh, and consequently an increase in the average 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.[39] This is a clear illustration that the relationship between the average usage and Block 1 usage is not the same across months. Staff's choice of model imposes this restriction on its analysis, and is therefore unreasonable. The analysis has only been done for the Residential class, but a similar analysis would likely expose the same deficiency in the Staff's Small General Service regression model.

Q. What reason does Staff give for using the cumulative frequency analysis rather than the regression analysis for the Residential class?

A. Staff states that the regression analysis did not produce a reasonable result. Given the analysis above, it is clear that Staff's regression analysis produces unreasonable results for the Residential class because of the basic assumptions underlying it are unreasonably restrictive.

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[38] Recall the definition of β. In Staff's regression, β represents the increase in the Block 1 percentage that results for a one unit increase in the average usage.

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

Q. Does Staff describe the cumulative frequency method it uses to determine Residential Block 1 usage or the methods merits?

A. Not really. Staff provided no explanation of their method in direct testimony. Staff provides a few sentences describing the method and its merit in rebuttal. Staff describes the method by stating it "performed an analysis using the change in average usage per customer when kWh is normalized to develop a normalized percentage of usage for the first rate block."[40] Staff touts the merits by stating the "Cumulative frequency distribution analysis is generally preferred, because it uses the actual distribution of customer bills within a billing month to determine that if that billing month was less than or greater than normal how would the adjusted level of kWh be distributed across customer bills."[41]

Staff indicates that they use the results of the normalization of total kWh in their cumulative frequency analysis, but that is about it. As I explained in rebuttal, there are many other important moving parts in the analysis and there are deficiencies throughout Staff's analysis.

IV. SEASONAL PRORATION

Q. Does Staff make any incorrect statements about the direct testimony related to seasonal proration?

A. Yes. Staff states that "Ameren Missouri's direct testimony does not address the change in how seasonal rates are applied or steps Ameren Missouri has taken to account for the implementation of seasonal rates."[42] But, I actually explained as follows in my direct testimony: "The seasonal dimension of the days adjustment is relevant in this case, because the Company's billing processes, as reflected in its tariffs, were updated to feature proration of seasonal rates as a

[40] *Id.*, p. 6, ll. 8-9.
[41] *Id.*, p. 7, ll. 7-10.
[42] File No. ER-2021-0240, Robin Kliethermes Rebuttal Testimony, p. 6, ll. 19-21.

result of the settlement of the Company's last electric rate case (File No. ER-2019-0335). The seasonal billing proration policy makes summer rates effective for the calendar days of June 1 through September 30, rather than effective for the summer months per the billing periods and meter read dates defined by the Company's meter reading schedule. This seasonal days adjustment ensures that usage is normalized consistent with this new definition of seasonal rate application, and that the billing units reflect summer usage that is consistent with current billing practices." [43]

Q. Does Staff make any incorrect statements about the results of the Company's seasonal proration adjustment?

A. Yes. Staff incorrectly characterizes the results of the Company's seasonal proration adjustment. At the time of direct, the Company made the seasonal proration adjustment simultaneously with the days adjustment and called it the seasonal days adjustment. The Company has since separated the days adjustment and seasonal proration adjustment into two discrete adjustments. Regardless, Staff makes factually inaccurate statements about the results of the seasonal days adjustment included in the Company's direct testimony and workpapers.

Specifically, Staff states "Ameren Missouri's 365 day adjustment results in a **negative adjustment to summer usage**, whereas as the implementation of an accurate seasonal rate proration should result in more usage being billed on summer rates rather than winter rates."

I clearly state in my direct testimony: "In the proposed test year, the seasonal days adjustment decreases winter billing units and **increases summer billing units** across all customer classes."[44] The billing unit workpaper provided by the Company with direct also illustrates that the seasonal days adjustment increases summer usage. An excerpt of the workpaper from direct which shows this fact is attached as Schedule NSB-S2.

