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MISSOURI PUBLIC SERVICE COMMISSION

FILE NO. ER-2024-0319

REBUTTAL TESTIMONY

OF

NICHOLAS BOWDEN

ON

BEHALF OF

UNION ELECTRIC COMPANY

D/B/A AMEREN MISSOURI

St. Louis, Missouri
January 2025

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OF

NICHOLAS BOWDEN

FILE NO. ER-2024-0319

I. INTRODUCTION

Q. Please state your name and business address.

A. My name is Nicholas Bowden. My business address is One Ameren Plaza, 1901 Chouteau Ave., St. Louis, Missouri.

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

A. Yes, I am.

Q. To what testimony or issues are you responding?

A. My rebuttal testimony responds to issues covered under the following topics.

1. Billing Units and Normalized Revenues
2. Revenue Requirement Allocations
3. Rate Design

Q. What specific Billing Unit and Normalized Revenue testimony will you address?

A. I will address five billing unit and normal revenue topics from Staff's testimony. I will address three subtopics under topic one and one or more issues within each subtopic.

1. Staff's Weather Normalization Adjustment
   A. Residential and Small General Service("SGS") Block Normalization

B. Residential and SGS Time-of-Use Normalization

C. Total Usage Weather Normalization

2. Staff's MEEIA Annualization Adjustment

3. Staff's Solar Annualization Adjustment

4. Staff's Economic Development Incentive Annualization Adjustment

5. Staff's Growth Adjustment

Q. What Revenue Requirement Allocation Testimony will you address?

A. I will respond to four Revenue Requirement Allocation proposals.

1. Staff's proposal
2. Consumers Council of Missouri ("CCM") position
3. Midwest Energy Consumers Group ("MECG") proposal
4. Missouri Industrial Energy Consumers ("MIEC") proposal

Q. What Rate Design Testimony will you address?

A. There are three parties' testimony that I will address. Party-specific issues I address are noted below each party here:

1. Staff's Rate Design proposals

   A. Residential customer charge proposal

   B. Evening-Morning Savers on peak adjustments proposal

   C. Monthly charges for Legacy Time-of-Day rate schedules

   D. Rider B proposal

2. MECG Rate Design proposal

   A. Non-residential rate design progress report

   B. Demand and energy rates

C. Electric vehicle rate proposal

3. CCM Rate Design proposal

A. Residential customer charge proposal

II. BILLING UNIT AND NORMAL REVENUE

1. Staff's Weather Normalization Adjustment

Q. Can you provide a summary of the billing unit and normal revenue issues you identified in Staff's proposal?

A. Yes. Weather normalization is the most unique and involved of the adjustments made to test year billing units in the development of normal revenues. As a result, it is the most likely to suffer from problems and therefore I devote a lot of time and effort to the evaluation of Staff's weather normalization of billing units and revenues. Typically, I think about the weather normalization in two steps. First, weather normalization of total kilowatt-hours ("kWh"), then weather normalization of a few of the discrete billing unit components of total kWh. Examples of discrete components of total kWh that Staff normalized in this case are Residential and SGS block kWh and Residential and SGS time-of-use kWh.[1] I begin with a discussion of Staff's normalization of discrete components and then move to total weather normalization. I start this way because several discrete component normalization results look unreasonable when subjected to basic evaluations. Starting from these results, I step through Staff's workpapers to reveal unreasonable choices.

[1] Recall that several of the Company's rates are structured in "blocks", where different kWh of usage are subject to different prices. The easiest example to think about is the residential rate, where customers are subject to one rate for the first 750 kWh of monthly usage in non-summer months, and a different rate for all usage above that threshold. Even with accurate weather normalization of total kWh, making sure that the weather adjustment occurs in the proper usage block is critical to accurately determining normalized revenues.

In the first example, Residential block normalization, I trace the mechanics and discuss the issues of one result in great detail. I do this to show that the results aren't the result of data entry error or some other trivial mistake, but rather they are the result of deliberate choices Staff made in how it conducted its analysis. Then, I will discuss a few other issues with block normalization more briefly.

In a second example, SGS time-of-use normalization, I will explain how Staff undertakes a somewhat complicated and tedious set of calculations but misses the fact the result was never going to be applicable. Staff's inappropriate application of the time-of-use normalization leads to results which are clearly unreasonable. I will then examine a few other odd results of Staff's time-of-use weather normalization and draw some attention to Staff's choice to use time-of-use normalization results to develop the monthly normalization factors for the Residential and SGS classes' total usage.

Finally, I will address total weather normalization. I will outline two general problems with Staff's statistical methods. I discussed these two issues in ER-2022-0337, but hope a refined discussion based on clearer understanding and simpler presentation will help Staff and the Commission understand the issues. In addition to the two methodological issues, Staff also made an unreasonable decision to choose 'alternative' monthly weather normalization factors for the Residential and SGS classes. In this case, Staff produced total weather normalization factors for all classes using their traditional modeling approach, but also produced monthly weather normalization factors from their time-of-use results for Residential and SGS classes. Staff chooses to apply monthly factors based on the time-of-use results, and I will discuss why that is unreasonable.

A. Residential and Small General Service "SGS" Block Normalization

Q. Can you describe an unreasonable result found in Staff's Residential block normalization?

A. Yes. Generally speaking, when total kWh usage decreases as a result of the weather-normalization, we expect both block 1 and block 2 kWh usage to decrease. Similarly, if total kWh usage increases, then we expect both block 1 and block 2 kWh usage to increase. We do not expect block 1 kWh usage and block 2 kWh usage to move in opposite directions. There is an intuition to the logic. For example, if it is colder than normal in the winter and therefore usage is higher than normal, there is no reason whatsoever to expect either block of residential usage to be *lower* than normal. If the total usage reduction, associated with normalizing the abnormally high usage down, is accomplished by decreasing usage in one block and increasing usage in the other block, then this implies usage was somehow lower than normal in the block that increased.

Staff explicitly acknowledges this logical principle in testimony. "It is expected that a general increase in usage would increase the usage in both rate blocks … ".[2]

Staff produces results where block 1 and block 2 usage move in opposite directions which defies logic, contradicts Staff's own statement, and renders Staff's adjustment facially unreasonable.

Q. Can you provide an example of this type of result?

A. Yes. Table 1 shows Staff's weather normalization of winter total and block usage for the Anytime Users and Evening-Morning Savers residential rate plans for the month of November.

[2] File No. ER-2024-0319, Michael L. Stahlman Direct Testimony, p. 6, ll. 11-12.

Table 1. November Residential Block Normalization Results

Nov-2023	Billing Unit	Pre Weather Normalization	Post Weather Normalization	Change
Anytime Users	Winter Total kWh	325,731,262	320,891,636	-4,839,626
	Block 1 kWh	233,886,856	249,564,853	15,677,997
	Block 2 kWh	91,844,406	71,326,783	-20,517,623
Evening Morning Savers	Winter Total kWh	408,648,977	402,577,382	-6,071,595
	Block 1 kWh	317,088,645	347,492,703	30,404,058
	Block 2 kWh	91,560,332	55,084,679	-36,475,653

The kWh in the Pre and Post column are taken from Staff's billing unit and normal revenue workpaper. The change column is the 'basic evaluation' step that I perform. The Company performs this evaluation to ensure its results are logical. Here the change column shows illogical results which are large in magnitude. For example, Staff's total weather normalization results dictated a 6 million kWh decrease in winter usage for Evening-Morning Savers customers in November. Staff's block normalization results indicate that the 6 million kWh decrease be achieved by decreasing block 2 usage by 36 million kWh, so that block 1 usage increases by 30 million kWh to achieve the total 6 million kWh adjustment.

In order for this result to occur, one of two things would need to happen. One, individual customers consuming more than 750 kWh would need to increase their block 1 usage above 750. This is impossible by the definition of the Anytime Users and Evening-Morning Savers rate plans. To make it more concrete, we can imagine 1 million customers consuming 786 kWh. By definition, each customer's block 1 usage would be 750 and block 2 usage would be 36. If each customer decreases their block 2 usage by 36 and increases their block 1 usage by 30, then the result would be a total decrease of 6 million kWh, a block 1 increase of 30 million kWh, and a block 2 decrease of 36 million kWh. The only problem is that, after this adjustment, each customer has 780 block 1 kWh, yet we know from the tariff definition of block 1 that block 1 kWh are limited to the first 750 kWh.

Two, only customers consuming less than 750 kWh would increase their usage, while only customers consuming more than 750 kWh would decrease their usage. While mathematically possible, it is hard to imagine the conditions under which this outcome is reasonable, since as I mentioned earlier, there is no reason to expect normal weather that was milder than actual weather to increase usage for any customers in any usage range.

Q. What causes Staff to produce this unreasonable result?

A. There is a general cause and a specific cause of this result. Staff's general block normalization modeling approach is very vulnerable to a basic and well-known statistical problem. The problem of small sample sizes. It appears to me that, in an attempt to remedy this problem, Staff made a bad choice. They choose to include some obviously inappropriate data in their model.

Q. Can you explain why Staff's general approach is vulnerable?

A. Yes, but first let's talk about what the Company does as a contrast. The Company uses monthly block normalization models with 17 years of historical weather and block usage data for each month. Either the sample size is 17 observations per month or 136 observations for the 8 winter months in total. The Company estimates the relationship between weather and block usage for each month and then uses that estimated relationship and the difference between actual and normal weather to normalize block kWh.

In contrast, Staff only uses test-year data to estimate the relationship between actual usage-per-customer and actual block usage. Staff then uses normal usage-per-customer from the total weather normalization result to normalize block usage. In the past, the Company has criticized Staff for choosing a block normalization model that does not incorporate weather directly. I still think this fact makes Staff's modeling approach inferior to the Company's, but it is not the primary identifiable source of the unreasonable results here, so I will not belabor the point here. Staff's choice to use only the test-year data to estimate the relationship between actual usage-per-customer and actual block usage is the general source of the problem.

The Company's tariff defines eight winter months and four summer months.[3] The residential rate plans only have block usage in the winter months.[4] Staff chooses to only use test-year data, so Staff only has one residential class-level block usage observation per month. This means Staff cannot estimate a relationship between usage-per-customer and block-usage on a monthly basis by regression methods since at least two observations are required to define a line. This forces Staff to group the months together to increase their sample size. In the past, Staff had grouped all months together, so they would have 8 observations (as compared to 136 for the Company). In the past, we criticized this choice of general approach because it assumes a single relationship between usage-per-customer and block-usage exists across all months, despite seasonal variation in weather patterns that impacts the distribution of customer usage. The Company showed in the past how this

[3] Seasonal proration of summer and winter kWh for billing periods complicates the exposition, but not the basic facts. Generally, customers will have two billing months that cross the summer-winter seasonal boundaries, June 1 and October 1, so customers will have two bills with both summer and winter kWh on them. This will leave them with 3 pure summer kWh bills and 7 pure winter bills. Across 12 bills there are 4 months' worth of summer kWh and 8 worth of winter kWh.
[4] Other classes, LGS and SPS in particular, have block usage in summer and winter.

assumption is contrary to the facts since different winter months have different distributions of customer usage. It is the distribution of customer usage that will determine the relationship between any specific average usage-per-customer and the proportion of usage in each block. While this criticism still stands, it too is not the primary source of the problem I observe here, so I will say no more about it.

Now, let's get to the point where Staff's general problem of small sample size leads to a bad decision. In this case, Staff did not combine all monthly usage-per-customer and block usage observations into a single model. Instead, Staff grouped observations into 'shoulder' and 'winter' months. This change could be viewed as an improvement, as it would at least partially group months seasonally where we might expect more similar distributions of underlying customer usage. It moves in the direction of addressing the Company's criticism above about the distributional differences in usage across months. However, it appears to be the first of two choices which directly lead to the unreasonable result shown above.

Q. What is the second choice?

A. Staff's choice to separate the eight winter months into two groups, 'shoulder' and 'winter', would reduce the already small sample size of eight to something smaller in each model. In order to compensate for the decreased sample size, Staff generated additional usage-per-customer and block-usage observations, by using residential billing units at the rate plan level. Specifically, Staff chooses to calculate usage-per-customer and block-usage observations for the Anytime Users, Evening-Morning Savers, and Legacy Time-of-Day rate plans. Staff then chooses to use these rate plan level observations to estimate the usage-per-customer and block-usage models. This is the critical choice that is ultimately unreasonable.

Q. Can you explain why this second choice is unreasonable?

A. Yes. Staff estimates the relationship between usage-per-customer and block usage for 'shoulder' months using eight 'shoulder' month observations. Three observations come from Anytime Users data, three come from Evening-Morning Savers, and two come from the Legacy Time-of-Day rate schedule. What is the problem with that choice? The Legacy Time-of-Day observations are *obvious* outliers, but Staff includes them. Furthermore, Staff gives the outliers as much weight as the Anytime Users and Evening-Morning Savers observations when the number of customers on the Legacy Time-of-Day rate is nearly zero. The outliers have a significant impact of the estimated relationship and on the normalization of block usage, especially in November.

Q. Why do you call the Legacy Time-of-Day observations outliers?

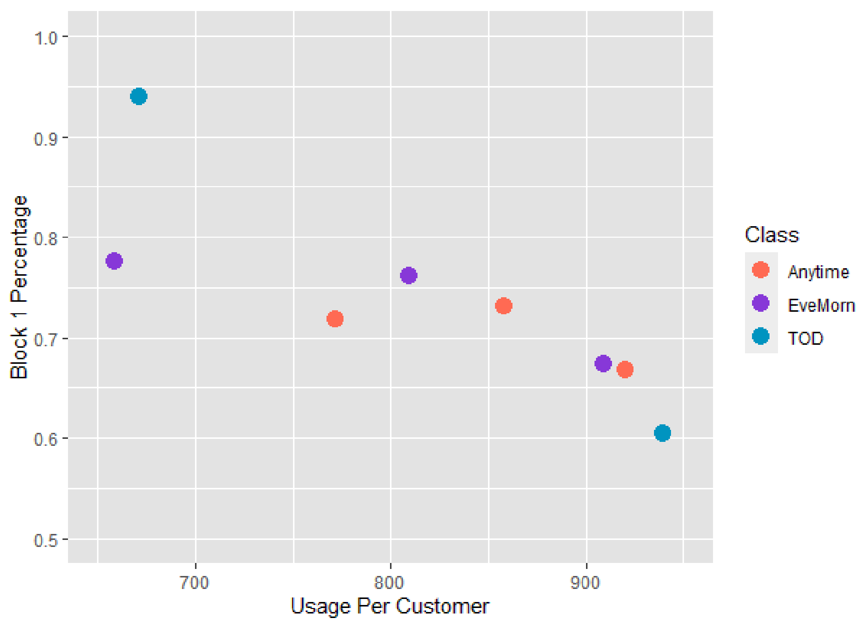
A. It is a textbook example. "Outliers can also arise when sampling from a small population when one or several of the members of the population are very different in some relevant aspect from the rest of the population."[5] The population of interest for block normalization is the rate plan level usage-per-customer and block-usage observations from the test-year. The Legacy Time-of-Day rate plan data is very different from the population in one obvious and relevant aspect. The obvious relevant aspect is the number of customers on the Legacy Time-of-Day rate plan relative to the Anytime Users and Evening-Morning Savers rate plans.

[5] Wooldridge, Jeffrey, *Introductory Econometrics*, 3rd Edition, p. 328.

Q. Can you illustrate why it was unreasonable for Staff to include the Time-of-Day usage-per-customer and block-usage observations in the model used to normalized block usage?

A. Yes. Figure 1 shows the eight observations Staff used in their 'shoulder' month block normalization model by Residential rate plan.

