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SOAH DOCKET NO. 473-19-3864

DOCKET NO. 49421

APPLICATION OF CENTERPOINT ENERGY HOUSTON ELECTRIC, LLC FOR AUTHORITY TO CHANGE RATES	§ § § § §	**BEFORE THE STATE OFFICE OF ADMINISTRATIVE HEARINGS**

DIRECT TESTIMONY OF

ALICIA MALOY

INFRASTRUCTURE & RELIABILITY DIVISION

PUBLIC UTILITY COMMISSION OF TEXAS

JUNE 12, 2019

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EXHIBITS

I. STATEMENT OF QUALIFICATIONS

Q. Please state your name, occupation and business address.

A. My name is Alicia Maloy. I am employed by the Public Utility Commission of Texas (Commission) as a Senior Infrastructure Analyst in the Infrastructure and Reliability Division. My business address is 1701 N. Congress Avenue, Austin, TX 78711-3326.

Q. Please briefly outline your educational and professional background.

A. My professional experience includes serving in various roles at the Commission and the Illinois Commerce Commission (ICC). At the ICC, I served as a Policy Advisor to Commissioners Elliott and McCabe for over 4 years, and as a Rate Analyst within the Rates Division for over 3 years. As a Policy Advisor, I researched, analyzed, and developed policies and opinions relating to the industries regulated by the ICC and the Federal Energy Regulatory Commission (FERC); and I conferred with the ICC Commissioners on controversial problems and proposed revisions to orders and filings. As a Rate Analyst, I developed and provided expert written and oral testimony on rate proceedings before the ICC.

My current role at the Commission includes analyzing policy and cost issues regarding Energy Efficiency Cost Recovery Factor applications, reconciling of advanced metering system costs, performing weather normalization adjustments, considering requests to integrate into Electric Reliability Council of Texas (ERCOT), considering

requests for service area boundary modifications, making recommendations for needed amendments to Commission rules that affect utilities, and making recommendations for telecommunications numbering requests. I have been employed with the Commission since October 2015. A more detailed resume is provided in Attachment AM-1.

Q. Have you previously testified or provided memoranda in lieu of testimony before this Commission?

A. Yes, a list of the proceedings in which I have provided testimony, memoranda, or affidavits before the Commission appears as Attachment AM-2. In addition, I have included the proceedings in which I provided testimony at the ICC in AM-2.

II. PURPOSE OF TESTIMONY

Q. What is the purpose of your testimony?

A. The purpose of my testimony is to address CenterPoint Energy Houston Electric, LLC's (the Company) proposed weather normalization adjustment.

Q. What information have you relied upon in your evaluation of the Application?

A. I have relied primarily upon the testimony and workpapers of Dr. J. Stuart McMenamin, the II-H Schedules and workpapers, and responses to requests for information (RFIs).

Q. What statute and PUC Substantive Rules have you referred to in making your evaluation and arriving at your conclusions and recommendations?

A. I referred to 16 Texas Administrative Code (TAC) § 25.234.

III. CONCLUSIONS AND RECOMMENDATIONS

Q. Please summarize your findings and recommendations in this case.

A. Based on my review of the Company's weather normalization adjustment, I recommend rejection of the Company's weather normalization adjustment to test year sales and adoption of my weather normalization adjustment to test year sales based on the following:

- I use a 10-year normalized time period, which is consistent with Commission precedent, and the Company uses a 20-year normalized time period, which is inconsistent with Commission precedent;
- My weather normalization regression models use the same 10-year time period as the normalized time period, and the Company uses a 4-year time period

which is different than their 20-year normalized time period, creating a mismatch in the time periods used;

- I excluded the test year from my weather normalization regression models, which is consistent with Commission precedent, and the Company includes the test year within their weather normalization regression models, which is inconsistent with Commission precedent; and
- I include only variables within my weather normalization regression models that are statistically significant at a minimum of 95%, and the Company includes some variables within their weather normalization regression models that are not statistically significant at 95%.

Q. What is the impact of your proposed weather normalization adjustment?

A. My weather adjustments impact present revenues and rate design.

IV. WEATHER NORMALIZATION DESCRIPTION

Q. Please describe the purpose of a weather normalization adjustment.

A. Consumption of electricity can vary depending on temperature fluctuations. If the temperature is warmer than normal or colder than normal during summer months, then this typically results in higher or lower consumption of electricity, respectively, for these months. Conversely, if the temperature is warmer than normal or colder than normal during winter months, then this typically results in lower or higher

consumption of electricity, respectively, for these months. Weather normalization adjustments are made to test year sales to remove the impacts from abnormal energy consumption during the test year due to temperature fluctuations. The weather-adjusted sales are then used to calculate revenues and rates for each customer class. This ensures that rates set in a proceeding do not under-recover or over-recover the utility's revenue requirement due to abnormal weather.