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[43] File No. ER-2021-0240, Nicholas Bowden Direct Testimony, p. 15, ll. 5-13.
[44] *Id*., p. 15, ll. 15-16.

I understand why Staff was initially confused, even though the statement in my direct is clear. As you can see in Schedule NSB-S2, the summer seasonal days adjustment and each monthly summer days adjustment has a negative sign on it. Staff looked at these numbers and incorrectly concluded the seasonal days adjustment decreases summer usage. The formulas in the workpaper show that the monthly seasonal days adjustment numbers are subtracted from the weather normalized kWh to produce the seasonally days adjusted kWh. The result of this subtraction of a negative value increases summer usage.

Furthermore, the Company and Staff met to discuss Staff's concerns about the current implementation of the seasonal days/proration adjustment on August 9, 2021. In that meeting, the Company explained the logic and mechanics of the seasonal days adjustment implemented in direct. After the meeting concluded, Staff made an email inquiry. I responded to that email inquiry via email, which is attached as Schedule NSB-S3, describing the Company's historical convention of subtracting days adjustments, and how that meant the signs on the adjustments were reversed, so that subtracting negative monthly kWh adjustments meant increases in revenue (and therefore necessarily usage).

Q. Does Staff make any incorrect statements about Data Requests ("DRs")?

A. Yes. Staff states "Staff's data request inquiring about detailed billing cycle data was objected to by the utility and Staff has not received any further information to propose a more accurate adjustment."[45] DR 0554 is not a mere request for existing data, and noted in the Company's objection, requires a complex analysis that the Company had not already performed. The Company understood that Staff envisioned that the Company would recalculate the bills of all 1.2 million customers for the billing periods in which a customer's bill included both winter and

[45] File No. ER-2021-0240, Robin Kliethermes Rebuttal Testimony, p. 8, ll. 5-7.

summer months. This process would be prohibitively time-consuming to do manually, and incredibly complicated to do programmatically. It would effectively require the Company to write a program to mimic the Company's existing billing system.

After the August 9, 2021 meeting discussed above, the Company was able to perform another analysis, which allows the precise calculation of the effect of seasonal proration on revenues. The analysis was done at the rate class level and provided to Staff through updated response to DR 0554 on August 18, 2021. Staff submitted another data request, MPSC 848, on September 22, 2021 effectively asking the Company to perform the same analysis it did in response to MPSC DR 0554 *at the bill cycle group level*. The Company performed that analysis and submitted it in response to DR 848 on September 24, 2021. The Company also showed that the analysis done at the billing cycle level is equivalent to the analysis done at the rate class level. Accordingly, the Company has provided data staff with the necessary information.

V. MEEIA MARGIN RATES

Q. Does Staff make any incorrect statements about the calculation of MEEIA Margin Rates?

A. Yes. Staff claims that "Ameren Missouri's calculated MEEIA margin rates for its direct filed Large Power class used the hourly end use load shapes in a manner that were inconsistent with the calculation of the MEEIA margin rates for all other classes." Staff continues by stating that "This inconsistency led to a customer's demand being reduced by a much higher ratio in the winter months than the summer months for the installation of an energy efficient air-conditioner, which is an unreasonable assumption given the predominate summer use of such an efficiency measure."[46] The most concrete claim is that customer's demand is reduced by a "much

[46] ER-2021-0240, Robin Kliethermes Rebuttal Testimony, p. 9, ll. 10-16.

higher" ratio in the winter months than the summer months for the installation of efficient air-conditioners. The preceding sentence appears to indicate that Staff's concern relates to the LPS class. The demand to energy ratios used in the MEEIA margins rates analysis filed in direct for the SPS and LPS classes for energy efficient air-conditional installation are reported below in Table 4.

Table 4. Energy Efficient Air Conditioner Demand to Energy Ratios

Class	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec
SPS	0	0	0	1	2.35	1.68	1.43	1.56	1.73	1	0	0
LPS	0	0	0	1	2.57	1.98	1.38	1.60	1.98	1	0	0

The ratios are consistent across the two classes, and the ratios are lower in winter than summer. Staff's statement that the ratio is "much higher" is simply incorrect.