Figure 1. Staff Shoulder Month Block Normalization Data



The Anytime Users and Evening Morning Savers observations exist across a range of monthly usage-per-customer values, and block usage (block 1 usage as a percentage of total usage) is within the bounds of 65% and 80%. In Table 2 below, you can see the minimum and maximum are 67% and 78% respectively. Each of the two Legacy Time-of-Day observations, on the other hand, exist on the extremes of the monthly usage-per-customer range and the percentage of usage in block 1 is 60% and 94% for the two observations. They both fall outside of the range of the observations associated with the other classes – and by a significant amount. The two observations are 17% greater than the next largest observation and 7% below the next smallest respectively. It is theoretically possible that these values are still relevant, but the relevant aspect mentioned above will clearly illustrate why they are not.

Table 2 shows the 8 observations Staff uses to estimate their model including the rate plan and month the observations come from, and the number of customers associated with the observation. The number of customers is the relevant aspect which makes the Legacy Time-of-Day observation very different from the Anytime Users and Evening-Morning Savers observations. Remember, it's the application of this model to usage from the Anytime Users and Evening-Morning Savers that produced the unreasonable results.

Table 2. Staff Shoulder Month Block Normalization Data

Observation	Usage Per Customer	Block 1 Percentage	Number of Customer
Anytime Oct	858	73%	453,618
Anytime Nov	772	72%	437,058
Anytime June	920	67%	284,302
TOD Nov	940	60%	**8**
TOD June	671	94%	**4**
Even-Morn Oct	809	76%	632,387
Even-Morn Nov	659	78%	649,786
Even-Morn June	909	67%	804,661

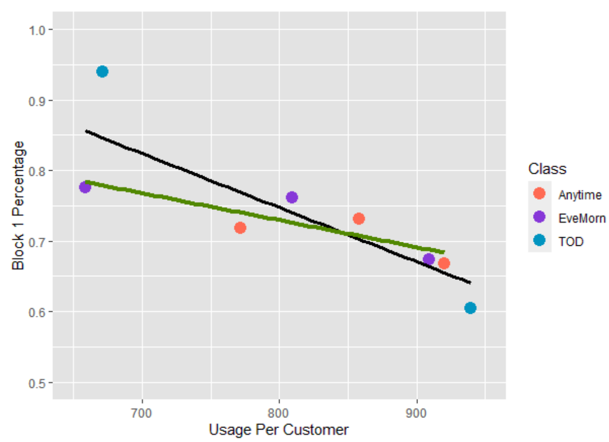
The two observations for the Legacy Time-of-Day rate (in bold font) represent usage associated with *8 and 4 customers for November and June respectively*. These 2 observations are given *equal weight* in determining the relationship between usage-per-customer and block-usage as the other 6 observations which are associated with between *284,302 and 804,661 customers*. This is patently unreasonable on its face.

If Staff wanted to include these observations, then they should have given the observations something like one **one-hundred-thousandth** of the weight as the Evening-Morning Savers and Anytime Users observations. Weighting observations is technically possible, but practically speaking a weight of one one-hundred-thousandth is zero, and zero weight is mathematically equivalent to excluding the observation. So practically speaking, Staff should have excluded these observations.

Q. Can you provide an intuitive explanation of the technical impact these outlier observations have on Staff's model and the result?

A. In Figure 2, the impact these observations have on the model is illustrated graphically. The relationship Staff estimates, inclusive of these two outlier data points, is illustrated by the black line. If the two outlier data points are removed, and the relationship is estimated again, then the result is the green line. **The difference between the black and green lines is the impact the outliers have on the model.**

Figure 2. The Outliers' Impact on Staff's Shoulder Block Normalization Model



The influence of the June Legacy Time-of-Day, the 94%, observation is perhaps the most striking. It is easy to see, both in Table 2 and Figure 1, that this point is extreme. However, the same is true, although it is less extreme, about the November Legacy Time-of-Day observation. They are extreme on opposite ends, but they have the same directional effect on the estimated relationship, i.e. the black line. The June Legacy Time-of-Day observation 'pulls' the black line up on the left and the November Legacy Time-of-Day observation 'pulls' the black line down on the right, both making the estimate of the relationship 'steeper'.

The impact that the outliers have on the result is measured by the vertical distance between the two lines for a given usage-per-customer value on the horizontal axis. The greater the distance the greater the ultimate impact of the outliers on the block normalization result. Here is how it happens: Staff determines the normal usage-per-customer using the results of their total weather normalization model. Then Staff takes the normal usage-per-customer results and uses this model (the black line) to calculate the normal block 1 percentage. If normal usage-per-customer is near the intersection of the two lines (approximately 850 kWh), then there is no difference in the result, i.e. the black and green lines yield the same block 1 percentage. However, if the normalized usage-per-customer is far from that intersection, then the impact of the outliers on the result is great, i.e. the block 1 percentage associated with the black line is much different from the block 1 percentage associated with the green line. This is exactly what happens in November. Staff's normalized usage for Anytime Users and Evening Morning Savers for November is 760 and 649 kWh respectively. This is towards the left end of the graph in Figure 2, where the difference between the two lines is greatest. This means that the block usage for approximately one million Anytime User and Evening-Morning Savers customers is primarily determined by the kWh usage of 4 and 8 Legacy Time-of-Day customers. That's unreasonable.

Q. Can you provide an estimate of the impact this decision has on Staff's calculation of the Company's normal revenue?

A. Yes, I've calculated the impact of including the two outliers on the usage and revenue associated with Anytime Users and Evening-Morning Savers for the month of

November. Removing the two outliers completely resolves the illogical result (i.e., the normalization of the blocks moving in opposite directions) for Evening-Morning Savers, but not for Anytime Users. The change reverses the illogical flow of all 30 million kWh for Evening Morning Savers, but only reverses the illogical flow of approximately 10 million kWh of the 15 million kWh for Anytime Users. Table 3 shows the usage results produced by Staff's model when the outliers are excluded (results associated with the green line).

Table 3. Block Usage Results After Removing Outliers

Nov-2023	Billing Unit	Pre-Weather Normalization	Post Weather Normalization Outlier Removed	Change Outlier Removed
Anytime Users	Winter Total kWh	325,731,262	320,891,636	-4,839,626
	Block 1 kWh	233,886,856	238,972,690	5,085,834
	Block 2 kWh	91,844,406	81,918,946	-9,925,460
Evening Morning Savers	Winter Total kWh	408,648,977	402,577,382	-6,071,595
	Block 1 kWh	317,088,645	316,981,260	-107,385
	Block 2 kWh	91,560,332	85,596,123	-5,964,209

In order to determine the revenue impact of including outliers, I determine the revenue impact of Staff's model with outliers and the revenue impact of Staff's model without outliers separately, and then take the difference. The results of this analysis are shown in Table 4.

Table 4. Analysis of Outlier Impact on Revenue

	Rates	kWh Change	Revenue Change Staff	kWh Change Outlier Correct	Revenue Change Outlier Correct
Anytime Users	0.0934	15,677,997	1,464,325	5,085,834	475,017
	0.0627	-20,517,623	-1,286,455	-9,925,460	-622,326
			177,870		-147,309
	Total Anytime Revenue Change				-325,179
Evening Morning Savers	Rates	kWh Change	Revenue Change Staff	kWh Change Outlier Correct	Revenue Change Outlier Correct
	0.0919	30,404,058	2,794,133	-107,385	-9,869
	0.0616	-36,475,653	-2,246,900	-5,964,209	-367,395
			547,233		-377,264
	Total Evening Morning Revenue Change				-924,497
Total Revenue Change					-1,249,676

The analysis is conducted in terms of the impact of removing the outliers. Therefore, removing the outliers reduces Staff's calculation of the Company's normal revenue by $1.25 million. Conversely, Staff's inclusion of the outliers increased their calculation of the Company's normal revenue by $1.25 million.

Table 4 also provides another illustration of the unreasonableness of Staff's block normalization. In Staff's model of weather normalization, a 4.8 million *decrease* in Anytime Users usage actually *increased* revenue by $177 thousand and a 6.1 million *decrease* in Evening-Morning Savers kWh actually *increased* revenue by $547 thousand. These results are counter intuitive because they are illogical. Counter intuitive directional changes in block 1 kWh or total dollars would be identified by basic evaluation techniques.

Q. If you went a step further and constrained Staff's model so that it did not produce any illogical kWh changes, what would the revenue impact be?

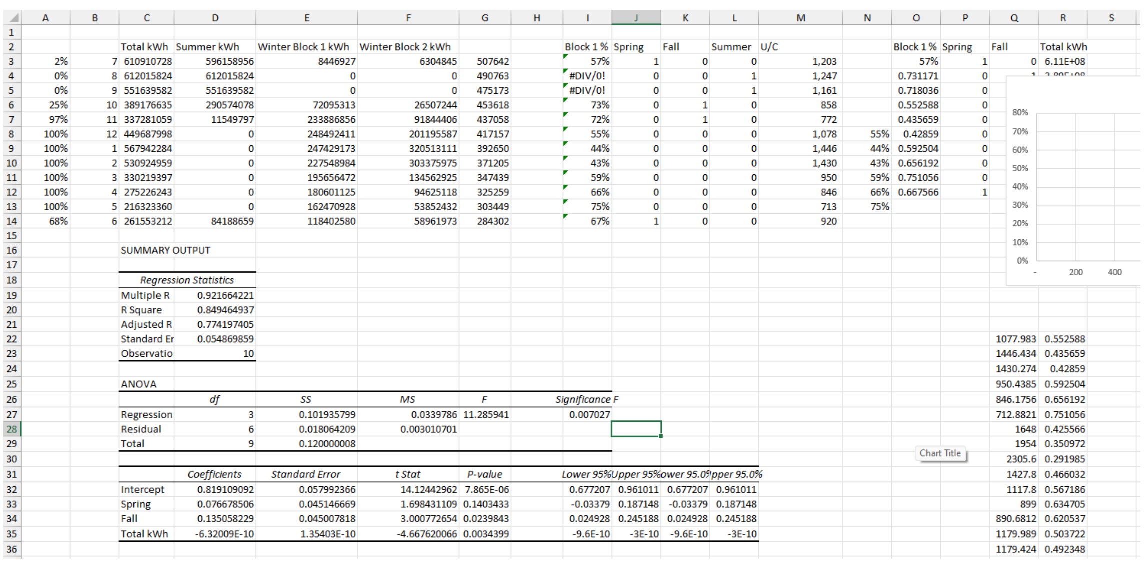
A. If we simply constrained the change in Anytime Users block 1 usage to 0 and allowed the block 2 usage to account for the entire 4.8 million kWh decrease, then the total change in normalized revenue would be a decrease of $1.4 million rather than $1.25 million. This constraint results in the minimum possible revenue reduction for the associated total usage decrease that would potentially be reasonable to use for purposes of weather normalization in this case. Any other combination of block 1 and block 2 usage reductions, i.e. any non-zero reduction in block 1 usage, would result in an even greater revenue decrease.

Q. Why do you spend so much time discussing this one issue? Is it the only unreasonable thing Staff has done related to billing units and normalized revenue?

A. No, there are other issues, and I will address several more later, but there are two reasons I spend so much time discussing this issue. First, I spent a lot of time understanding this issue, because the illogical nature of the result made the issue stick out early in my review, when I had time to carefully work through Staff's workpapers and understand the issue in depth. Second, I spend significant time because I want to illustrate something to the Commission. It takes significant time and effort to understand unreasonable decisions in this type of complex modeling, and I want to illustrate the Company's capacity to understand. Furthermore, issues like this one raise real concern about whether Staff made reasonable decisions in this case more generally concerning normalized billing units and revenue. If there are real concerns about the reasonableness of Staff's decisions in this case, then there are real concerns about the reasonableness the billing units and normal revenue Staff produced in this case. If neither are reasonable, then neither should be relied on to set rates in this case.

The time and effort required to understand decisions increases when testimony fails to mention new or unexpected models that play a significant role in determining outcomes. This is magnified when workpapers papers poorly present work that wasn't mentioned in testimony, but significantly impacts outcomes. In the specific case of the residential block normalization, these two things are true. As we mention above, Staff estimated two normalization models for residential block usage, one 'shoulder' and one 'winter'. Staff presents a few facts about the 'winter' model in testimony but fails to even mention the existence of another 'shoulder' model. As far as presentation in the workpaper, there are several models estimated on the residential block normalization sheet without clear indication of which models were ultimately used to normalize billing units. In fact, the model which was least clearly identifiable in the workpaper was ultimately the one that Staff chose for the 'shoulder' month normalization. Furthermore, the data used in the final model was copied and pasted as values from multiple locations within the sheet without any labeling, so it wasn't clear what the data even represented.[6] What the data really represented was key to understanding why it wasn't reasonable to include that data.

Figure 3. The Top-Left of Staff's Residential block normalization workpaper



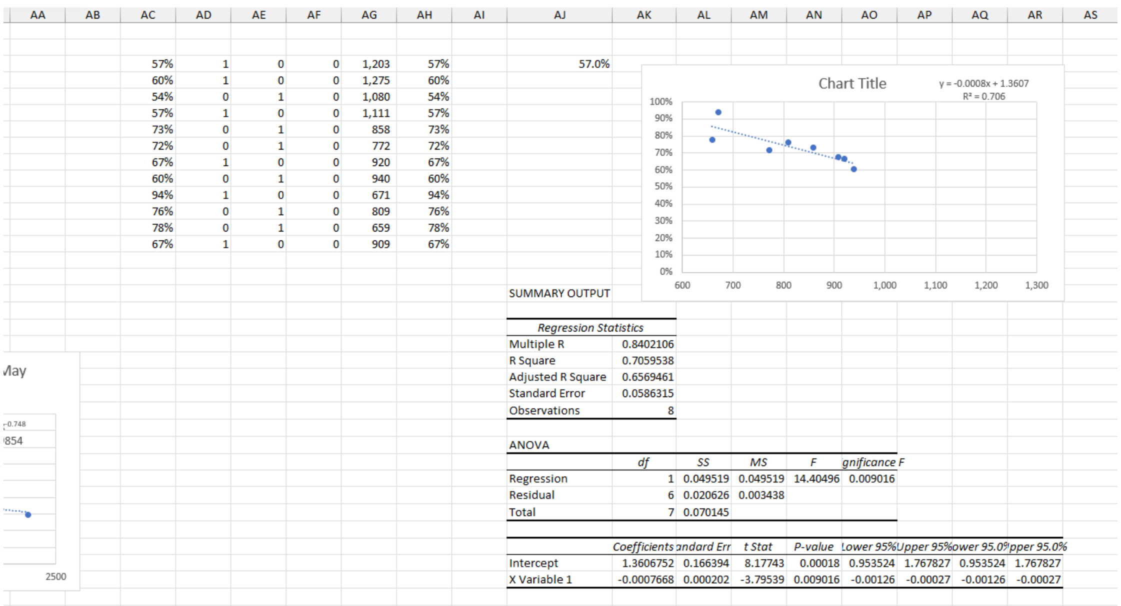
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1																			
2			Total kWh	Summer kWh	Winter Block 1 kWh	Winter Block 2 kWh			Block 1 %	Spring	Fall	Summer	U/C		Block 1 %	Spring	Fall	Total kWh	
3	2%	7	610910728	596158956	8446927	6304845	507642		57%	1	0	0	1,203		57%	1	0	6.11E+08	
4	0%	8	612015824	612015824	0	0	490763		#DIV/0!	0	0	1	1,247		0.731171	0	1	[illegible]	
5	0%	9	551639582	551639582	0	0	475173		#DIV/0!	0	0	1	1,161		0.718036	0			
6	25%	10	389176635	290574078	72095313	26507244	453618		73%	0	1	0	858		0.552588	0			
7	97%	11	337281059	11549797	233886856	91844406	437058		72%	0	1	0	772		0.435659	0			
8	100%	12	449687998	0	248492411	201195587	417157		55%	0	0	0	1,078	55%	0.42859	0			
9	100%	1	567942284	0	247429173	320513111	392650		44%	0	0	0	1,446	44%	0.592504	0			
10	100%	2	530924959	0	227548984	303375975	371205		43%	0	0	0	1,430	43%	0.656192	0			
11	100%	3	330219397	0	195656472	134562925	347439		59%	0	0	0	950	59%	0.751056	0			
12	100%	4	275226243	0	180601125	94625118	325259		66%	0	0	0	846	66%	0.667566	1			
13	100%	5	216323360	0	162470928	53852432	303449		75%	0	0	0	713	75%					
14	68%	6	261553212	84188659	118402580	58961973	284302		67%	1	0	0	920						
15																			
16			SUMMARY OUTPUT																
17																			
18			Regression Statistics																
19			Multiple R	0.921664221															
20			R Square	0.849464937															
21			Adjusted R	0.774197405															
22			Standard Er	0.054869859													1077.983	0.552588	
23			Observatio	10													1446.434	0.435659	
24																	1430.274	0.42859	
25			ANOVA														950.4385	0.592504	
26				df	SS	MS	F		Significance F								846.1756	0.656192	
27			Regression	3	0.101935799	0.0339786	11.285941		0.007027								712.8821	0.751056	
28			Residual	6	0.018064209	0.003010701											1648	0.425566	
29			Total	9	0.120000008												1954	0.350972	
30																	2305.6	0.291985	
31				Coefficients	Standard Error	t Stat	P-value		Lower 95%	Upper 95%	ower 95.0%	pper 95.0%					1427.8	0.466032	
32			Intercept	0.819109092	0.057992366	14.12442962	7.865E-06		0.677207	0.961011	0.677207	0.961011					1117.8	0.567186	
33			Spring	0.076678506	0.045146669	1.698431109	0.1403433		-0.03379	0.187148	-0.03379	0.187148					899	0.634705	
34			Fall	0.135058229	0.045007818	3.000772654	0.0239843		0.024928	0.245188	0.024928	0.245188					890.6812	0.620537	
35			Total kWh	-6.32009E-10	1.35403E-10	-4.667620066	0.0034399		-9.6E-10	-3E-10	-9.6E-10	-3E-10					1179.989	0.503722	
36																	1179.424	0.492348	

[6] This is particularly troublesome, given Staff's vociferous complaints in several recent dockets (see, for example the testimony of J Luebbert in the Company's MEEIA 4 application case, File No. EO-2023-0136) about the Company including "hard-coded" values in workpapers.