Q. What methodology is used to estimate the impact of weather on energy sales?

A. The impact of weather on energy sales is determined by calculating the difference between test year degree days and normalized degree days for both heating degree days (HDD) and cooling degree days (CDD), then multiplying these results by monthly weather coefficients determined from regression models. This is represented in the following equation:

$$\text{Weather Impact}_t = (HDD_t - NHDD_t)*Chdd_t + (CDD_t - NCDD_t)*Ccdd_t$$

Where:

- Weather Impact$_t$ is the overall weather adjustment to sales for the customer class.
- HDD_t and CDD_t are the actual heating and cooling degree days in test year 2018 for month t.
- $NHDD_t$ and $NCDD_t$ are the normalized heating and cooling degree days for the normalized time period of 2008-2017 for month t.

- $Chdd_t$ and $Ccdd_t$ are the heating and cooling degree day weather coefficients determined from regression models for month t. The weather coefficients express the relationship of how an increase or decrease in temperature impacts kilowatt hour sales.

How each component of the equation is determined is explained in greater detail below.

Q. Please describe the weather data used in your adjustments.

A. Hourly dry bulb temperatures[1] were gathered from the National Oceanic and Atmospheric Administration website for years 2008-2018 from the Houston Intercontinental Airport, the Houston William P. Hobby Airport, and the Sugarland Regional Airport weather stations. These are the same weather stations used by the Company.[2]

Q. How did you compute average daily temperatures?

I first compiled all of the hourly temperatures in a day for each day of the normalized time period and the test year. Next, I smoothed the hourly temperatures by giving the

[1] Dry bulb temperatures are measured by thermometers not affected by the moisture of the air. When people refer to the temperature of the air, they are normally referring to its dry bulb temperature. *Dry Bulb, Wet Bulb, and Dew Point Temperatures*, NATIONAL WEATHER SERVICE (NOAA), http://www.weather.gov/source/zhu/ZHU_Training_Page/definitions/dry_ wet bulb definition/dry_wet_bulb.html.

[2] Direct Testimony of J. Stuart McMenamin at 37.

current hour a 25% weight and the previous hour a 75% weight. Finally, I calculated the average daily temperatures by averaging the 24 hourly smoothed temperatures for each day.

Q. Why did you smooth the hourly temperatures?

A. The dry bulb temperatures are measured by thermometers located outside. Thermostats that control heating, ventilation, and air conditioning (HVAC) equipment are located inside structures such as homes and commercial buildings. These structures typically have insulation which will cause a lag in changes to inside temperatures from changing outside temperatures. Smoothed temperatures reflect a better representation of when HVAC equipment is utilized in structures, and therefore improve weather normalization models.

Q. What are HDD and CDD and how each is computed?

A. HDD and CDD are measures of temperature in comparison to a reference temperature. HDD are computed by taking the reference temperature and subtracting the average daily temperature. CDD are computed by taking the average daily temperature and subtracting the reference temperature. I used the reference temperature of 65 degrees.[3] For example, if the average daily temperature is 45 degrees, then HDD would be calculated by subtracting the 45 degrees from the 65 degree reference temperature,

[3] NOAA uses the reference temperature of 65 degrees when computing degree days. *Understanding the Preliminary Monthly Climate Data*, NOAA, http://w2.weather.gov/climate/f6.php.

resulting in 20 HDD. If the average daily temperature is 80 degrees, then CDD would be calculated by subtracting the 65 degree reference temperature from the 80 degrees, resulting in 15 CDD.[4] I computed the daily HDD and CDD for each weather station. Once completed, I averaged the daily HDD and CDD across weather stations. This results in calendar month HDD and CDD for the utility as a whole.

Q. Please describe the Company meter reading schedules for customer meters.

A. The Company uses two schedules for reading customers' meters. One schedule is for interval demand recorder (IDR) meters, and the other is for non-IDR meters[5] called the Customer Information Systems (CIS) read schedule.[6] The Secondary Service Greater than 10 KVA and Primary Service customer classes each have customers with IDR meters. The Residential Service, Secondary Service Less than or equal to 10 KVA, Secondary Service Greater than 10KVA, and Primary Service customer classes have customers served by non-IDR meters.

[4] For both HDD and CDD, when the calculation resulted in a negative number, this was changed to zero. For example, in July there would be zero HDD.

[5] "Non-IDR meters" include advanced meters.