It is probably also worth noting that Staff's general logic related to this issue is incorrect. The Company generally agrees that the ratio of demand to energy ratio for air conditioner upgrades is approximately zero in winter months. However, the reason the Company generally agrees it is zero is slightly different than the rationale Staff attempts to forward. The Company generally agrees that the ratio is zero in winter, because there is zero demand reduction and zero energy reduction. However, the Company does not agree that we should expect higher ratios in the months when an energy efficiency measure is predominately used, i.e. used more. In fact, we should expect the opposite. This is shown in Table 4. In the summer months with the highest temperature we see lower ratios. If we assume there is a maximum kW savings associated with an energy efficiency measure and that maximum savings is reached within a month, then the more the energy efficiency measure is used in the month, the more kWh savings, and the lower the demand to energy ratio.

Q. Does this conclude your surrebuttal testimony?

A. Yes, it does.

1M			
	Totals	Winter	Summer
CustomerCount	12,918,156	8,612,104	4,306,052
Total kWh	13,320,152,233	8,531,978,706	4,788,173,527
Total Block 1 kWh	9,610,344,838	4,822,171,311	4,788,173,527
Total Block 2 kWh	3,709,807,396	3,709,807,396	0

1MTOD			
	Totals	Winter	Summer
CustomerCount	1,044	696	348
Total kWh	1,516,424	1,002,360	514,064
Total Block 1 kWh	974,893	460,828	514,064
Total Block 2 kWh	541,531	541,531	0
Off Peak kWh	445,792	0	445,792
On Peak kWh	77,397	0	77,397

1MTOU2			
	Totals	Winter	Summer
CustomerCount	108	72	36
Total kWh	129,798	85,899	43,899
Total Block 1 kWh	110,784	66,885	43,899
Total Block 2 kWh	19,014	19,014	0
Off Peak kWh	39,711	19,154	20,558
On Peak kWh	53,482	30,140	23,342

1MTOUSmartSaver			
	Totals	Winter	Summer
CustomerCount	180	120	60
Total kWh	146,413	91,518	54,895
Total Block 1 kWh	122,827	67,932	54,895
Total Block 2 kWh	23,586	23,586	0
Off Peak kWh	33,299	12,970	20,329
Mid Peak kWh	48,679	16,787	31,892
On Peak kWh	5,995	3,322	2,673

2M Total			
	Totals	Winter	Summer
Total Customer Count	1,838,308	1,225,539	612,769
Single Phase Customer Count	1,141,084	760,863	380,221
Three Phase Customer Count	465,359	309,979	155,380
UnMetered Customer Count	84,530	56,497	28,033
No Customer Charge Customer Count	131,663	87,673	43,989
Single Phase TOU Customer Count	13,956	9,370	4,586
Three Phase TOU Customer Count	1,716	1,156	560
Total kWh	3,080,417,038	1,992,646,899	1,087,770,139
Base kWh	2,434,765,642	1,386,270,876	1,048,494,765

Seasonal kWh	531,841,609	531,841,609	0
Off Peak kWh	71,763,806	47,198,289	24,565,517
On Peak kWh	39,710,263	25,780,031	13,930,232
Cell kWh	2,335,719	1,556,093	779,625

3M Total			
	Totals	Winter	Summer
Customer Count	128,077	85,385	42,692
TOU Customer Count	528	354	174
Total kWh	7,112,096,566	4,542,930,144	2,569,166,422
Base kWh	3,995,122,502	3,995,122,502	0
Seasonal kWh	547,201,397	547,201,397	0
Total Block 1 kWh	2,588,775,707	1,575,878,991	1,012,896,716
Total Block 2 kWh	2,765,396,447	1,679,965,882	1,085,430,565
Total Block 3 kWh	1,210,116,770	739,277,629	470,839,140
Off Peak kWh	30,915,510	20,152,158	10,763,352
On Peak kWh	15,488,017	9,893,232	5,594,785
Demand kW	22,329,546	14,603,347	7,726,199