The source of the data is not identified, but it appears to be Anytime Users usage data and any Anytime Users specific block normalization model. It appears that this portion of the workpaper was not used by Staff in its final analysis.

Scrolling down, we find more unused unlabeled data and analysis. It turns out to be Legacy Time-of-Day and Evening Morning data and model results which are partially deleted. Then moving back up and to the right of the above screenshot, we find Figure 4.

Figure 4. Data and Model Used for Staff's Should Model



AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ
		57%	1	0	0	1,203	57%		57.0%
		60%	1	0	0	1,275	60%		
		54%	0	1	0	1,080	54%		
		57%	1	0	0	1,111	57%		
		73%	0	1	0	858	73%		
		72%	0	1	0	772	72%		
		67%	1	0	0	920	67%		
		60%	0	1	0	940	60%		
		94%	1	0	0	671	94%		
		76%	0	1	0	809	76%		
		78%	0	1	0	659	78%		
		67%	1	0	0	909	67%		

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.8402106
R Square	0.7059538
Adjusted R Square	0.6569461
Standard Error	0.0586315
Observations	8

ANOVA

	df	*SS*	*MS*	*F*	*gnificance F*
Regression	1	0.049519	0.049519	14.40496	0.009016
Residual	6	0.020626	0.003438		
Total	7	0.070145			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	1.3606752	0.166394	8.17743	0.00018	0.953524	1.767827	0.953524	1.767827
X Variable 1	-0.0007668	0.000202	-3.79539	0.009016	-0.00126	-0.00027	-0.00126	-0.00027

In Figure 5, I zoom in to highlight the data used by Staff to estimate their 'shoulder' month block normalization model. There are no column labels, i.e. no indication of what the variables definitions. There are no row labels, i.e. indication of the rate plan or months from which the data came. There is also no indication that some of the data is extraneous, i.e. not used to estimate the model.

Figure 5. Staff Shoulder Month Model Data

AB	AC	AD	AE	AF	AG	AH	AI	AJ
	57%	1	0	0	1,203	57%		
	60%	1	0	0	1,275	60%		
	54%	0	1	0	1,080	54%		
	57%	1	0	0	1,111	57%		
	73%	0	1	0	858	73%		
	72%	0	1	0	772	72%		
	67%	1	0	0	920	67%		
	60%	0	1	0	940	60%		
	94%	1	0	0	671	94%		
	76%	0	1	0	809	76%		
	78%	0	1	0	659	78%		
	67%	1	0	0	909	67%		

After some searching, we identify the source of the data points and which of the data points are ultimately used in the model. You can see the data is randomly ordered (yellow) and not all data is used (only the information in the tan rows is used).

Figure 6. Staff Shoulder Month Model Data Explained

AC	AD	AE	AF	AG	AH	AI
57%	1	0	0	1,203	57%	anytime July
60%	1	0	0	1,275	60%	TOD July
54%	0	1	0	1,080	54%	TOD Oct
57%	1	0	0	1,111	57%	eveMorn July
73%	0	1	0	858	73%	anytime Oct
72%	0	1	0	772	72%	anytime Nov
67%	1	0	0	920	67%	anytime June
60%	0	1	0	940	60%	TOD Nov
94%	1	0	0	671	94%	TOD June
76%	0	1	0	809	76%	Eve Morn Oct
78%	0	1	0	659	78%	Even Morn Nov
67%	1	0	0	909	67%	Eve Morn June

Under these conditions, it's difficult to identify what decisions were made and assess the significance of their impact. We did that from top to bottom for this issue in this case. It took a lot of time. We want to impress upon the Commission the thought and care the Company puts into its model choices and results, by illustrating our ability to understand Staff's choices and results even when Staff provides little direction. We also want to illustrate by this example and the others that follow that Staff did not make reasonable choices. And ultimately, those unreasonable choices produced unreasonable billing units and normal revenue results, so they cannot be relied upon in this case.

Q. Do you have any other comments on the outliers and statistics more generally, which are worth keeping in mind as we consider the statistical modeling choices Staff made throughout their normalization of billing units?

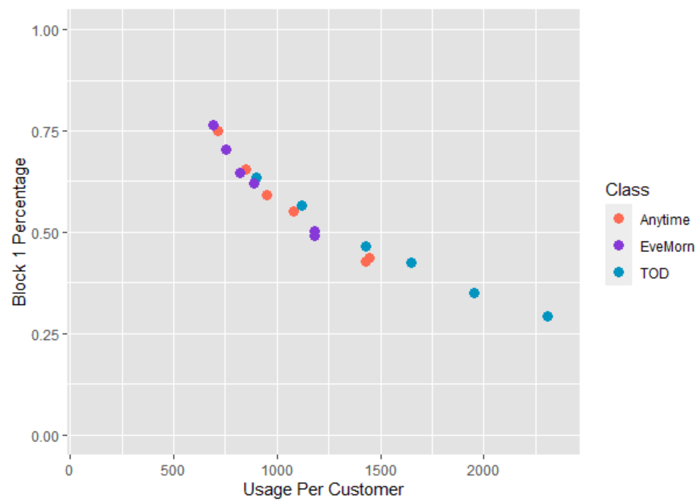
A. Yes. The Legacy Time-of-Day observations themselves illustrate the same point about imprecision (or high variance) as the point we made, implicitly, above about imprecision in Staff's model. Imprecision in Staff's model is best illustrated in Figure 2 by the degree to which the estimated relationship (the line) moves when just two observations are removed. Small sample sizes lead to imprecise estimates. In statistics, imprecision is synonymous with high variance. If a statistical estimate is imprecise, it means the estimate has high variance.

You can also see the high variance in the Legacy Time-of-Day observations themselves. In one month, with 8 customers, the block 1 percentage is 60%. In the other month, when there are 4 customers, the block 1 percentage is 94%. There are a small number of customers (observations) that determine the block 1 percentage, and the block 1 percentage varies greatly. Again, small sample size leads to a lot of variance. Of course, these are different months, but we do not see the 34% variation in the other two residential rate plans which have hundreds of thousands of customers. The deviations between June and November for the other two rate plans are 5% and 11% respectively.

Q. Does Staff allow Legacy Time-of-Day outliers to influence its residential block normalization 'winter' model?

A. Yes. Legacy Time-of-Day observations have equal weight in the determination of Anytime Users and Evening-Morning Savers block normalization in all 'winter' months as well. Figure 7 shows the 'winter' observations by residential rate plan.

Figure 7. Staff's 'Winter' Block Normalization Data



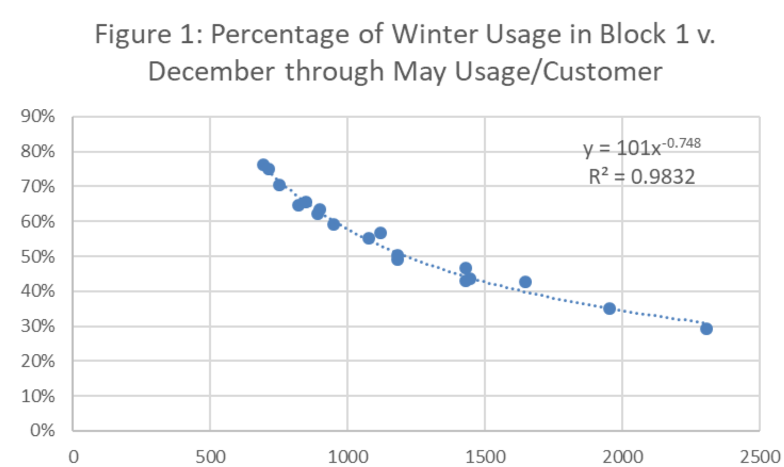
Half of the Legacy Time-of-Day observations lie to the right and below all of the Anytime Users and Evening-Morning Savers observations. Also, if you imagine a line running through the Legacy Time-of-Day observations separately from a line running through the Anytime Users and Evening Morning Savers, you'd imagine two lines with different slopes. These outlier observations represent the relationship between usage-per-customer and block-usage of between 5 and 6 Legacy Time-of-Day customers, while the other observations represent between 303,449 and 785,243 Anytime Users or Evening Morning Savers customers. They, too, are clearly outliers and inappropriate to include in a model that is applied to the broader residential population.

Q. Do you have any other concerns about Staff's residential block normalization 'winter' model?

A. Yes. Staff has likely succumbed to a common statistical pitfall when they choose to estimate a power function. Typically, regressions are used to estimate linear relationships. If you estimate some non-linear relationship, typically, you'd have a theoretical or intuitive reason for doing so. Staff does not appear to have a theoretical reason for estimating a power function.

In Testimony, Staff said this. "First, I graphed the Residential Block 1 usage as a percentage of total winter usage against total Residential rate schedule usage per customer. The resulting figure, shown as Figure 1 below, indicated that all residential rate schedules could be combined to form an estimate and that a power function was the best functional form for the regression."[7] Staff's Figure 1 is reproduced as Figure 8 here.

Figure 8: Staff Figure 1



It's not clear how the figure indicates that all residential rate schedules 'should' be combined, but they certainly 'could' be combined and that is what Staff does. The Company's

[7] File No. ER-2024-0319, Michael L. Stahlman Direct Testimony, p. 5, ll. 7-10.

Figure 7 above and the facts about the Legacy Time-of-Day observations are evidence that all the residential rate plans should *not* be combined. It is also unclear what indicates that a power function is the 'best' functional form.

Later comments in Staff's testimony related to the SGS block normalization hint at the common pitfall Staff has likely succumbed to. Staff states that 'while a quadratic formulation with a dummy variable for shoulder month periods performed satisfactorily for single phase rate schedule, (footnote 2) a similar technique was insufficiently precise for the three phase rate schedule (footnote 3).'[8] Footnotes 2 and 3 report the Adjusted R-squared of Staff's regressions. This suggests that Staff relied heavily upon the R-squared metric to dictate functional form selection. This is common pitfall.[9]

One of the foremost educators on the subject, Jefferey Wooldridge, has this to say in Section 6.3 of his Introductory Econometrics. 'Until now, we have not focused much on the size of R-squared in evaluating our regression models, because *beginning students tend to put too much weight on R-squared*. As we will see shortly, *choosing a set of explanatory variables based on the size of the R-squared can lead to nonsensical models*.'[10] The choice of functional form of variables is part of choosing the set of explanatory variables. When a power function is estimated, the usage-per-customer variable is transformed by the natural logarithm prior to estimation. The variable in levels and the natural logarithm of the variable are different variables from a technical perspective. Staff offers no theoretical or intuitive reason for selecting different functional forms for different models of the relationship between

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[8] File No. ER-2024-0319, Michael L. Stahlman Direct Testimony, p. 6, ll. 9-11.
[9] Stock, James and Watson, Mark, *Introduction of Econometrics*, 2nd Edition pg. 238 Key Concept 7.4 R-squared and Adjusted R-squared: What They Tell You – And What They Don't.
[10] Wooldridge, Jeffery, *Introductory Econometrics*, 3rd Edition, p. 206-207(emphasis added).

usage-per-customer and block-usage, but Staff does prominently display the R-squared statistic in its testimony and workpapers.

To put a finer point on the things Staff says about its functional form selection, Wooldridge also has this to say, "Nothing about the classical linear model assumptions requires R-squared be above any particular value."[11] Furthermore, "The zero conditional mean assumption is what determines whether we get unbiased [accurate or true] estimators of the ceteris paribus effects of the independent variables, and the size of the R-squared has no direct bearing on this."[12] If Staff has used R-squared to determine 'satisfactory performance' or 'sufficient precision', then Staff is illustrating that they have succumbed to a common pitfall in regression analysis.

A practical implication of over-emphasizing R-squared is sometimes called overfitting. There are natural unobserved sources of variation in all measured things, even in the most controlled laboratory. We are not talking about anything like the laboratory setting. There are all kinds of sources of unobserved variation in customer usage data. A useful regression analysis will seek to identify the underlying relationship between variables using data that has other sources of variation in it, sometimes referred to as noise. "An R-squared or adjusted R-squared near 1 means that the regressors are good at predicting the values of the dependent variable in the sample".[13] If you focus on increasing R-squared, then the model will predict the values **in the sample** well. If you overfit the noise, or unobserved sources of variation, in the data then the model may not predict well **outside of the sample**. In this case, predicting normal block usage outside of the sample is what Staff is trying to do. The more

[11] Wooldridge, Jeffery, *Introductory Econometrics*, 3rd Edition, p. 207.
[12] Wooldridge, Jeffery, *Introductory Econometrics*, 3rd Edition, p. 207.
[13] Stock, James and Watson, Mark, *Introduction to Econometrics*, 2nd Edition p. 237.

Staff focuses on maximizing R-squared, the more likely Staff overfits the model, and predicts out-of-sample normal block usage poorly. The evidence suggests that Staff is overfitting their block normalization models, as well as including outliers, and therefore normalizing block usage poorly. It is not reasonable to rely on poorly normalized block usage to determine normal revenue and rates.

Q. Did you also review Staff's SGS block normalization?

A. Yes.

Q. Do you have any summary observations about Staff's SGS block normalization?

A. Yes. There are a few interesting differences between Staff's SGS and Residential block normalization, but also many similarities. Some of the differences highlight points I made earlier related to past general criticisms of Staff's approach. I will briefly describe those differences and provide a little more information about the Company's approach to highlight why Staff's general approach dictates the need for extra steps. Those extra steps could look like improvements, but in fact, they rely on average results in earlier steps, that mean the apparent improvement is just that, apparent, not actual.