[6] CenterPoint Response to Staff's RFI 03-21U.

Q. How did you convert calendar month HDD and CDD into billing month HDD and CDD?

A. The Company provided the two billing schedules for reading customer meters from 2008-2018 in response to Staff's RFI 3-21. For HDD, I multiplied the number of read cycles for each day with the averaged HDD across weather stations for each corresponding day. I then summed these amounts for each month for each year. I then divided each monthly amount by the number of read cycles for that month. This same calculation was performed for CDD. Conversions for both calendar month HDD and CDD into billing month HDD and CDD was performed for both billing schedules. The results for years 2008-2017 represent $NHDD_t$ and $NCDD_t$ from the equation above, and the results for year 2018 represent HDD_t and CDD_t from the equation above.

Q. How are the monthly weather coefficients calculated?

A. The customer class (class) sales and the billing month HDD and CDD for that respective customer class are incorporated into the class weather normalization model. The class sales represent the dependent variable in the model, and the billing month HDD and CDD represent the independent variables in the model. The data for each class model can be seen in Exhibit AM-3. Next, the data is imported into regression software.[7] Then models are run to determine the best fitting equation for each class. A generic equation can be represented as follows:

[7] Staff uses EViews for regression software.

Customer Class Sales = $C + B_1$*JanHDD + … + B_{12}*DecHDD + B_{13}*JanCDD + … + B_{24}*DecCDD

Where:

- Customer Class Sales represents the sales for that customer class over the time period 2008-2017.
- C represents the constant term for each customer class.
- B_1 through B_{24} represent the monthly weather coefficients.
- JanHDD through DecHDD and JanCDD through DecCDD represent the monthly HDD and CDD over the time period 2008-2017.

As can be seen in the equation, B_1 through B_{24} are the monthly weather coefficients that represent $Chdd_t$ and $Ccdd_t$ in the equation on page 7 of my testimony. However, not all HDD and CDD months will have a coefficient. The best fitting equation for the class will determine which months will have a coefficient.

Q. What are some statistical tests that can be used to evaluate weather normalization regression models?

A. One statistical test is the R-squared test statistic (R-squared) value. The R-squared value is a measure of how much of the variation in the dependent variable can be explained by the independent variables for that regression model. For weather normalization regression models, the R-squared value would be a measure of how well variation in electricity sales can be explained by all the monthly HDD and CDD in reference to electricity sales.

Another statistical test is the T-statistic, which measures the significance of the correlation of the independent variable to the dependent variable in the regression model. T-statistics are reported for each independent variable. For weather normalization regression models, each T-statistic would measure the statistical significance of the monthly weather coefficients.

One other statistical test to examine is the Durbin-Watson test statistic, which tests for autocorrelation. Autocorrelation refers to the correlation of the model's error terms for different time periods, and frequently occurs in time series regression models like weather normalization models.

Q. Please describe the significance of the R-squared value.

A. The R-squared value is always between zero and one. The closer the R-squared value is to one, the more the variation of the dependent variable is explained by the independent variables in that regression model. The closer the R-squared value is to zero, then the less the variation of the dependent variable is explained by the independent variables in that regression model.

Q. Does a larger R-squared value indicate that the results from that regression model are more favorable than a regression model with a smaller R-squared value?

A. Not necessarily. When evaluating a regression model, the R-squared value is one of several factors to consider in evaluating a regression model. Another factor to consider is if the independent variables are theoretically valid. For example, changes in electricity sales can be explained by fluctuating weather, which is theoretically valid and should be included in the regression model. In addition, R-squared values typically increase as more independent variables are added to the regression model. Continuing with the example, changes in electricity sales may not be as well explained by average household age since average household age would have only minor impacts to electricity sales in comparison to weather fluctuations. By including average household age in the regression model, the R-squared value would increase. However, the average household age may not be a good independent variable to include theoretically.

Q. Please describe the significance of the T-statistic.

A. The T-statistic is a measure of the statistical significance of the independent variable's coefficient calculated from the regression model. A T-statistic with a value greater than 1.96 is considered to be statistically significant at a 95% confidence level. This means that there is a 95% confidence that the coefficient is statistically valid. A T-statistic with a value less than 1.96 would decrease the level of confidence that the

coefficient is statistically valid in the regression model. For example, a coefficient for a HDD variable with a T-statistic of 1.96 means that there is 95% confidence that the coefficient is an accurate prediction of the correlation between the HDD variable and electricity sales. The impact of a variable may not be meaningful if the confidence level is low.