Total 4M			
	Totals	Winter	Summer
Customer Count	7,982	5,321	2,661
TOU Customer Count	215	143	72
Total kWh	3,541,973,165	2,273,417,696	1,268,555,469
Base kWh	2,042,688,482	2,042,688,482	0
Seasonal kWh	231,311,033	231,311,033	0
Total Block 1 kWh	1,043,076,436	641,273,412	401,803,024
Total Block 2 kWh	1,265,768,599	779,059,179	486,709,420
Total Block 3 kWh	999,265,300	619,226,164	380,039,137
Off Peak kWh	75,981,286	47,435,390	28,545,896
On Peak kWh	35,538,295	22,629,387	12,908,908
Demand kW	7,694,283	4,961,006	2,733,277
Rider B 34.5/69 kV Demand kW	823,731	540,366	283,366
Rider B 138 kV Demand kW	6,446	4,231	2,215
Reactive kVar	1,292,368	791,551	500,817

11M			
	Totals	Winter	Summer
CustomerCount	768	512	256
TOU Customer Count	60	40	20
Total kWh	3,670,972,943	2,350,373,895	1,320,599,048
Off Peak kWh	223,723,093	145,287,046	78,436,046
On Peak kWh	111,771,641	71,930,162	39,841,479
Demand kW	6,652,481	4,288,418	2,364,063
Reactive kVar	341,894	212,925	128,970
Rider B 34.5/69 kV Demand kW	1,779,850	1,162,324	617,527
Rider B 138 kV Demand kW	628,570	411,630	216,940

Residential Weather Adjusted Billing Units						
	202005	202006	202007	202008	202009	202010
Weather Factor	0.9853	0.9667	0.9437	0.9846	1.0361	0.9800
Block 1 Factor	0.7395					0.7172
	1M	1M	1M	1M	1M	1M
	202005	202006	202007	202008	202009	202010
CustomerCount	1,070,806	1,072,025	1,072,888	1,073,690	1,073,657	1,073,088
Total kWh	782,015,557	968,071,070	1,289,505,598	1,325,079,145	1,238,136,354	812,234,246
Total Block 1 kWh	575,615,061	968,071,070	1,289,505,598	1,325,079,145	1,238,136,354	585,672,412
Total Block 2 kWh	206,400,496	0	0	0	0	226,561,834
Customer Charge per Month	9	9	9	9	9	9
Low Income Pilot Program Charge per Month	0.06	0.06	0.06	0.06	0.06	0.06
Summer Energy Charge		0.1181	0.1181	0.1181	0.1181	
Winter Block 1 Energy Charge	0.0804					0.0804
Winter Block 2 Energy Charge	0.0538					0.0538
Total Residential BASIC Revenue Estimate	67,085,300	124,041,740	162,010,976	166,219,478	155,951,236	68,999,266

1M
Totals
12,860,243
13,362,130,453
9,724,610,104
3,637,520,349
1,275,814,913

Residential Seasonal Days Adjusted Billing Units						
	202005	202006	202007	202008	202009	202010
Total kWh Days Adjustment	2,296,045	-3,002,277	-3,999,141	-4,109,465	-3,839,830	2,384,769
Block1 kWh Days Adjustment	1,690,040	-3,002,277	-3,999,141	-4,109,465	-3,839,830	1,719,569
Block 2 kWh Days Adjustment	606,004	0	0	0	0	665,199
	1M	1M	1M	1M	1M	1M
	202005	202006	202007	202008	202009	202010
CustomerCount	1,070,806	1,072,025	1,072,888	1,073,690	1,073,657	1,073,088
Total kWh	779,719,512	971,073,346	1,293,504,739	1,329,188,610	1,241,976,184	809,849,477
Total Block 1 kWh	573,925,021	971,073,346	1,293,504,739	1,329,188,610	1,241,976,184	583,952,843
Total Block 2 kWh	205,794,492	0	0	0	0	225,896,635
Customer Charge per Month	9	9	9	9	9	9
Low Income Pilot Program Charge per Month	0.06	0.06	0.06	0.06	0.06	0.06
Summer Energy Charge		0.1181	0.1181	0.1181	0.1181	
Winter Block 1 Energy Charge	0.0804					0.0804
Winter Block 2 Energy Charge	0.0538					0.0538
Total Revenue Estimate	66,916,818	124,396,309	162,483,275	166,704,806	156,404,720	68,825,225