Regardless, these differences aren't as compelling as what Staff itself says about their own SGS block normalization results. Staff has this to say after completing a brief description of their choices. "This indicates that the rate block adjustment analysis is highly sensitive [to modeling choices] and could benefit from additional data points."[14] This is effectively confirmation of the criticisms I outlined above related to Residential results and Staff's method generally – specifically that using only test year observations results in insufficient sample

[14] File No. ER-2024-0319, Michael L. Stahlman Direct Testimony, p. 7, ll. 1-2.

sizes to estimate reasonable models or produce reasonable results in this case. None of the differences between Staff's modeling treatment of the SGS and Residential classes resolve that issue. Staff's choice to use only actual test year observations makes their results sensitive, i.e. they vary or change a lot when small changes are made to the input data or model. In the Residential case, combining Residential rate plan data (including Legacy Time-Of-Day with Anytime and Evening-Morning) was an input data choice which exposed the high degree of variance in the model.

In the SGS block normalization analysis, Staff chooses to separate single phase and three phase customers. Staff's tendency to overfit models by selecting functional forms based on R-squared decreases the precision of out-of-sample estimates of block usage, i.e. the normalization step. Staff's statement about highly sensitive models comes directly after they discuss fitting two different functional forms, one quadratic and one power function form, to the two different groups of SGS customers. The Company's monthly models of SGS block kWh based on 17 years of weather and block data are not 'highly sensitive' like Staff's models. In fact, the Company's model grows in precision over time as more historical weather and block kWh data are added to the well specified model. The Company is not changing the functional form or splitting data along different lines from case to case, because the Company's general framework is well designed. Staff’s general framework is not well-designed, and the collection of ad hoc decisions which vary from case to case illustrate this. The collection of ad hoc decisions lead to unreasonable models and unreasonable SGS block usage results in this case.

Q. Do you have any other concerns about Staff's SGS block normalization?

A. In the prior question, I alluded to the pitfalls of putting too much weight on R-squared. In simple terms, it can lead to nonsense. Staff produced separate block normalization models for single phase and three phase SGS customers. Staff said, 'a quadratic formulation' … 'performed satisfactorily for the single-phase rate schedule'.[15] This was followed by a footnote indicating the adjusted R-squared was 99.3%. Wow, that's high, but what sense does a quadratic make? The estimated equation represents a parabola opening upward. As usage-per-customer increases initially, block 1 usage (known as base in SGS schedules) as a percent of total usage will decrease, but at some usage-per-customer level (approximately 1770 kWh), the relationship will reverse, and the parabolic shape will necessarily mean that block 1 usage as a percent of total will start to increase. Staff followed this by saying "a similar technique [or functional form] was insufficiently precise for the three phase rate schedule".[16] I conclude that Staff is likely basing these decisions on R-squared statistics for different functional forms, rather than some well-founded conceptual framework. Like Stock and Watson said: "R-squared and adjusted R-squared tell you whether the regressors are good at predicting, or 'explaining' the values of the dependent variable in the sample of data on hand."[17] R-squared will not tell you that you have the right set of regressors or functional form needed to estimate the dependent variable well outside of the sample. Predicting (normalizing) the dependent variable (block kWh) **outside of the sample** is precisely what Staff is doing, and R-squared will not tell you if the model will do that well. The smaller your sample or more arbitrarily you choose a functional form, the more likely you

[15] Case No. ER-2024-0319, Michael L. Stahlman Direct, p. 6, ll. 9-10.
[16] Case No. ER-2024-0319, Michael L. Stahlman Direct, p. 6, ll. 10-11.
[17] Stock, James and Watson, Mark, *Introduction of Econometrics*, 2nd Edition p. 238.

have overfitted the model and will not predict well out of sample. If this sounds repetitive, it is because I discussed the issue above in the context of Residential block normalization. The same issue applies here to the SGS block normalization.

Q. Why does Staff have to make these choices (splitting the data)?

A. Staff has to split the model because they do not model block usage and weather directly. Staff models the relationship between usage-per-customer and block usage. Staff uses their model of weather and total usage to come up with normal usage-per-customer, and uses this to normalize block usage. It is worth noting that Staff normalizes usage-per-customer for both single phase and three phase customers using a *single* SGS total weather normalization factor. The appearance of increased granularity resulting from splitting the single phase and three phase customers in the block normalization step is undermined by the fact that the two usage-per-customer values are generated using a SGS class average, i.e. they are not single phase and three phase specific. Splitting them apart is just an added step which is 'required' because of Staff's initial choice not to model the relationship between block usage and weather directly.

Q. Why doesn't the Company have to split the SGS block data?

A. The average single phase customer and the average three phase customer have different levels of usage-per customer. However, each SGS customer has their own baseline defining block 1 and block 2 usage. Therefore, block usage as a percentage of total usage is much more consistent across the two groups than usage-per-customer. Plus, those block percentages, which are closely related across the two groups (single and three phase) are highly correlated with (and actually caused by) the weather.

Below in Figure 9 is a reproduction of Staff Figure 2 with dashed horizontal lines added. Figure 9 shows how the range of usage in block 1 doesn't vary significantly between single phase and three phase SGS customers. It's only the level of usage-per-customer that varies significantly. The Company models the relationship between weather and block 1 percentage directly, which obviates the differences between these subgroups and allows the Company to estimate the relationship in a single model.

Figure 9: Staff Figure 2 with Dashed Lines Added

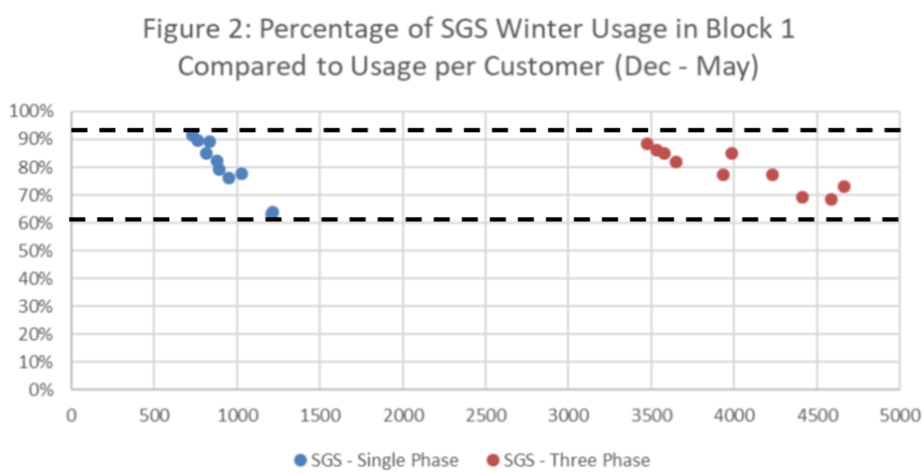

Figure 10 more clearly shows how block usage for single and three phase customers doesn't only exist within a similar band but are highly correlated across months.[18]

[18] August and September 2023 are omitted because these months do not have any winter kWh, and therefore have no block kWh, since the SGS rate plan like the residential rate plans only have block rates in the winter.

Figure 10: SGS Block 1 Percentage for Single and Three Phase Customers

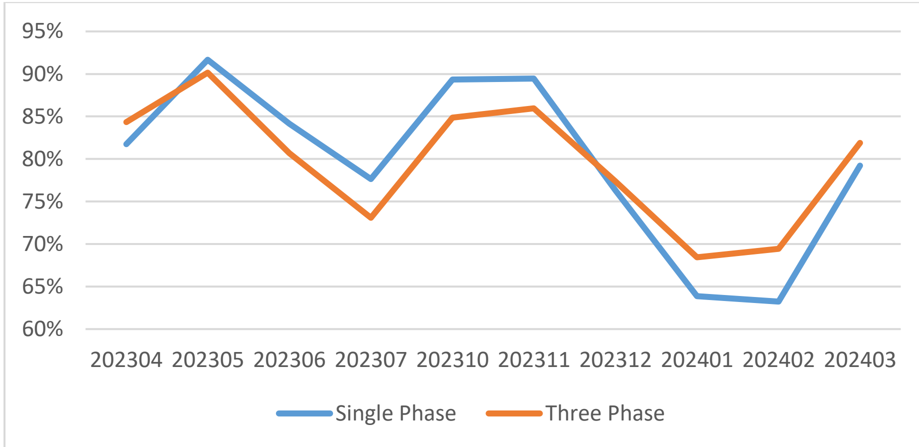

Figure 11 shows the relationship between block usage for single and three phase customers and heating degree days("HDD").[19] Most importantly, Figure 11 shows how a single linear relationship between weather (HDD) and block usage for single phase and three phase customers accurately and parsimoniously describes the data well. Parsimony is an important principle in regression analysis. The more simply specified a model is, the more likely it is, that the model captures the underlying relationship and not the noise in the sample. All the ad hoc complexity in Staff's choices about splitting data and functional form further exacerbate the small sample size problem and makes it more likely that Staff is modeling the noise rather than the relationship. Models based on the noise in small samples rather than fundamental underlying relationships won't produce reasonable block normalization results.

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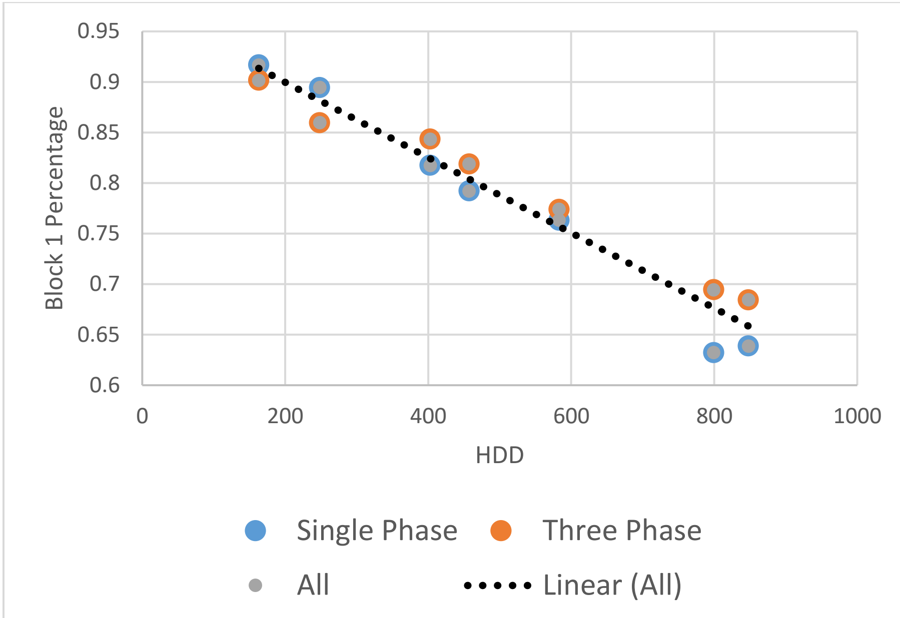
[19] Heating degree days is superior to average temperature for monthly measure since HDD aggregates daily deviations below a HDD baseline without offsetting them by warmer than HDD baseline days. Expected load for a four day period of 40, 40, 60, 60 would be different than a four day period of 50, 50, 50, 50 even though they have the same average temperature. If the HDD baseline was 50, the scenario one would have HDD = 20 and scenario two would have HDD = 0.

Figure 11: Relationship between Weather and SGS Block 1 Percentage



Q. Can you summarize your analysis of Staff's SGS Block Normalization?

A. Yes. Staff's choice to estimate their block normalization using the relationship between usage-per-customer and block usage, rather than weather, causes Staff to split their SGS data, and then fit two different functional forms without any a priori logic. These additional choices compound the small sample problem Staff has initially created for itself. The fact that they state concern about the same point I am making about variance, imprecision or high sensitivity, shows Staff has doubt about whether they have generated reasonable block normalization results in this case. If Staff has not generated reasonable block normalization results, then their results should not be used to determine normal revenue or rates in this case.

B. Residential and SGS Time-of-Use Normalization

Q. Did the Company consider applying new time-of-use weather normalization techniques in this case?

A. Yes. Early in the case, Staff reached out to me to discuss time-of-use normalization and indicated that they intended to perform a distinct and novel time-of-use normalization in this case. I indicated to Staff that we also considered time-of-use weather normalization, specifically for the residential Evening-Morning Savers rate plan. The other time-of-use rate plans, the Legacy Time-of-Day plans that exist in each class, had been in existence for some time, but the Evening-Morning Savers schedule is relatively new and, more importantly, applied to a majority of residential customers, largely by default, during the test period. The Evening-Morning Savers on-peak period is very broad and the on-peak to off-peak rate differential is very small. Ex ante, one shouldn't expect too much behavioral change as a result nor should one expect significantly different weather effects. The analysis undertaken by the Company showed no significant difference between the effects of weather normalization on the on-peak kWh than the off-peak kWh. There were also limitations on the analysis associated with data availability. These two things together caused the Company to continue to apply total weather normalization proportionally to time-of-use periods as both the Company and Staff had done in the past. For rate plans like Evening-Morning Savers, where on-peak usage is greater than off peak usage, the proportional application of total weather normalization factors will increase on-peak usage by more in absolute kWh than it increases off-peak usage. This is a reasonable result given it is reasonable to expect weathers effect on the absolute number of kWh to be greater in the broad on-peak period. Staff, however, did choose to undertake a distinct and novel weather normalization analysis and apply the results to certain time-of use rate plans in this case.

Q. Can you summarize the issues with Staff's time-of-use weather normalization in this case?

A. Yes. Broadly speaking there are two issues. First, Staff applies time-of-use normalization factors that are derived from hourly data for an entire class to the subset of customers on the time-of-use rates plans within that class. This choice is not clearly unreasonable for the Evening-Morning Saver's rate plan, because the majority of residential customers are on that plan and likely arrived there by default rather than voluntary choice. However, these facts are not true for Legacy Time-of-Day SGS customers or residential customers on more advanced time-of-use rates; the Overnight Savers, Smart Savers, and Ultimate Savers rate plans. Ultimately, Staff partially recognized the issue and choose not to apply time-of-use weather normalization factors to the more advanced residential rate plans. Specifically, Staff said, "While other TOU rate schedules were considered, this analysis was only ultimately applied to the Residential Evening and Morning rate schedule and the SGS Time of Day rate schedule due to the small number of customer in other rate schedules."[20] Staff fails to recognize that it is not the small number of customers in the other rate plans that matters per se, but rather that the customers on those rate plans are fundamentally different than the average customer in the class. I will show clearly how this second fact is true for SGS Time-of-Day customers and how Staff's choice to normalize their time-of-use usage is unreasonable.

Second, Staff's time-of-use weather normalization model is lengthy and tedious involving a large number of mathematical and logical transformations as well as assumptions. This complexity makes the calculations difficult to track and increases the probability for error. There are some unreasonable results in the application of time-of-use weather normalization results to the Evening-Morning Savers class, which cast doubt on the general reliability of the time-of-use normalization results. The general reliability of the time-of-use normalization results is extremely important in this case, because Staff chose to apply a

[20]File No. ER-2024-0319, Michael L. Stahlman Direct Testimony, p. 4, ll. 1-4.

monthly aggregate of their time-of-use weather normalization model results to weather normalize total kWh for the residential and SGS classes. This issue will be addressed in more detail in the section of total weather normalization.

Q. Can you explain the general procedure Staff used to develop time-of-use weather normalization factors in this case?

A. Yes. Staff uses the results of their class-level total usage weather normalization model and actual hourly class-level usage data to conduct their time-of-use weather normalization analysis.[21] Actual hourly class-level usage was provided to Staff in response to Data Request MPSC 529.

Both Staff and the Company use daily class-level total usage and daily weather data to estimate models that produce monthly total usage weather normalization factors.[22] In the first step, the relationship between usage and weather is estimated using actual daily usage and actual daily weather inputs. In the second step, the estimated relationship and normal weather are used to produce daily normalized usage outputs. At this point we have described general steps from the total weather normalization procedure historically used by both Staff and the Company to produce monthly weather normalization factors. Now we diverge into the Staff's time-of-use weather normalization. Staff uses the daily actual and normal usage values to generate daily weather normalization factors. Staff uses these daily weather normalization factors to normalize the class-level hourly data provided in response to MPSC 529. Both Staff

[21] This fact is one of two that underlie the concern the Company has about Staff's use of their time-of-use weather normalization model results to weather normalize total usage for the residential and SGS classes. They are derived from the same source but produce different results. I would expect them to produce the same result if performed at the same level of quality. The fact that Staff chose the results from the more complex novel model, rather than their standard model seems unreasonable.