Q. Please describe the significance of the Durbin-Watson test statistic.

A. The Durbin-Watson test statistic provides a measure to test for autocorrelation and ranges between zero and four. If there were no autocorrelation in a model, the result would be two. Therefore, a Durbin-Watson test statistic should be as close to two as possible. When a weather normalization model results in a Durbin-Watson test statistic that is not close to two, an autoregressive term is included in the model to correct for autocorrelation. All Staff models include an autoregressive term of first order.

V. WEATHER NORMALIZATION CALUCATIONS BY CUSTOMER CLASS

Q. For which classes does the Company propose to adjust test year sales due to weather?

A. The Company proposes to adjust test year sales due to weather for the following classes: the Residential Service, Secondary Service Less than or equal to 10 KVA,

Secondary Service Greater than 10KVA, and Primary Service classes for customers with IDR and non-IDR meters.[8]

Q. Do you propose adjustments to test year sales due to weather for these same classes?

A. Yes.

Q. What are the variables the Company used in their weather normalization regression models (regression models)?

A. The Company incorporates monthly binary variables for January through November, day of the week variables for Monday through Sunday, specific holiday variables for holidays from "New Year's day though Christmas"[9], annual binary variables to account for changes in use per customer, class specific binary variables to account for irregular data, HDSpline and CDSpline variables, two-day weighted lag of HDSpline and CDSpline variables with 85%/15% weights, a binary variable for weekend and holidays interacted with HDSpline and CDSpline, spring day variable interacted with HDSpline and CDSpline, and a fall day variable interacted with HDSpline and CDSpline.[10]

[8] Schedule II-H-2.1.

[9] Based on the Company's model data, this should be "Christmas through New Year's Day".

[10] Direct Testimony of J. Stuart McMenamin at 16-17.

Q. What are the variables you used in your regression models?

A. Historical billing-month sales for years 2008-2017 are used as the dependent variable for each class regression model. Independent variables consist of monthly HDD and CDD variables for months that are determined to be statistically significant, and an autoregressive term of first order for each class.

Q. How did you determine which monthly HDD and CDD variables to use in each class regression model?

A. Each class regression model is run including various combinations of HDD and CDD variables until the best fit model is determined. My models include only variables that have a T-statistic that is at least 1.96, which means that there is at least a 95% confidence level that the coefficient for that variable is valid. The results for each class regression model can be seen in Exhibit AM-4.

Q. How did you calculate the weather normalization adjustments to test year sales for each class?

A. I first calculated the difference between the 10-year normalized weather data and the actual weather data from the test year for each month (Step 1). Next, I multiplied the results from Step 1 times the monthly HDD and CDD coefficients resulting from each class regression model (Step 2). The HDD and CDD results from Step 2 are then added for each corresponding month, resulting in monthly weather adjustments to test

year sales for each class (Step 3). To determine the overall sales adjustments for each class, the monthly adjustments are summed (Step 4). These calculations are shown in Exhibit AM-5.

Q. Please describe how the test year weather compared to the 10-year normalized weather and how this impacts electricity consumption during the test year.

A. On average the test year had greater sales of electricity compared to the 10-year normalized time period. The Company's results also show that the test year had greater sales of electricity compared to their 20-year normalized time period.[11]

Q. How were your weather adjustments to class electricity sales used?

A. I provided the weather-adjusted sales from Exhibit AM-5 to Staff expert witness Brian Murphy. Mr. Murphy used these adjustments to calculate present revenues and class rate design.

[11] Schedule II-H-1.2

VI. COMPARISON OF COMPANY AND STAFF WEATHER NORMALIZATION

A. NORMALIZED TIME PERIOD

Q. Which time period did the Company use for their normalized time period?

A. The Company used weather data for the 20-year time period between 1998 and 2017.[12]

Q. What time period did Staff use for their normalized time period?

A. Staff used weather data for the 10-year time period between 2008 and 2017.

Q. Is the Company's proposal to use a 20-year weather normalization adjustment period consistent with Commission precedent?

A. No. The issue of using a 10-year normal period was a contested issue in Docket Nos. 40443[13], 43695[14], and 46449[15]. In Docket No. 40443, the Commission found:

> 51. Weather data is not randomly distributed by year. There can be weather trends.
>
> 52. The use of a 30-year period for normalizing weather is not a reasonable means of capturing such trends.
>
> 53. The use of 10 years of data is a reasonable means of capturing such weather trends.

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[12] Direct Testimony of J. Stuart McMenamin at 36.

[13] *Application of Southwestern Electric Power Company for Authority to Change Rates and Reconcile Fuel Costs*, Docket No. 40443, Order on Rehearing at 44 (Mar. 6, 2014).