Days Adjustment	Winter	Summer
10,127,170	25,077,882	-14,950,712

1M
Totals
12,860,243
13,352,003,283
9,725,162,912
3,626,840,371
1,275,848,418

Change in Usage (Total kWh)	-2,296,045	3,002,277	3,999,141	4,109,465	3,839,830	-2,384,769

Summer Billing Units Increase

14,950,712

From: Bowden, Nicholas
To: Kliethermes, Robin; Wills, Steven M
Cc: Cox, Kim
Subject: RE: Days adjustment and proration
Date: Monday, August 9, 2021 5:25:27 PM

Hi Robin,

1. Steve was saying it correctly. He was pointing to a negative kWh adjustment number and saying increase. I followed the convention used in previous cases to calculate those kWh adjustment numbers we were looking at (convention: revenue – calendar). This unfortunately gives kWh adjustment numbers with signs that are opposite of what is intuitive for interpretation. Those adjustments end up getting subtracted from the weather normalized kWh, which serves to reserve the sign for both the change in kWh and revenue. For instance, if we look at one of the residential summer months, and subtract weather normalized revenue from days adjusted revenue, we see an positive number. An increase in revenue due to the days adjustment, although the days adjustments for the summer months are negative.

2. For this year, all customers usage will be prorated based on the number of days of the billing period in each season. This implicitly assumes equal number of kWh per day. Next year, customers with AMI will have their kWh allocated based on their interval data. The usage in the hours (days) in winter calendar months will be billed at winter rates and the usage in the hours (days) in summer calendar months will be billed at summer rates. The decision to implement the change next year and not now is a function of the stage of the AMI rollout, the number of customers actually billed on interval data (only TOU customers), and the complexity associated with making this programmatic change to the billing system.

Nick

From: Kliethermes, Robin <Robin.Kliethermes@psc.mo.gov>
Sent: Monday, August 9, 2021 3:31 PM
To: Bowden, Nicholas <NBowden@ameren.com>; Wills, Steven M <SWills@ameren.com>
Cc: Cox, Kim <Kim.Cox@psc.mo.gov>
Subject: [EXTERNAL] Days adjustment and proration

Steve and Nick,

Just a couple of questions to follow up from our discussion today.

1. In looking at the days adjustment again, it looks like it is coming through on revenues as a negative adjustment to summer and positive adjustment to winter. Is that correct? I thought on the phone call it was mentioned that because calendar month had more summer usage than revenue month it was going to result in a positive adjustment to summer and negative

adjustment to winter due to the proration.

2. Also, it was mentioned that the proration assumes equal percent of usage per day. Is that only for non-AMI customers or all customers including those with AMI meters?

Thanks,
Robin

Robin Kliethermes
Rate and Tariff Examination Manager
Missouri Public Service Commission
Phone: (573)-522-3782

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-2021-0240

AFFIDAVIT OF NICHOLAS BOWDEN, PhD

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

Nicholas Bowden, PhD, being first duly sworn on his oath, states:

My name is Nicholas Bowden, PhD and on his oath declare that he is of sound mind and lawful age; that he has prepared the foregoing *Surrebuttal 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, PhD.
Nicholas Bowden, PhD

Sworn to me this 5th day of November, 2021.