[22] There are some differences which we outline later, but this general approach and a lot of the specifics have been generally accepted by both the Company and Staff as the basis for producing monthly total usage weather normalization factors. On the contrary, monthly aggregates of hourly weather normalized usage has never been the basis for monthly total usage weather normalization factors.

and the Company have daily average and daily peak models, and therefore have daily actual and daily normal numbers for daily peak and daily average usage. This allows Staff to normalize each hour within each day differently. It's hard to assess the quality of this part of the procedure without more time due to its complexity, but a cursory evaluation doesn't indicate any obvious issues with this step.[23]

The next few steps are the most complex and novel. Staff uses the Company's bill cycle meter read schedule to aggregate calendar actual and normal hourly usage data to usage between the start and end date for each bill cycle.[24] This is done separately for daily totals and different time-of-use periods. These bill cycle start and end data aggregates are then scaled (to eliminate the overlapping bill cycle effect) using the proportion of actual revenue-month test-year sales by bill cycle.[25] Finally, the revenue month version of the scaled bill cycle usage data is aggregated to primary-month actual and normal usage for total monthly and several time-of-use periods using an assumed relationship between revenue and primary month.[26] The ratio of primary-month normal usage to primary month actual usage for total usage and

[23] The general process for weather normalizing hourly class kWh here is similar to the general process used by the Company to weather normalize system hourly kWh for fuel cost modeling.
[24] The result of aggregating this way is an increase of total usage by approximately 21 times, because each bill cycle captures approximately 30 days and overlaps with approximately 21 bill cycles before and after it. The degree of overlap associated with any one bill cycle decreases as you move farther away from that bill cycle in both directions. This decreasing overlap is symmetric on either side of each bill cycle and results in this factor of 21 increase. For example, the aggregate of the overlapping actual usage is 269,883,894,336 and the scaled version is 12,948,493,883. A factor difference of 20.84.
[25] A bills revenue month is projected by the meter read schedule, but the actual realized revenue month is determined by the date the meter is read within its reading window and potential exceptions which delay accounting recognition of the billed revenue. The actual revenue month of a bill is determined by the date the bill is recognized for accounting purposes.
[26] The primary month of a bill is predetermined by the meter read schedule. It can vary from the revenue month when the actual date revenue associated with the bill is recognized for accounting purposes varies from the average expected date on the meter read schedule. This is predominantly true for early and late bill cycles, where variation in the accounting recognition crosses into a different month than the meter read schedule expected with some regularity.

several time-of-use period usages is used to define total and time-of-use weather normalization factors.

Q. Can you explain why it is unreasonable for Staff to apply their time-of-use weather normalization to the SGS Legacy Time-of-Day customers?

A. Yes. Staff uses SGS class-level daily and hourly usage data to derive time-of-use normalization factors using the method described above. Approximately 5% of SGS customers voluntarily chose the Legacy Time-of-Day rate plan. Presumably, customers who voluntarily choose this rate schedule are different than average. The important difference is that they consume a lower proportion of their total usage on-peak relative to the average customer in the class. If this wasn't true, voluntary selection of the Time-of-Day rate would increase their bill and that is not a rational choice. Furthermore, more than half of the Time-of-Day customers are unmetered and operate individual devices on a predetermined schedule, and these devices usage does not vary based on weather. Staff did not appear to recognize this, but it has been a fact for a long time. The test year actual usage data alone strongly suggest this fact.

Another important fact is that Staff did not use the incremental change in on-peak usage modeled for the entire SGS class to make an incremental change to the Time-of-Day actual on-peak usage, but rather Staff used the final proportion of total usage that was on-peak for the entire SGS class to replace the proportion of total usage that was on-peak for the Time-of-Day customers.[27]

[27] For example, assume actual on-peak usage for the entire class was 46% of total usage. Assume weather-normalization indicated that the normal on-peak usage for the entire class was 47% of total usage. That would be a 1% incremental change in on-peak usage. Now assume the SGS Legacy Time-of-Day actual on peak usage was 36% of total usage. An application of the incremental change would produce normal on-peak usage of 37%. Replacement would involve simple substitution of the 37% with 47%.

Q. Can you provide some quantitative evidence to support your position?

A. Yes. Table 5 shows the actual percent of SGS Legacy Time-of-Day usage that occurred on-peak during the test year, the normalized percent produced by Staff's time-of-use weather normalization, and the difference between the two.

Table 5. SGS Time-of-Day On-Peak Usage (% of Total Usage)

Month	Actual	Normal	Difference
Jul-2023	36%	47%	11%
Aug-2023	37%	47%	10%
Sep-2023	37%	46%	9%
Oct-2023	37%	47%	10%
Nov-2023	37%	45%	8%
Dec-2023	34%	39%	5%
Jan-2024	33%	38%	5%
Feb-2024	36%	38%	2%
Mar-2024	37%	40%	3%
Apr-2024	36%	41%	5%
May-2024	37%	45%	7%
Jun-2024	36%	44%	8%

Figure 12 shows the actual and normal on-peak percentage graphically. Two additional years of actual data are added to make the facts even clearer.

Figure 12: SGS Time-of-Day On-Peak Usage (% of Total Usage)

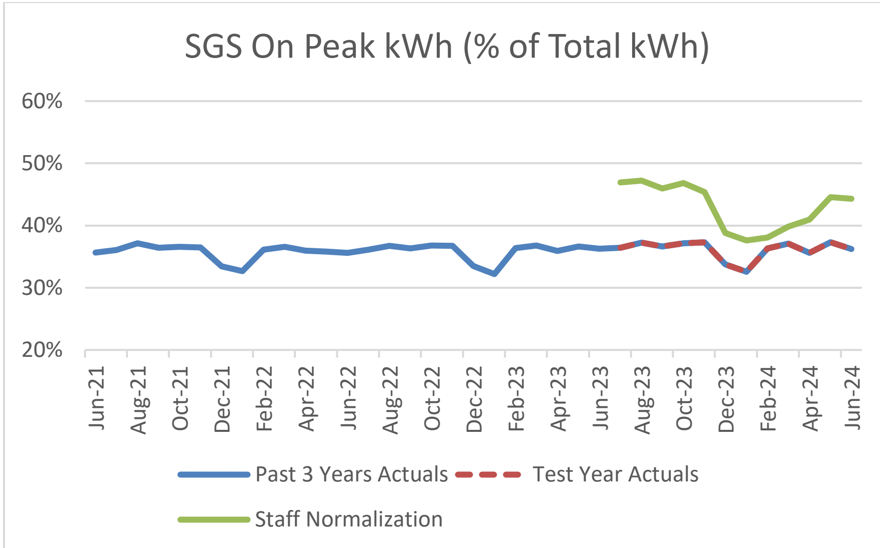


Figure 12 shows how the SGS TOU customers on-peak usage as a percentage of their total usage is relatively constant at around 35 or 36%. It dips predictably in December and January but shows no evidence of increasing above 36 or 37% at any point in time across the three years shown here. Staff's normalization (the green line) has this on-peak usage *markedly higher than any observed month over the past three years in every month*, including some months as high as 47%. This is an unreasonable adjustment. The source of the unreasonableness is clear. Staff used on-peak and off-peak weather normalization ratios for the entire class, when the SGS TOU subclass is clearly different from the average member of the entire SGS class.

Q. Can you quantify the impact of Staff's unreasonable choice to normalize SGS TOU subclass using the entire SGS class?

A. Yes. In order to perform the analysis, we make one simplifying assumption. We assume that the on-peak to off-peak kWh ratio is not weather sensitive, i.e. I use the average actual summer and winter on-peak percentage and weather normalized total to calculate reasonable weather normalized on and off-peak kWh. This assumption is reasonable given the observation that the ratio is relatively constant by month across several years as shown in Figure 12. In the final row of the Revenue Difference column of Table 6, we can see that Staff's choice to weather normalize SGS Time-of-Day customer billing units using the entire classes normalized hourly billing units increases revenue by $648,275.

There is another fact displayed in the Rates column of Table 6 that is worthy of note. The on-peak to off-peak rate differentials for the SGS Legacy Time-of-Day rate plan are large relative to the differentials in other non-residential Legacy Time-of-Day and the residential Evening-Morning rate plans. This makes the revenue impact larger relative to what it would have been had the rate differential been something smaller like it is for those other rate plans. Staff's choice to normalize the SGS Legacy Time-of-Day usage by these means is clearly unreasonable, and the fact about rate differentials makes it more impactful.

Table 6: Revenue Impact of Staff's SGS Time-of-Use Weather Normalization

Billing Unit	Rates	Staff kWh	Staff Revenue	Reasonable kWh	Reasonable Revenue	Revenue Difference
Summer On Peak	0.1779	20,677,035	3,678,445	17,268,903	3,072,138	606,307
Summer Off Peak	0.0726	23,781,919	1,726,567	27,190,051	1,973,998	-247,430
Winter On Peak	0.1172	35,671,580	4,180,709	31,128,430	3,648,252	532,457
Winter Off Peak	0.0535	51,190,165	2,738,674	55,733,315	2,981,732	-243,059
Total		131,320,699	12,324,395	131,320,699	11,676,120	648,275

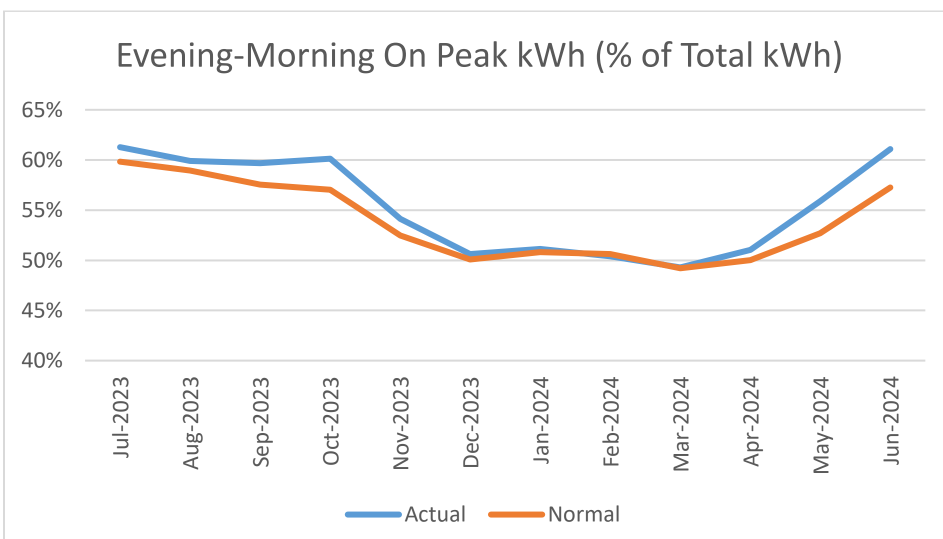
Q. Do you have the same level of concern for the time-of-use normalization applied to Evening-Morning Savers?

A. Not exactly. I mentioned the differences between the SGS Legacy Time-of-Day customers and Evening-Morning customers. Specifically, Evening-Morning make up a much larger proportion of the Residential class total and, perhaps more importantly, many if not most customers end up on the rate plan by default. However, a summary analysis does raise some concern about the efficacy of the time-of-use normalization. Table 7 and Figure 13 show the actual and Staff's weather normalized on-peak usage as a percentage of total usage for Evening-Morning Savers.

Table 7. Evening-Morning Savers On-Peak Usage (% of Total Usage)

Month	Actual	Normal	Difference
Jul-2023	61%	60%	-1%
Aug-2023	60%	59%	-1%
Sep-2023	60%	58%	-2%
Oct-2023	60%	57%	-3%
Nov-2023	54%	52%	-2%
Dec-2023	51%	50%	-1%
Jan-2024	51%	51%	0%
Feb-2024	50%	51%	0%
Mar-2024	49%	49%	0%
Apr-2024	51%	50%	-1%
May-2024	56%	53%	-3%
Jun-2024	61%	57%	-4%

Figure 13. Evening Morning Savers On-Peak Usage (% of Total Usage)



The curious thing about the table and the figure are that all the normalized values are less than the actual values. We know there are some differences in total usage between the Evening-Morning Savers and Anytime Users customers, who make up the vast majority of the remainder of the residential class, but we do not know anything about the difference in their relative on-peak usage as a percentage of the total usage. I have witnessed the evolving differential in total usage and presume it is a function of the non-random nature of the geographical rollout of Advanced Metering Infrastructure ("AMI") and subsequent default process rather than behavioral change associated with the rate plans or voluntary rate plan selection, but this is also unknown. And regardless, the result of Staff's weather normalization is either no change or a decrease in every month. This is curious because I would expect some variation in the time-of-use weather normalization effect just like we see some variation in the total weather normalization effect. What I mean by variation here is some negatives and some positives. However, it is not clear whether my expectation is wrong, the application of the entire class to Evening-Morning customers distorts the outcome, or if there is something more fundamental wrong with Staff's novel time-of-use normalization calculation.

Q. Are there any other odd or unreasonable results associated with Staff's time-of-use normalization?

A. Yes. Above I showed results for Evening-Morning customers on a primary month basis. However, primary months which contain billing cycles, which cross the seasonal boundaries (June 1 and October 1) have both summer and winter usages. If you look at Staff's on-peak ratios for the summer and winter usage separately, you will find some odd and unreasonable results. Table 8 shows summer and winter total and on-peak usage as well as summer and winter on-peak usage as a percent of total for the Evening-Morning Savers rate plan in the months of July and November.

Table 8. Unreasonable Evening-Morning Time-of-Use Normalizations

Billing Unit	Actual July	Normal July	Actual November	Normal November
Summer kWh	618,673,234	612,300,800	19,296,115	19,009,419
Winter kWh	21,698,211	21,474,716	408,648,977	402,577,382
Summer On Peak	379,181,588	375,770,262	10,973,828	18,055,719
Winter On Peak	13,216,605	3,438,855	220,711,931	203,124,084
Summer On Peak %	61%	61%	57%	95%
Winter On Peak %	61%	16%	54%	50%

Staff's weather normalization results for July winter on peak usage (16%) and November summer on-peak usage (95%) are clearly unreasonable (note that all other on peak ratios in this table are within the range of 50% to 61%, making these two observations extreme outliers). It's not entirely clear what is driving these results. It appears to be something in the different definitions of time needed to convert calendar hourly data into revenue month billing cycle data then to primary month data with winter and summer billing units, but exactly where reason gets lost is not clear.

Q. Can you summarize your findings related to time-of-use normalization?

A. Yes. Staff performed a novel and complex set of calculations and data transformations to produce time-of use normalization factors. Regardless of the quality of the calculations, Staff chose to apply SGS normalization factors derived from class level data to a subset of characteristically different SGS customers who voluntarily chose the Legacy Time-of-Day rate plan, and it was unreasonable to do so in that it overstated the normal revenues associated with Staff's billing unit calculations. Staff's application of time-of-use weather normalization factors to the residential Evening-Morning customers did not change on-peak usage significantly, but did universally decrease the on peak usage percentage which is unexpected. In two months, Staff weather normalization procedure produced unreasonable results for seasonally differentiated on-peak usage in the Evening-Morning Savers rate plan.