[14] *Application of Southwestern Public Service Company for Authority to Change Rates*, Docket No. 43695, Order on Rehearing at 44 (Dec. 18, 2015).

[15] *Application of Southwestern Electric Power Company for Authority to Change Rates*, Docket No. 46449, Order on Rehearing at 44 (Dec 16, 2016).

In Docket No. 43695, the Commission found:

> 238. It is reasonable for SPS to calculate its normal weather based on a 10-year period in order to be consistent with the Commission's decision to use a 10-year period in the most recent SWEPCO base rate case, Application of Southwestern Electric Power Company for Authority to Change Rates and Reconcile Fuel Costs, Docket No. 40443, Order on Rehearing (Mar. 6, 2014).

In Docket No. 46449, the Commission found:

> 271. Weather data are not randomly distributed by year. There can be weather trends, including both warming and cooling trends.
>
> 272. The use of a 30-year period for normalizing weather is not a reasonable means of capturing such trends.
>
> 273. The use of 10 years of data is a reasonable means of capturing such weather trends.
>
> 274. The use of 10 years of data is more sensitive to weather patterns during the test year.
>
> 275. The weather-normalization adjustment should be applied to adjust billing units and allocation factors for a 10-year weather-normalization period, based on the class billing determinants and external allocation factors used to calculate rates using a 10-year weather normalization period.

In addition, in Project No. 39465, the Order for the rulemaking adopting 16 Texas Administrative Code § 25.243, the Commission stated the following for the weather normalization time period for distribution cost recovery factor proceedings: "There can be weather trends, and the commission concludes that the use of ten years of data is a reasonable means of capturing such trends."[16] The rate-filing package thus requires a 10 year time period.

[16] *Rulemaking Relating to Periodic Rate Adjustments*, Project No. 39465, Order Adopting New § 25.243 as Approved at the September 15, 2011 Open Meeting (Sept. 27, 2011).

Q. What is your recommendation regarding the weather normalization time period?

A. The Commission should reject the Company's weather normalization adjustments because of their use of a 20-year normalized time period which is inconsistent with Commission precedent, and accept Staff's weather normalization adjustments using of a 10-year weather normalized period, which is consistent with Commission precedent.

B. WEATHER NORMALIZATION REGRESSION MODEL TIME PERIOD

Q. What time period does the Company use for its weather normalization regression models?

A. According to the data provided by the Company, the Company uses four years of data from 2015-2018, including the test year, for its weather normalization regression models.[17]

Q. What time period did Staff use for its weather normalization regression models?

A. Staff uses 10 years of data from 2008-2017, excluding the test year and consistent with the normalized time period, for its weather normalization regression models.

[17] WP-II-H-2.2, Metrix ND Model Files, RS_AR1, SVS_AR1, SVL_AR1, PVS_AR1, SVL_IDR_AR1, PVS_IDR_AR1.

Q. What is your recommendation regarding the time period for weather normalization regression models?

A. I have two recommendations for the time period for the weather normalization regression models. First, the time period for the weather normalization regression models should be the same as the normalized time period. When these time periods are not the same, this creates a mismatch of time periods in the equation found on page 7 of my testimony, which is ultimately used to calculate weather adjustments to to test year sales. In reference to the equation, the Company calculates $NHDD_t$ and $NCDD_t$ using 20 years. Once these amounts are subtracted from test year HDD_t and CDD_t, the Company then multiplies this amount by coefficients ($Chdd_t$ and $Ccdd_t$) that are determined using a four year time period.

Second, the Company uses the test year within the time period used in its weather normalization regression models. Using the test year within the weather normalization regression models may create a bias toward the actual test year weather. In Docket No. 43695, the Commission determined that the factors included in the calculation of normal weather should be independent of the test year weather to which the normal weather is compared.[18]

[18] *Application of Southwestern Public Service Company for Authority to Change Rates*, Docket No. 43695, Order on Rehearing at 44 (Dec. 18, 2015).

The Commission should reject the Company's weather normalization adjustments since there is a mismatch of time periods between the normalized time period and the time period used for the weather normalization regression models, and accept Staff's weather normalization adjustments since Staff uses the same time period for the normalized time period and the time period used for the weather normalization regression models. The Commission should also reject the Company's weather normalization adjustments since the Company uses the test year in the time period for the weather normalization regression models, which is inconsistent with Commission precedent, and adopt Staff's weather normalization adjustments since Staff does not use the test year in its weather normalization regression models, which is consistent with Commission precedent.

C. STATISTICAL SIGNIFICANCE OF VARIABLES IN WEATHER NORMALIZATION REGRESSION MODELS

Q. Does the Company's weather normalization regression models include variables that are not statistically significant at the 95% confidence level?