C. Total Usage Weather Normalization

Q. Can you explain the relationship between total usage and other billing units discussed above?

A. Yes. Let's put lighting classes aside for a moment and focus on the following five classes, Residential, SGS, Large General Service ("LGS"), Small Primary Service ("SPS"), and Large Primary Service ("LPS"). Every class but LPS has multiple kWh billing units due to the existence of block rates in the Company's tariffs, at least in the winter season. The standard LGS and SPS rate schedules have three and four kWh billing units (blocks) in summer and winter respectively. Most Residential customer's rate plan has two kWh usage billing units in winter months, block 1 usage and block 2 usage. The Legacy Time-of-Day rate plan for the SGS class has on-peak and off-peak kWh billing units.

In these cases, total kWh is not a billing unit strictly speaking. It is the sum of the block or time-of-use billing units. In the case of LPS year-round and most Residential and SGS customers rates schedules in summer, total kWh *is* a billing unit (i.e., there are no block rates associated with those class/month combinations). Regardless, total kWh usage is the total number of kWh consumed by a customer during a billing cycle. *Total kWh may or may not be a billing unit.* When total kWh is not a billing unit, it is the sum of the several applicable kWh billing units associated with a customer's rate schedule.

Q. At a high level, what are the unreasonable decisions Staff made in the context of total weather normalization?

A. There are three high level decisions Staff made in the context of total weather normalization that are unreasonable:

1. Staff chooses to include an autoregressive term, yesterday's total kWh, in their model of the effect of today's weather on today's total kWh. Yesterday's total kWh does not *cause* today's kWh and therefore does not belong in a model of the causal relationship between weather and total kWh. The inclusion of yesterday's total kWh leads to imprecision in the estimate of weather's effect on today's total kWh;

2. Staff chooses to remove the impact of unobservable variables on kWh in its 'weather normalization.' This means that Staff's weather normalization does more than remove the impact of abnormal weather. Removing the impact of unobservable variables is synonymous with omitting the residuals from the definition of actual and normal total kWh; and

3. Staff chooses to construct a second set of monthly weather normalization factors for the Residential and SGS classes that are inferior to their first set. Staff than chooses to use those second set of factors for the Residential and SGS classes.

Autoregressive Term

Q. Why is Staff's choice to include an autoregressive term, yesterday's total kWh, in its regression model used for weather normalization unreasonable?

A. There is no reason to believe that yesterday's total kWh causes today's total kWh. If there is no reason to believe that yesterday's kWh cause today's kWh, then there is no reason to include yesterday's total kWh in a model that is intended to estimate the causal relationship between today's total kWh and weather.

Q. Why do you say there is no reason to include yesterday's total kWh in a model of today's total kWh and weather? Isn't yesterday's total kWh a good predictor of today's total kWh?

A. Yes, yesterday's total kWh is a good predictor of today's total kWh, but that is part of the problem, not a defense of its inclusion. I think Staff disagrees, but I believe their disagreement is based on misunderstanding.

Q. Why do you believe Staff would disagree with the prior statement? Did Staff justify the inclusion of yesterday's total kWh based on its ability to predict today's kWh?

A. It was not stated in Staff's direct testimony in this case but has been part of Staff's justification in the past. I also believe Staff believes that we are trying to predict today's total kWh usage. It is not true. We are trying to weather normalize today's total kWh usage, and there is a difference between predicting today's usage and weather normalizing today's usage. I don't know if Staff agrees that there is a difference. The second issue, the fact that Staff removes unobservable sources of variation, the residuals from the regression, also suggest this belief that there is no difference. The residuals from a regression of weather and total kwh are by definition not related to weather, but represent some number of actual kWh usage. When they are removed from the equation that determines today's total kWh, you are not weather normalizing, you are predicting today's total kWh.

Q. Why do you say that the fact that yesterday's total kWh is a good predictor of today's total kWh is part of the problem?

A. Yesterday's total kWh is a good predictor of today's total kWh because yesterday's total kWh is highly correlated with today's weather, which is the real cause of today's total kWh. It's a good predictor because it's correlated with the underlying cause, not because it is the underlying cause. If it's not the underlying cause, there is no reason to be included in a model which seeks to estimate the relationship between the underlying cause, today's weather, and today's total kWh. The only thing we need to accurately estimate the relationship between today's weather and today's total kWh is strict exogeneity.[28] There is no evidence that the strict exogeneity assumption fails in a model which includes today's weather and today's total kWh. Even if the assumption failed, there is no reason to believe that including yesterday's total kWh would solve the problem. There is evidence however that including yesterday's total kWh will reduce the precision of our estimate of the relationship between weather and today's total kWh. The evidence is that yesterday's total kWh is highly correlated with today's weather. That correlation is what makes yesterday's total kWh a good predictor and also a problem, a source of imprecision in the estimate of weather's effect of today's total kWh.

In my opinion, and I said it before, the thing we care about is an accurate (in statistical language, an unbiased estimate) and precise (low variance) estimate of the relationship between weather and today's total kWh, because it's the only thing we need to know to remove the effect of abnormal weather. This again highlights the difference in perspectives between the Company and Staff. Staff, consciously or not, believes we are trying to estimate today's total kWh as a function of normal weather and other stuff, like yesterday's total kWh. In the past, Staff has said things like, "The inclusion of a lagged dependent variable

[28] I will define and discuss this concept in more detail later in this section of my testimony, but one intuitive understanding relates to the direction of causality. In our situation, weather is exogenous if daily weather causes daily total kWh and daily total kWh do not cause the daily weather. There are a lot of variables especially in economic applications whose relationship is intertwined, and causality is complicated. There aren't many variables which are as clearly exogenous as the daily weather.

[yesterday's total kWh] is motivated conceptually by the need to capture the common type of electricity usage patterns."[29] This statement has nothing to do with the weather but has everything to do with predicting total kWh usage.

We are not trying to predict total kWh, we are trying to remove the impact of abnormal weather. I said it above and I will say it again, there is a difference between predicting today's total kWh and weather normalizing today's total kWh.

Q. You say including yesterday's total kWh causes imprecision in the estimate of the effect of weather on today's total kWh. Can you provide more detail?

A. Yes. The first thing you must understand and accept is causality. Variation in weather causes variation in total kWh. Temperature goes up in nature, temperature goes up in buildings, thermostat set points are triggered, air conditioning goes on, total kWh usage goes up. That is causal. If your air conditioning goes on today, does it cause your air conditioning to go on tomorrow? No. It may be more likely because there is correlation between today's and tomorrow's weather but it's not causal. If you accept this fact, then yesterday's total kWh does not belong in a model intended to estimate the causal relationship between today's weather and today's total kWh. In other words, yesterday's total kWh is irrelevant to a model intended to estimate causal effects. Jeffery Wooldridge has this to say, "As we will see in Section 3.4 including irrelevant variables can have undesirable effects on the variances of the Ordinary Least Squares ("OLS") estimators."[30] OLS, or ordinary least squares, is the name of the procedure used to estimate most regressions. The OLS estimator we are interested in here is the estimate of the relationship between weather and today's total kWh. Earlier we discussed how precision and variance are synonymous in statistics. If we turn to Section 3.4

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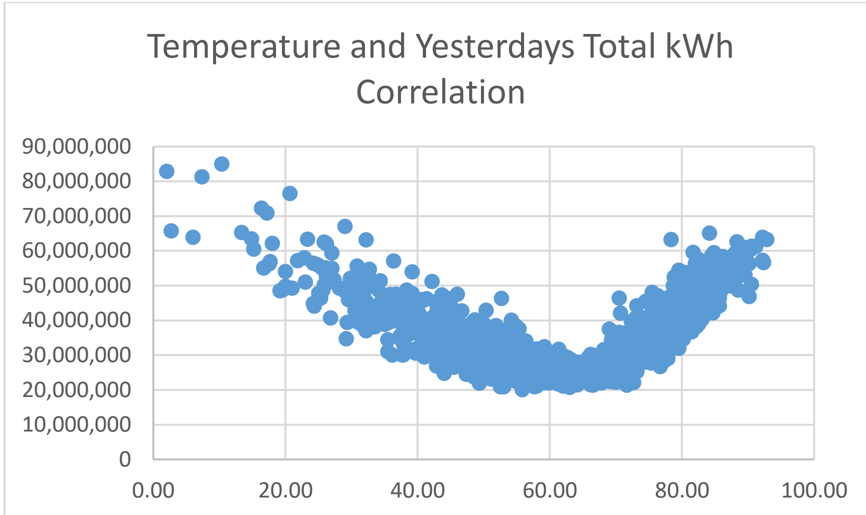
[29] File No. ER-2022-0337, Hari K. Poudel, PhD Surrebuttal Testimony p. 3, ll. 1-3.
[30] Wooldridge, Jeffery, *Introductory Econometrics*, 3rd Edition, p. 95.

of Wooldridge's text, we see the definition of the variance of the estimate of the OLS estimator, the effect of weather on today's total kWh. In that equation, you will see the correlation between the OLS estimator and other variables in the model. Specifically, one minus the correlation is in the denominator. If an irrelevant variable is included in the model and that irrelevant variable is correlated with the causal variable of interest, the variance or imprecision of the OLS estimator increases. Since OLS is just math, it doesn't "know" anything about causality, it only "knows" correlation. When you provide it with two correlated variables, it can't tell which one is causing the outcome variable to vary, and it imprecisely estimates the real causal variable. The inclusion of an irrelevant variable that is correlated with the variable of interest will cause the variance, imprecision, of the estimated relationship to increase.

Q. Can you provide evidence that yesterday's total kWh and today's weather are correlated?

A. Yes. Figure 14 shows the relationship between yesterday's total kWh and today's weather for the residential class. Temperature is on the horizontal axis and yesterday's load is on the vertical axis.

Figure 14. Correlation between yesterday's total kWh and today's weather.



The correlation between yesterday's total kWh and today's weather is complicated in the sense that they are negatively correlated at lower temperatures and positively correlated at higher temperatures. However, this is very similar to the correlation between today's total kWh and today's weather. The way both Staff and the Company specify temperature in their weather models recognizes this by use of a piecewise linear weather variable. Each linear piece corresponds to different parts the range of temperature and captures this correlation, some on the negative slope and some on the positive. The fact is that different pieces of the piecewise weather variable will be correlated with different segments of yesterday's total kWh and the imprecision problem discussed above persists without loss of generality. One way to show this numerically would be to split the data along the breakpoints of the piecewise weather variable and calculate the correlation with yesterday's total kWh for each piece. Another way to do this more quickly is to split the data by month, since months roughly correspond to different temperature bands between the breakpoints and calculate the correlation between today's weather and yesterday's total kWh by month. The result of that analysis is shown in Table 9.

Table 9. Correlation between Today's Weather and Yesterday's Total kWh

Month	Correlation
Jul-2023	0.80
Aug-2023	0.87
Sep-2023	0.84
Oct-2023	-0.09
Nov-2023	-0.84
Dec-2023	-0.70
Jan-2024	-0.86
Feb-2024	-0.65
Mar-2024	-0.56
Apr-2024	0.19
May-2024	0.72
Jun-2024	0.86

Table 9 shows correlation is large and negative in cold months associated with the downward sloping part of Figure 14,[31] low in shoulder months where the temperature is near to the inflection or flat point of Figure 14, and high and positive in warm months associated with the upward sloping part of Figure 14.

Q. Above you say, 'The only thing we need to accurately estimate the relationship between today's weather and today's total kWh is strict exogeneity?' What is strict exogeneity and what evidence do you have that the assumption does not fail?

A. Strict exogeneity is the 'crucial assumption' for unbiased or accurate estimates in time series regression analysis.[32] The assumption says that the expectation of the unobserved variation, the error term or residuals, is zero conditional on the regressors; weather in our case. This is also called the zero conditional mean assumption. It's best understood in terms of correlation. The zero conditional mean assumption implies that there is zero

[31] Lack of correlation would result in values very close to zero. Positive or negative values closer to 1 (or negative 1) than they are to zero signify higher levels of correlation of the variables.
[32] Wooldridge, Jeffery, *Introductory Econometrics*, 3rd Edition, p. 349-351.

correlation between the residuals of a regression and the variable we care about, weather. Figure 15 shows the lack of correlation between the residuals of the Company's residential weather model and daily temperature.

Figure 15. Strict Exogeneity of Weather

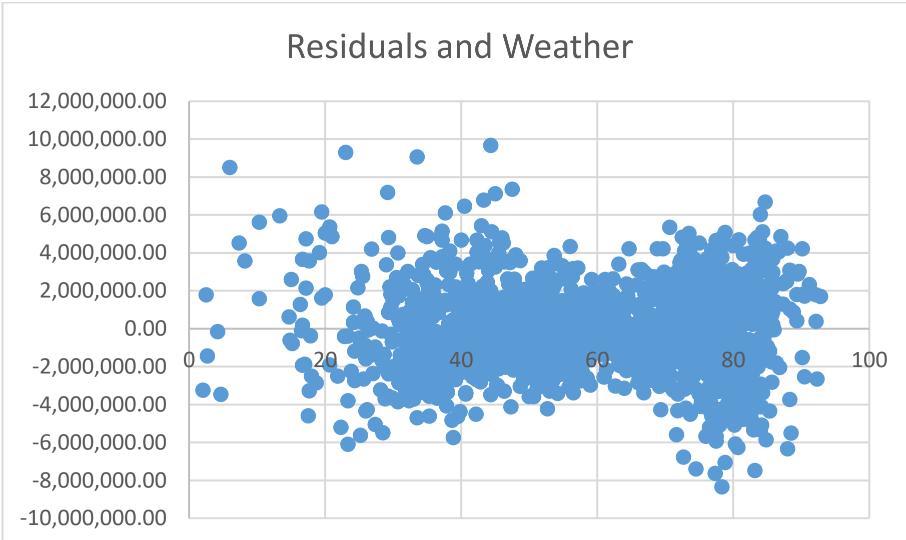


Figure 15 shows that the mean of the residuals (measured on the vertical axis) is zero along all values of temperature (measured on the horizontal axis). I compute the correlation between temperature and the residuals and get 0.00000003. That's indistinguishable from zero and good evidence that we get an unbiased or accurate estimate of the relationship between weather and today's total kWh in a model without yesterday's total kWh.

Q. Has Staff made any other arguments in the past to support their inclusion of yesterday's total kWh?

A. Yes. Staff has argued that yesterday's total kWh should be included because not including it indicates 'a possible autocorrelation issue'.[33]

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[33] File No. ER-2022-0337, Hari K. Poudel, PhD, Surrebuttal Testimony, p. 4, l. 4.

Q. Is autocorrelation an issue?

A. No. Econometric theory tells us that ‘as long as the explanatory variables are strictly exogenous, the βs (estimated relationship) are unbiased (accurate), regardless of the degree of serial correlation (autocorrelation).’[34] *Autocorrelation does not make the estimate of the relationship between weather and today’s total usage inaccurate.* The most important thing is an accurate estimate of this relationship and autocorrelation has no bearing on this. Staff has made false, albeit somewhat confused statements about this in the past. Staff said this when the test statistic for autocorrelation shows no autocorrelation in their model with yesterday's total kWh, 'this provide empirical support for the claim that Staff's model, which includes a lagged dependent variable (footnote 7), has accurately forecasted the relationship between weather and electricity usage.'[35] The use of the term forecast is confused here and somewhat suggests Staff is conflating estimation of the model and model prediction. For a moment, let's assume Staff meant accurately estimate the relationship, because you don't forecast or predict the relationship, you estimate it, and you can use that estimate to make forecasts, or predictions, or normalizations as is our case. But to the point, if Staff means to say that the lack of autocorrelation provides empirical support that they have accurately estimated the relationship, that is false. The estimate of the relationship is unbiased (accurate) if weather is strictly exogenous, and autocorrelation has nothing to do with it.

Staff Removes Residuals before Calculating Normalization Factors

Q. How do you know that Staff removes the unobservable sources of variation from their actual and normal daily loads used in weather normalization calculations?

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[34] Wooldridge, Jeffery, *Introductory Econometrics*, 3rd Edition, p. 413.
[35] File No. ER-2022-0337, Hari K. Poudel, PhD, Surrebuttal Testimony p. 4, l. 10 to p. 5, ll. 1-2.

A. The daily actual total kWh and daily predicted kWh are clearly identifiable in Staff's MetrixND[36] Energy Model file. I compared the actual total kWh and predicted kWh to the values used to produce daily normalization factors in Staff's time-of-use weather normalization workpaper. I can clearly see that the values in that file are the model predicted values rather than the actuals, i.e. the residuals are omitted. There is not clear evidence that Staff has omitted the residuals from its standard monthly weather normalization calculations, but the fact about the time-of-use normalization suggests its possible. Furthermore, the time-of-use weather normalization calculations were used to produce the monthly total weather normalization factors for the Residential and SGS class. Therefore, we know the residuals were omitted from those two normalization factor calculations at the least.

Q. What is wrong with omitting the residuals?

A. When a regression model is estimated, there is variation in the outcome variable that is explained by the explanatory variables in the model. The outcome in our case is today's total kWh and the explanatory variable of greatest interest is the weather. Some of the variation in today's total kWh will be explained by variation in weather, but some won't. The unexplained variation will be captured in a term called the 'error' or residual. Error term is really a misnomer. The best way to think about it is other variables that are unobserved or unmeasurable. I prefer unobserved variation or residual, because there are real things out there that we don't observe that are causing today's total kWh to vary.[37] Those unexplained variations are real, not an error, they are just not the weather. Staff removes this unobserved

[36] MetrixND is the statistical software package that both the Company and Staff use to conduct statistical load modeling, such as weather normalization modeling.

[37] For example, imagine a manufacturing facility which has a one-day production outage due to labor dispute. The variation in the class total usage for that day created by this labor dispute is not related the weather, and it would appear in the residual. When Staff throws out the residuals, they end up distorting weather normalization in a random way based on real events unrelated to the weather.

variation or residual when they use the predicted values of the regression model. They do this for actual and normal versions of the model. Then they take the ratio of these two values to compute weather factors. Even though the unobserved variation is the same in both the actual and normal versions of today's total kWh, and would be in both the numerator and the denominator of the weather factor, they do not cancel out. That is not how the math works. By construction of OLS, the sum of the errors is zero across the whole period, but there will be positives and negatives scattered across the months. The impact could be small, but there is no reason to eliminate it. It is real variation in today's total kWh that could just as easily be kept and should be. This is memorialized in a peer-reviewed published article written by two MPSC Staff employees and a University of Missouri professor.[38] The inclusion of the residuals in the weather normalization process is captured in equations 3 through 6 of that article. Equations 3 and 6 provide the clear mathematical expression that the unobserved variation or error term is intended to be included in both the actual total kWh and normal total kWh values used to calculate weather-normalization factors. When Staff uses the predicted and simulated values from their model, they are excluding the residuals whether they know it or not. This article is something that Staff has cited in the past and provides some of the foundational aspects of the weather normalization models used by both Staff and the Company. Staff has denied this issue exists in the past.[39]

Q. Can you provide a simple numeric example of the issue?

A. Yes. Imagine actual total kWh is 100 and the weather model with actual weather predicts it to be 96 kWh. This means the residual unexplained by weather is 4.

[38] Won, Seoung Joun, Wang, X. Henry, Warren, Henry E. *Climate Normals and Weather Normalization for Utility Regulation*,p. 405-416, Energy Economics, Volume 54 (2016).
[39] File No. ER-2022-0337, Hari K. Poudel, PhD, Surrebuttal Testimony p. 5, ll 14 -20 and p. 6 ll. 1-4.

Now assume the weather model with normal weather predicts 90 kWh. This implies the effect of abnormal weather is 96 – 90 = 6 kWh. If we subtract the effect of abnormal weather from actual total kWh we get 100 – 6 = 94, which is what the weather model predicts under normal weather conditions plus the residual, 90 + 4 = 94. Now think about the two potential weather normalization factors. The one with the residual is 94/100 = 0.94 and the one without is 90/96 = 0.9375. The 100 kWh is the billing units we are normalizing. If we apply the 0.94 we get 100*0.94 = 94, which is the actual total kWh minus the impact of abnormal weather. If we apply the second factor without the residuals, 0.9375, to the billing units, we get 100*0.9375 = 93.75 kWh. The 94 is the right number, its actual total kWh minus the effect of abnormal weather. The 93.75 is nothing. It's not the actual minus abnormal weather. It's not the level predicted by the weather model under normal weather conditions. It's just something slightly different than the right answer. Hence my position, that Staff does 'more' than normalize for weather. In fact, depending on the sign of the daily residual (some are positive and some are negative), Staff could be doing 'more' or 'less'. The important thing is that what Staff is doing is not accurate.

Two Total Normalization Factors

Q. Did Staff calculate two total kWh weather normalization factors for some customer classes?

A. Yes. Staff calculated two total normalization factors for the Residential and SGS classes. First, Staff constructs monthly total kWh weather normalization factors using the traditional means, aggregating the results of their daily total kWh weather normalization results directly. Second, Staff uses the same daily total kWh weather normalization results it directly aggregates in the first case to normalize hourly kWh data, and then aggregates those hourly values to compute monthly normalization factors. We discussed the complexity and novelty of that hourly normalization procedure in some detail and presented some odd, if nothing else, results. If we take a step back and look at the second version of monthly normalization factors, we can see that they are computed using the normalized results of the first. The only conceptual difference is that the second set first produces hourly normal kWh from the daily normal kWh, then sums those up to get the monthlies. If the hourly normal are derived from the daily normal kWh used in the first aggregation, then it seems like they both should produce the same result since the hourly normal kWh are just a more granular version of the daily normal kWh. The fact is that in Staff's analysis they do not produce the same result. The unreasonable thing Staff does is to choose the version that went through a large set of novel, complex, and tedious calculations, rather than the one that those novel, complex and tedious calculations started with but didn't go through.

Q. Can you summarize the issues with Staff's total weather normalization testimony?

A. First, Staff includes yesterday's total kWh in its model of the relationship between today's total kWh and the weather. Including this variable creates imprecision in the estimate of the relationship between today's total kWh and the weather. An accurate estimate of this relationship is the most important to get from the weather model. There is no apparent weather normalization benefit of including this variable in the weather model. The inclusion of the variable may indicate Staff is more interested in predicting total kWh than weather normalizing total kWh and there is a difference. Second, Staff removes residuals from their definitions of actual and normal total kWh, and this causes weather normalization factors to do 'more' or 'less' than weather normalize. Third, Staff creates two sets of monthly total weather normalization factors for the Residential and SGS classes. The second set is based on the same inputs as the first, but goes through an extra set of novel and tedious calculations. There is a principled reason to believe two sets should be equal, but they are not. There is not a good reason to think the second set is superior, and more reason to believe the contrary, but Staff chooses the second set.

2. Staff's MEEIA Annualization Adjustment

Q. Did you review Staff's MEEIA Adjustment in this case?

A. Yes.

Q. Did you find any errors in that calculation?

A. Yes. I found a handful of data entry and one simple formula error which I provided to Staff by email on December 17, 2024.

Q. Did correcting the simple errors 'correct' Staff's MEEIA Adjustment?

A. In my view, yes. The Company produces an estimate of the MEEIA adjustment associated with Staff direct test period, aka the update period. After changing a few input data differences and one formula error, just a reference that missed one cell, the Company and Staff's models produced answers within a few kWh. Those few kWh could be traced to minor rounding differences in some inputs. The differences were so minor that I'd say the outcomes were the same. In the last case, Staff and the Company had aligned on the correct inputs, but I recall some less trivial difference in the outcomes that were presumably tied to differences in our models that we couldn't identify.

Q. Did Staff accept the errors they made and agree to correct them?

A. Not exactly. Staff indicated after discussion and several emails that they had no other concerns aside from one which continued to be the subject of conversation at the time of drafting this testimony.

Q. What issue continued to be the subject of conversation?

A. The subject of conversation continued to be the exclusion of residential demand response optimization savings from the annualization adjustment. The Company changed its treatment of residential demand response optimization in the MEEIA annualization adjustment since the last case. The change makes good sense in principle and benefits customers (i.e. increases normalized usage and revenue, which reduced the required rate increase needed to achieve the revenue requirement).

Q. Do you expect Staff to accept the corrections you offered and reflect those corrections in their True-up testimony.

A. Yes, I do. But for the record, I will present those errors here.

1. For the residential, SGS, LGS, SPS, and LPS classes, staff used inputs from the Planning Year ("PY") 2023 December 2023 Throughput Disincentive calculation file provided in response to Data Request MPSC 265. The correct file, which included all PY 2023 MEEIA measures and evaluated savings is the PY 2023 June 2024 calculation file also provided in response to MPSC 265.

2. For the SGS and LGS class, monthly end use load shapes were misaligned with monthly savings. End use load shapes were organized from July to June and savings from January to December.

3. For SGS, LGS, SPS and LPS, total installed savings omits savings from one end-use category in every month (the formula error I referenced above).

4. For the residential, SGS, LGS, SPS, and LPS classes, Demand Response Event Net Energy ("DRENE") savings is not added back to offset the annualization adjustment.

5. For residential, demand response optimization (non-event) savings are not excluded from total savings.

3. Staff's Solar Annualization Adjustment

Q. Did Staff make an adjustment for behind-the-meter solar installations made in the test year?

A. No.

Q. Is it reasonable for Staff to make a behind the meter solar adjustment?

A. Yes. The level of solar generation capacity installed by customers behind Company's meters, which reduced Company sales and revenues, is known and measurable because of the Company's safety inspection process that is conducted as part of these installations and their application for net metering. A reasonable calculation of generation given the known capacity of behind the meter generation can be performed to determine how behind the meter generation will impact billing units and revenue as a result of known installations made during the test year. The Company provided such a calculation with its direct testimony, and that calculation should be used to annualize test year billing units.

4. Staff's Economic Development Incentive Annualization Adjustment

Q. Did Staff make a reasonable Economic Development Incentive Adjustment?

A. Yes, the Company's estimate of the Economic Development Incentive Annualization Adjustment for Staff's direct test year, aka the update period, was reasonably close to the adjustment calculated by Staff. There is room for discretion in the calculation of the Economic Development Incentive Annualization Adjustment because customers receiving the incentive for the first time are typically ramping up their usage, as is the nature of the incentive. There is room for discretion in the choice of months used to calculate the expected annual impact of the discount given there is no bright line between this ramp period and when the customer is consuming at the 'full capacity' level expected in the future.

Q. Will Economic Development Incentives be the subject of True-up data and calculations?

A. Yes, we expect the Staff and the Company to produce reasonably similar Economic Development Incentive Annualization Adjustments in true up direct testimony.

5. Staff's Growth Adjustment

Q. Did Staff make a Growth Adjustment in their direct case?

A. Yes, but Staff's growth adjusted billing units and revenue is not directly comparable to the Company’s growth adjusted billing units and revenue because it is made using a different end date. Staff sets customer counts in all months of their test period equal to customer counts in June 2024, the end of the update period that Staff analyzed for its direct case. The Company forecasts customer counts out to December 2024, the true-up date in this case, and makes a pro forma adjustment to set customer counts in all months of our test period equal to customer counts forecast for December 2024. There is nothing mechanically wrong with Staff’s growth adjustment as far as I saw, but Staff's growth adjusted billing units are just not comparable to the Company’s. In true-up, I expect both Staff and the Company to adjust customer counts in all months to equal actual customer counts observed in December 2024.

III. REVENUE REQUIREMENT ALLOCATION

Q. What do you think about Staff's revenue allocation in this case?

A. Staff's revenue requirement allocation is supported by Staff's cost of service. There are a number of significant problems with Staff's cost of service that are outlined by Company witnesses Hickman, Wills, and Phillips. The big picture prospective provided by

Company witness Wills gives you a sense of distance between Staff's cost of service and reasonable. Given the number and magnitude of issues associated with Staff's cost of service, the Commission should reject Staff's revenue requirement allocation proposal.

Q. What do you think about CCM's revenue requirement allocation position?

A. CCM primarily represents the interest of residential consumers and yet takes a position that is basically supportive of the Company's cost of service study. I will later take issue with one other policy position CCM takes related to residential customer interests, but here I think they got it right. CCM explicitly supports the Company's revenue requirement allocation, which allocates a percentage increase to the residential class that is greater than the total revenue requirement percentage increase in this case. That greater-than-total increase is a small fraction, just 0.25%, but CCM supports it. When asked "Do you support the Company's revenue requirement allocations?" CCM witness Palmer says "Yes. The Company has mitigated some of my concern around its CCOSS methodologies by exercising judgement when using its CCOSS to inform revenue allocation and rate design."[40] CCM witness Palmer could have very simply recommended an equal percentage increase to all classes, but instead Palmer saw the broader picture and made the reasonable choice to support the Company's big picture view of the facts and fairness.

Q. Why do you say CCM Witness Palmer 'saw the broader picture'?

A. CCM Witness Palmer did some specific cost of service work in this case, but then looked up and saw the impact of the change in the context of the Company's cost of service and, presumably, general knowledge of the broader industry cost of service facts.

[40] File No. ER-2024-0319, Caroline Palmer Direct Testimony, p. 15. ll. 17-20.

CCM Witness Palmer made a single, but substantial conceptual and methodological change to the Company's cost of service. CCM witness Palmer changed the company's distribution allocator from a minimum system framework to a basic customer allocation method. The basic customer allocation method is generally recognized, but it is on one end of the distribution cost-allocator spectrum. The significant, but generally recognized modeling change didn't cause the Company's cost of service to change drastically.

I would like to thank CCM witness Palmer for acknowledging the reasonableness of the Company's proposal and, tacitly, the cost of service. We need other reasonable (an important qualifier) perspectives on cost of service to keep revenue allocation and rate design reasonable. At times this means making revenue shifts to classes who'd probably rather not receive them. If parties representing those classes are reasonable, we can continue to balance the interests of all classes, including those who might need to pay a greater share of the total.

Q. What do you think about MECG's revenue requirement allocation proposal?

A. From a cost of service perspective, I think MECG's proposal is reasonable. Generally, I share MECG witness Maini's views on economic efficiency and equity, although it is probably true that I have not placed as much weight as witness Maini has on it in this case.[41] Economic efficiency is achieved by definition when rates equal cost of service. I also think MECG's definition of equity is rates equal to cost of service. I don't think that is an unreasonable definition of equity or fairness, but I do think there are other equity perspectives. I think MECG witness Maini is also correct to assert that the Company has put 'emphasis on tempering rate [or bill] impacts'.[42] On the other side of the bill impact coin is the fact that

[41] File No. ER-2024-0319, Kavita Maini Direct Testimony, p. 21. ll. 4-10.
[42] File No. ER-2024-0319 Kavita Maini Direct Testimony, p. 23. l. 14.

customer classes with revenue requirement allocations above their cost of service have been paying bills that are too high and will continue to do so as long as rates do not move towards the cost of service. This is probably the perspective which I think provides the most credit to MECG's proposal in terms of reasonableness.

Q. What do you think about MIEC's revenue allocation proposal?

A. The perspective I shared above in response to MECG's revenue allocation proposal also applies to MIEC. Both MECG and MIEC express appreciation for the Company's effort to make a revenue adjustment or finally recognize the imbalance in rates but emphasize the need to do more. I think these expressions of appreciation reflect that fact that the Company's attempts to balance the competing interests of parties in recent cases ultimately resulted in proposals to increase revenue requirement allocations by equal percentages in each of those recent cases, and the Company's proposal in this case is an effort to finally recognize the imbalance in rates by making a revenue neutral revenue requirement reallocation. Differential bill impacts are always a compelling reason for equal percentage increases, but the recognition of the imbalance in rates was paramount in this case.