A. Yes. All of the Company's weather normalization regression models include variables that are not statistically significant at the 95% confidence level. For example, within the residential weather normalization regression model, there are 18 variables included that are below the 95% confidence level. The confidence levels of these variables vary in range from approximately a 1% confidence level to a 94% confidence level. As stated earlier, the more variables included in a regression model, the higher the R-

squared value will be. However, even though including variables with low statistical significance may increase the R-squared value, they are not meaningful to the model and should not be included.

Q. Does the Staff's weather normalization regression models include variables that are not statistically significant at the 95% confidence level?

A. No. For all Staff weather normalization regression models that were used to determine the weather adjustment to sales for each class, all variables were at least statistically valid at the 95% confidence level.

Q. What is your recommendation regarding statistical significance of variables in weather normalization regression models?

A. I recommend the Commission reject the Company's weather normalization adjustments to test year sales because their weather normalization regression models include variables with low statistical significance, and accept Staff's weather normalization adjustment to test year sales because all variables included in the weather normalization regression models are statistically significant at a minimum of 95%.

VII. OVERALL RECOMMEDATION

Q. What is your overall recommendation for weather normalization adjustments to test year sales?

Based on my review of the Company's weather normalization adjustment, I recommend rejection of the Company's weather normalization adjustment to test year sales and adoption of my weather normalization adjustment to test year sales because:

- I use a 10-year normalized time period, which is consistent with Commission precedent, and the Company uses a 20-year normalized time period, which is inconsistent with Commission precedent,
- My weather normalization regression models use the same 10-year time period as the normalized time period, and the Company uses a 4-year time period which is different than their 20-year normalized time period, creating a mismatch in the time periods used,
- I excluded the test year from my weather normalization regression models, which is consistent with Commission precedent, and the Company includes the test year within their weather normalization regression models, which is inconsistent with Commission precedent, and
- I include only variables within my weather normalization regression models that are statistically significant at a minimum of 95%, and the Company includes some variables within their weather normalization regression models that are not statistically significant at 95%.

Q. Does this conclude your testimony?

A. Yes.

Exhibit AM-1

Statement of Qualifications

Alicia Maloy

I have a Bachelor of Science Degree in Economics as well as Management and Organizational Leadership with a minor in Mathematics from Illinois College and a Master of Science Degree in Economics with a focus on utility regulation from Illinois State University.

In 2008, I began my career at the Illinois Commerce Commission (ICC). My experience at the ICC includes serving as a Policy Advisor to Commissioners Elliott and McCabe for over four years. In this role I researched, analyzed, and developed policies and opinions relating to the industries regulated by the ICC and the FERC. I conferred with the Commissioners on controversial problems before the ICC and proposed revisions to orders, filings, and reports. In addition, I assisted in drafting dissenting opinions of Commissioner Elliott.

As a Rate Analyst at the ICC, I developed and provided expert written and oral testimony on cost of service studies, rate design, tariffs, reorganization and merger proceedings, proposed Certificates of Public Convenience and Necessity, and other utility tariff proposals within the context of electricity, natural gas, water and wastewater proceedings before the ICC.

In October 2015, I joined the Public Utility Commission as an Infrastructure Analyst. In March 2019, I was promoted to Senior Infrastructure Analyst. My current role at the Commission includes analyzing policy and cost issues regarding Energy Efficiency Cost Recovery Factor applications, reconciling of advanced metering system costs, performing weather normalization adjustments, considering requests to integrate into Electric Reliability Council of Texas, considering requests for service area boundary modifications, making recommendations for needed amendments to Commission rules that affect utilities, and making recommendations for telecommunications numbering requests.

Exhibit AM-2

ICC Docket Number	Description
12-0484	*Petition for approval of tariffs implementing ComEd's Proposed Peak Time Rebate Program*
12-0511 12-0512 (cons.)	*Proposed General Rate Increase for Gas Distribution Service by North Shore Gas Company and the Peoples Gas Light and Coke Company (Consolidated)*
13-0079	*Proposed general rate increase for gas service and an electric rate design revision by Mt. Carmel Public Utility Company*
13-0105	*Petition for approval of Peak Time Rebate Program by Ameren Illinois Company*
13-0362	*Application for approval of proposed reorganization of Liberty Energy (Midstates) Corp., Liberty Energy Utilities Co., and Liberty Utilities Co.*
13-0387	*Proposed revenue-neutral tariff changes related to rate design by Commonwealth Edison Company*
13-0552	*Proposed Rider Non AMI Metering by Commonwealth Edison Company*
14-0066	*Proposed general rate increase for electric service by MidAmerican Energy Company*
14-0396	*Petition for Issuance of a Certification of Public Convenience and Necessity to operate a water distribution system and wastewater collection system and issuance of an Order approving rate base by Aqua Illinois, Inc.*
14-0496	*Application pursuant to Section 7-204 of the Public Utilities Act for authority to engage in a reorganization, to enter into agreements with affiliated interests pursuant to Section 7-101 by Wisconsin Energy Corporation, Integrys Energy Group, Inc., Peoples Energy, LLC, the Peoples Gas Light and Coke Company, North Shore Gas Company, ATC Management Inc., and American Transmission Company, LLC*
15-0142	*Proposed general increase in gas delivery service rates and revisions to other terms and conditions of service by Ameren Illinois Company.*
PUCT Docket Number	
45213	*Application of Texas-New Mexico Power Company to Reconcile Advanced Metering System Costs*
45524	*Application of Southwestern Public Service Company for Authority to Change Rates*
45824	*Application of Southwestern Electric Power Company to Adjust its Energy Efficiency Cost Recovery Factor and Related Relief*
46002	*Application of Texas-New Mexico Power Company for Approval to Adjust its Energy Efficiency Cost Recovery Factor*
46024	*Application of Sharyland Utilities, L.P. to Adjust its Energy Efficiency Cost Recovery Factor and Related Relief*
46893	*Application of the City of McAllen to Provide Non-Emergency 311 Service*

Exhibit AM-2

46926	*Application of Southwestern Bell Telephone L.P. d/b/a AT&T Texas for Approval to Provide Non-Emergency 311 Service for City of Amarillo*
47116	*Application of Southwestern Electric Power Company to Adjust its Energy Efficiency Cost Recovery Factor and Related Relief*
47217	*Application of Texas-New Mexico Power Company for Approval to Adjust its Energy Efficiency Cost Recovery Factor*
47248	*Application of Sharyland Utilities, L.P. to Adjust its Energy Efficiency Cost Recovery Factor and Related Relief*
47576	*Application of the City of Lubbock through Lubbock Power and Light for Authority to Connect a Portion of its System with the Electric Reliability Council of Texas*
48334	*Application of Southwestern Electric Power Company to Adjust its Energy Efficiency Cost Recovery Factor and Related Relief*
48398	*Application of Southwestern Bell Telephone L.P. d/b/a AT&T Texas for Approval to Provide Non-Emergency 311 Service for City of McAllen*
48401	*Application of Texas-New Mexico Power Company for Authority to Change Rates*
48420	*Application of CenterPoint Engery Houston Electric, LLC for Approval to Adjust its Energy Efficiency Cost Recovery Factor*

Exhibit AM-3
Model Data for Residential Class

Residential Customer Class

Line No.	Year	Month	Sales	HDD_Jan	CDD_May	CDD_Jun	CDD_Jul	CDD_Aug	CDD_Sep	CDD_Oct
1	2008	1	1,735,076,439	374.14	0	0	0	0	0	0
2	2008	2	1,586,780,161	0	0	0	0	0	0	0
3	2008	3	1,323,068,845	0	0	0	0	0	0	0
4	2008	4	1,454,392,831	0	0	0	0	0	0	0
5	2008	5	1,567,865,091	0	406.65	0	0	0	0	0
6	2008	6	2,403,057,015	0	0	568.06	0	0	0	0
7	2008	7	2,954,492,103	0	0	0	583.28	0	0	0
8	2008	8	3,006,826,147	0	0	0	0	549.85	0	0
9	2008	9	2,890,014,898	0	0	0	0	0	399.42	0
10	2008	10	1,300,021,803	0	0	0	0	0	0	183.1
11	2008	11	2,224,837,731	0	0	0	0	0	0	0
12	2008	12	1,493,883,716	0	0	0	0	0	0	0
13	2009	1	1,762,728,630	322.69	0	0	0	0	0	0
14	2009	2	1,465,425,924	0	0	0	0	0	0	0
15	2009	3	1,296,075,145	0	0	0	0	0	0	0
16	2009	4	1,395,777,107	0	0	0	0	0	0	0
17	2009	5	1,611,930,029	0	396.02	0	0	0	0	0
18	2009	6	2,316,621,534	0	0	605.45	0	0	0	0
19	2009	7	3,219,445,530	0	0	0	652.64	0	0	0
20	2009	8	3,331,564,003	0	0	0	0	587.83	0	0
21	2009	9	3,152,812,016	0	0	0	0	0	408.15	0
22	2009	10	2,350,754,996	0	0	0	0	0	0	218.16
23	2009	11	1,741,450,715	0	0	0	0	0	0	0
24	2009	12	1,455,898,495	0	0	0	0	0	0	0
25	2010	1	2,015,122,628	526.62	0	0	0	0	0	0
26	2010	2	1,773,831,715	0	0	0	0	0	0	0
27	2010	3	1,697,871,188	0	0	0	0	0	0	0
28	2010	4	1,368,617,485	0	0	0	0	0	0	0
29	2010	5	1,521,876,801	0	422.36	0	0	0	0	0
30	2010	6	2,524,483,278	0	0	561.08	0	0	0	0
31	2010	7	3,094,397,419	0	0	0	586.27	0	0	0
32	2010	8	3,084,593,864	0	0	0	0	617.78	0	0
33	2010	9	3,325,681,590	0	0	0	0	0	432.47	0
34	2010	10	2,631,658,506	0	0	0	0	0	0	223.45
35	2010	11	1,820,982,118	0	0	0	0	0	0	0
36	2010	12	1,584,347,780	0	0	0	0	0	0	0
37	2011	1	1,836,824,502	504.55	0	0	0	0	0	0
38	2011	2	1,900,913,377	0	0	0	0	0	0	0
39	2011	3	1,593,740,640	0	0	0	0	0	0	0
40	2011	4	1,438,887,068	0	0	0	0	0	0	0
41	2011	5	1,996,402,980	0	440.91	0	0	0	0	0
42	2011	6	2,603,358,802	0	0	620.75	0	0	0	0
43	2011	7	3,477,177,376	0	0	0	660.88	0	0	0
44	2011	8	3,553,059,171	0	0	0	0	683.63	0	0