IV. <u>RATE DESIGN</u>

Q. What do you think about Staff's proposal that would keep the residential customer charge fixed at its current level?

A. Staff makes a cost of service argument to support their proposal to keep the monthly residential customer charge at $9.00. In order to maintain costs at this level, Staff uses a narrow definition of customer-related costs to estimate a cost of service based residential customer charge. I don't agree with Staff's definition of residential customer costs, and I don't find the estimates to be compelling. I do find the Company's definition of customer related costs compelling. The estimate of residential customer related costs from Company Witness Hickman's work is approximately $31 per month. Given the large gap between the Company's current residential customer charge and the Company's estimate of residential customer related costs, increasing the customer charge is good policy.

Additionally, Staff footnotes their analysis with the following, "Given AMI metering and online billing, I did not include incremental costs for meter reading, billing, or postage."[43] This statement unreasonably assumes that AMI and online billing are costless. Digital metering and billing have costs even if there is not a physical meter reader walking door to door or a physical envelope sent by mail. These complex digital systems have a real cost. And, to the point here, these costs are the same per customer regardless of the customer demand or energy. These are real costs that should be classified as customer-related costs and further justify increasing the fixed customer charge in this case.

Q. What do you think about Staff's proposal to increase the Evening-Morning Savers On Peak Adjustments?

A. I prefer the Company's proposal to keep the On Peak Adjustments constant in this case for a couple of reasons, but I do not think that Staff's proposal is unreasonable. Currently, the On Peak Adjustment rates are 0.25 and 0.5 cents per kWh for the winter and summer respectively. Staff's proposal, assuming the Company's revenue requirement request and revenue allocation, would produce On Peak Adjustment rates of 0.29 and 0.57 cents per kWh for the winter and summer respectively. The first reason I prefer to keep the adjustments at the current levels is consistency, simplicity, and salience. The rollout of the AMI meters needed to bill this rate schedule is wrapping up as we speak. The completion of the 6-month

[43] File No. ER-2024-0319, Sarah L.K. Lange Direct Testimony, p. 47, l. 16.

lagged default to this rate will complete around the time this case is completed. The last of the customers to receive AMI meters will just be exposed to the rate right when it would be changed by Staff's proposal. There is where the salience (or lack thereof) of Staff's suggestion comes in. The nice round numbers stand out. I think this increases the probability that a customer notices the new kind of charge on their bill and when they notice it, they have a better chance of understanding it.

The second reason to reject Staff's proposal is tied to the long-term intention of these rates. What is Staff's long-term goal for the Evening-Morning Savers on peak adjustment or the Evening-Morning Savers rate schedule more generally? To the best of my understanding, the level of the charge recommended by Staff is not directly linked to any cost-based measure. In principle, the broad on peak period has and/or will cause more of the total cost, but Staff's specific level of the charge appears to be more or less arbitrary. Given the absolute size of the adjustments is small and the general principle is a good one, choosing the small arbitrary level of the charge was reasonable initially. However, it makes sense to me to consider what the cost is intended to represent or what it is intended to achieve before we start changing it. Staff's testimony articulates no basis for making such a change.

Q. What do you think about Staff's proposal to eliminate the additional monthly charge associated with the Legacy Time-of-Day rates for non-residential customers?

A. We made the same proposal in our direct, so I support it. This is a small but tangible benefit that was born out the Company's Non-Residential Rate Design working docket. In that working docket, the Company used the Legacy Time-of-Day rate plan to illustrate the type of bill impact analysis the Company was prepared to do in that proceeding using AMI data. The juxtaposition of the rate with an extra customer charge and the AMI meter data led to the realization that the charge was no longer needed.

Q. What do you think about Staff's proposal to continue to hold the Rider B charge constant?

A. I think it is unreasonable. Rider B is intended to remove substation related costs from demand charges for customers taking service at voltages above the voltage level exiting those substations, i.e. those customers who can't possibly be using those substations. In ER-2022-0337, the Company showed that the level of substation cost in rates is nearly identical to the Rider B rates. Applying Rider B, which was very close to those dollar amounts, would remove those costs from rates. The Company still thinks that that is all that we need to know to demonstrate that Rider B is doing what it was intended to do. It is true, the Company has agreed to do more so Rider B is not necessary in the future, but those future rates will just do in one charge what is currently done with a secondary charge adjustment, Rider B. It will not change anything about the principled correctness in what Rider B is currently doing. It is likely that substations costs are increasing along with other costs generally, so it is reasonable to increase Rider B.

Q. What do you think about MECG's recommendation concerning a Non-Residential Rate Design workshop progress report and timeline?

A. I think it's a little bit confusing. In preparation for the workshops, the Company spent considerable time and effort acquiring meter data, developing analytical programs, conducting research, and developing an agenda aimed at facilitating constructive collaboration with the parties. The first slide, beyond the title slides, from the first workshop contained the following:

Report and Order from ER-2022-0337 issued June 14, 2023.

"What changes should be made, if any, to the Non-Residential, Non-Lighting rate options offered by the Company?"

1. "The Commission does not find that ***a shift between demand charges and energy charges*** *within the LGS and SPS rate classes is appropriate at this time. The Commission said as much in File No. ER-2021-0240. The Commission does find that this issue is appropriate for the* ***non-residential working docket****, where the parties can collaborate and look at ways to adjust these classes more toward their relative costs of service."*

2. "The Commission also finds it appropriate for MECG's proposed ***optional EV charging rate*** *to be examined in the* ***non-residential working docket****."*

I'm not sure what MECG witness Maini is imagining in the recommendation made here, but I know MECG has made demand and energy charge and optional EV proposals in this case. MECG is making these proposals when the Commission ordered the parties to address those issues collaboratively in the non-residential working docket. Those issues were the first issues put on the table, and I do not recall any MECG participation. The idea that MECG wants a progress report on a working docket primarily ordered to address their issues and where they had the opportunity, and frankly the expectation, to actively participate but failed to do so, is a little confusing. As far as a timeline, I'd say it depends but could be accelerated through active participation by the parties.

Q. What do you think about MECG's proposal to increase demand charges for the LGS and SPS class by 150%?

A. As MECG witness Maini correctly identified in testimony and I acknowledge above, the Company is interested in bill impacts. I do not feel comfortable supporting this proposal without knowing something about the distribution of bill impacts within the LGS and SPS classes. This would have been something that was perfectly feasible to study in the non-residential working docket. A collaborative study like that could have resulted in a Company proposal or Company support for an MECG proposal of this nature in this case.

Q. What do you think about MECG's EV rate proposal in this case?

A. I think MECG should have actively participated in the non-residential working docket where the Commission ordered this issue to be addressed collaboratively. In the first workshop, the Company actually presented some AMI data for EV charging stations that could be used for analysis and a survey of current EV rates used by other utilities. There was no input or feedback provided by the participants.

Q. What do you think about CCM's proposal not to change the Residential customer charge?

A. CCM makes a policy argument to support their Residential customer charge proposal. Generally, CCM argues that Residential customer charge increases harm low-income customers. Presumably, disproportionately to other residential customers, because it can't harm both groups of customers due to revenue neutrality. I accept that policy has a place, but I do not think the facts support CCM policy position.

Q. What leads you to believe the facts don't support the CCM policy position?

A. I conducted a low-income customer bill impact analysis comparing the Company's proposal and the CCM proposal.[44] The impact on the whole low-income group of the Company's proposal relative the CCM proposal is zero, practically speaking. Technically,

[44] The Company identified low incomes using customers who have qualified for the Company's Rider EEIC low-income exemption.

the Company's proposal increases the total paid by the low-income customer group over twelve months by $9 thousand. The total of those customers' bills is approximately $64.5 million over the same time period. That means that the Company's customer charge proposal, relative to CCM's, results in an increase of just 0.014% for the low-income group. Practically, speaking the total bill outcomes for the group is equal under the two proposals. Here are the actual numbers:

Table 10: Total Low Income Bills

Proposal	Total Bills ($)
Ameren	64,471,777
CCM	64,462,695

You could argue about the $9 thousand or what is practically different, but that's not the point. The point is that the residential customer charge policy position taken by CCM is not really supported by the facts. The fact above actually indicates that the residential customer charge isn't a big issue for low-income customers as a group. It's not a big issue because it doesn't clearly harm or benefit the low-income group in total.

There are a couple reasons we undertook this analysis. One, CCM requested low-income customer usage data in this case, so we had the data prepped and ready for analysis. Two, this residential customer charge issue gets a lot of attention in every case, and some of the facts we already knew didn't line up with some of the policy positions being taken by other parties.

Q. Did the analysis provide any additional insights that might guide better policy discussion in the future?

A. Yes, we looked at this question from a couple angles in our bill impact analysis and quantified another layer of the story. Generally, there are two kinds of low-income customers. One kind of low-income customer fits the assumption you need to make to believe that the increased customer charge will hurt low-income customers, i.e. that low-income customers are low-usage customers. CCM witness Palmer says it: "The impact is more acute for low-usage customers whose bills are relatively small and therefore more influenced by the customer charge. Low-usage customers are also more likely to be low-income and have less ability to pay high bills."[45] The other type of low-income customer does not fit this description. The other type of low-income customer consumes a lot of energy, especially in the winter. Presumably, these customers are electric space heat customers. They may also have inefficient homes and appliances. These customers are hurt by the CCM policy position. CCM witness Palmer doesn't explicitly recognize that these customers exist. The Commission should consider the CCM proposal in light of these facts.

CCM witness Hutchinson on the other hand constructs a narrative that fits the story of this second set of customers but does not recognize that support for the CCM policy position hurts the customers CCM witness Hutchinson expresses concern about. The customers with a high energy burden, which is a customer's energy bill as a percent of customer income. By definition, low-income and high usage customers have the highest energy burden of any customers since the numerator of the energy burden (energy expenditures) is higher for these high usage customers, and the denominator is low since they are low-income customers by definition. If one is largely concerned with energy burden, a *higher* customer charge will unambiguously benefit customers with the highest energy burdens.

[45] ER-2024-0319, Direct Testimony of Caroline Palmer, p. 16, ll.16-19

Q. Are there any other policy arguments related to low-income customers and customer charges that you would like to address before providing the other results of the analysis?

A. Yes. Both CCM witness Palmer and witness Hutchinson talk about customers' ability to control their bill better when usage or volumetric rates are higher. There is some truth in this, but customers still have very similar control of their bill when volumetric rates are a tiny fraction lower, as is the case with the Company's proposal. More importantly, what customers *could* do is far less compelling than what is *actually happening*. If the analysis showed that the CCM proposal hurt low-income customers, then the argument that low-income customers have more control still stands. Would witness Palmer and Hutchinson still make that argument under those conditions? Maybe yes, I don't know. Regardless, I think the impact a policy does have on customers' bills is far more compelling than what a policy might allow customers to do. Especially, when the facts don't show that they are doing that thing which they might.

Q. Please share the findings of the Company's low-income customer analysis.

A. The first fact, shown in Table 11, is that the average low-income customer uses more than the average residential customer.

Table 11: Average Residential Usage

	Low Income	All Residential
Apr-2023	1,059	843
May-2023	791	694
Jun-2023	896	874
Jul-2023	1,155	1,154
Aug-2023	1,244	1,223
Sep-2023	1,162	1,143
Oct-2023	886	830
Nov-2023	817	704
Dec-2023	1,174	962
Jan-2024	1,542	1,275
Feb-2024	1,568	1,264
Mar-2024	1,067	861

The total bills calculated under both the Company's and CCM's customer charge proposals by month are shown in Table 12.

Table 12: Total Low-Income Bills

Month	Ameren	CCM	Difference
Apr-2023	3,996,232	3,986,970	9,262
May-2023	3,280,731	3,261,184	19,547
Jun-2023	5,776,584	5,776,062	522
Jul-2023	7,393,781	7,408,812	(15,031)
Aug-2023	8,020,772	8,041,383	(20,611)
Sep-2023	7,590,110	7,605,898	(15,788)
Oct-2023	3,832,866	3,816,101	16,766
Nov-2023	3,566,644	3,546,999	19,645
Dec-2023	4,654,080	4,648,841	5,239
Jan-2024	5,864,964	5,874,673	(9,709)
Feb-2024	5,992,344	6,003,157	(10,813)
Mar-2024	4,502,670	4,492,615	10,056
Total	64,471,777	64,462,695	9,082

Now for the interesting stuff. There are winners (customers who realize lower bills), and losers (customers who realize higher bills) associated with each rate proposal, so let's look at the results on that basis. For the purposes of this presentation, winners have lower bills under the CCM proposal and losers have higher bills under the CCM proposal. Table 13 shows that there are more winners than there are losers. This fact supports CCM's policy position if the policy objective is to simply help more customers than they hurt.

Table 13: Number of Winners and Losers

Month	Winners	Losers	No Change	Total
Apr-2023	26,289	10,383	98	36,770
May-2023	31,335	5,748	106	37,189
Jun-2023	22,019	15,542	197	37,758
Jul-2023	15,878	22,059	163	38,100
Aug-2023	14,252	24,107	167	38,526
Sep-2023	15,709	22,981	189	38,879
Oct-2023	31,787	7,739	145	39,671
Nov-2023	32,932	6,406	106	39,444
Dec-2023	26,652	12,777	90	39,519
Jan-2024	23,054	17,154	108	40,316
Feb-2024	23,427	17,181	115	40,723
Mar-2024	29,360	11,753	103	41,216

The next natural question is one of the degrees to which winners win and losers lose. Table 14 presents the answer to that question. The customers who benefit, benefit by less, than the than the harm caused to those who are harmed.

Table 14: Average Bill Impact

Month	Winners	Losers
Apr-2023	0.71	-0.91
May-2023	0.72	-0.50
Jun-2023	0.60	-0.82
Jul-2023	0.56	-1.08
Aug-2023	0.55	-1.18
Sep-2023	0.55	-1.06
Oct-2023	0.64	-0.46
Nov-2023	0.70	-0.54
Dec-2023	0.68	-1.02
Jan-2024	0.65	-1.45
Feb-2024	0.67	-1.54
Mar-2024	0.71	-0.93
Total	7.75	-11.49

Finally, losers, as expected, have higher bills than winners. Again, they are the ones with the largest energy burden.

Table 15: Average Bills under CMM Proposal

Month	Winners	Losers
Apr-2023	74	196
May-2023	74	167
Jun-2023	94	237
Jul-2023	98	263
Aug-2023	99	273
Sep-2023	99	261
Oct-2023	80	164
Nov-2023	75	169
Dec-2023	76	204
Jan-2024	79	235
Feb-2024	78	242
Mar-2024	74	197
Total	1,000	2,608

Table 16 shows the different average usage of winners and losers. It is these differences in usage which really explain all the interesting results we see above.

Table 16 Average Monthly Usage

Month	Winners	Losers	All Residential
Apr-2023	613	2,188	843
May-2023	607	1,784	694
Jun-2023	524	1,424	874
Jul-2023	551	1,591	1,154
Aug-2023	558	1,651	1,223
Sep-2023	556	1,578	1,143
Oct-2023	675	1,745	830
Nov-2023	620	1,820	704
Dec-2023	636	2,298	962
Jan-2024	662	2,727	1,275
Feb-2024	651	2,820	1,264
Mar-2024	610	2,206	861
Average	605	1,986	986

Q. Any final conclusion from this analysis?

A. There will be low-income customers who are winners and who are losers if CCM's proposal is accepted. There will be more winners, but plenty of losers. Each loser loses by more than each winner, such that the impact on the whole group is effectively zero. Finally, those who lose are those who already have the largest energy burden. If helping low-income customers is CCM's intention, I don't think their proposal does that.

Q. Any recommendation for the Commission?

A. Yes, reject CCM's proposal. The facts do not clearly support their rationale and might actually contradict it. The Company made its proposal based on cost of service considerations. Now that I have more information about the low-income customer policy implications, I am even more enthusiastic in our recommendation that the Commission accept our residential rate design proposal, including the customer charge part of the proposal.

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	**)**	Case No. ER-2024-0319
Its Revenues for Electric Service.	**)**	

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 17th day of January, 2025