Exhibit AM-3
Model Data for Residential Class

45	2011	9	3,721,682,335	0	0	0	0	0	491.65	0
46	2011	10	2,873,799,850	0	0	0	0	0	0	232.45
47	2011	11	1,892,918,842	0	0	0	0	0	0	0
48	2011	12	1,639,099,381	0	0	0	0	0	0	0
49	2012	1	1,862,602,350	252.38	0	0	0	0	0	0
50	2012	2	1,538,885,589	0	0	0	0	0	0	0
51	2012	3	1,443,458,526	0	0	0	0	0	0	0
52	2012	4	1,658,872,671	0	0	0	0	0	0	0
53	2012	5	1,987,382,360	0	411.71	0	0	0	0	0
54	2012	6	2,612,260,364	0	0	541.71	0	0	0	0
55	2012	7	3,161,596,832	0	0	0	558.25	0	0	0
56	2012	8	3,154,413,631	0	0	0	0	595.57	0	0
57	2012	9	3,455,742,357	0	0	0	0	0	408.73	0
58	2012	10	2,698,002,286	0	0	0	0	0	0	227.67
59	2012	11	1,953,734,883	0	0	0	0	0	0	0
60	2012	12	1,651,217,120	0	0	0	0	0	0	0
61	2013	1	1,928,925,649	314.57	0	0	0	0	0	0
62	2013	2	1,724,090,249	0	0	0	0	0	0	0
63	2013	3	1,400,582,914	0	0	0	0	0	0	0
64	2013	4	1,502,843,167	0	0	0	0	0	0	0
65	2013	5	1,584,959,830	0	348.46	0	0	0	0	0
66	2013	6	2,423,540,043	0	0	580.8	0	0	0	0
67	2013	7	3,340,806,900	0	0	0	595.58	0	0	0
68	2013	8	3,361,177,532	0	0	0	0	583.87	0	0
69	2013	9	3,409,058,491	0	0	0	0	0	489.4	0
70	2013	10	2,955,278,660	0	0	0	0	0	0	200.86
71	2013	11	1,890,452,794	0	0	0	0	0	0	0
72	2013	12	1,757,290,901	0	0	0	0	0	0	0
73	2014	1	2,255,412,752	487.26	0	0	0	0	0	0
74	2014	2	1,965,584,309	0	0	0	0	0	0	0
75	2014	3	1,763,701,042	0	0	0	0	0	0	0
76	2014	4	1,481,646,723	0	0	0	0	0	0	0
77	2014	5	1,767,919,591	0	339.54	0	0	0	0	0
78	2014	6	2,331,013,531	0	0	515.87	0	0	0	0
79	2014	7	3,106,853,167	0	0	0	555.93	0	0	0
80	2014	8	3,290,567,949	0	0	0	0	580.44	0	0
81	2014	9	3,445,691,699	0	0	0	0	0	437.47	0
82	2014	10	2,752,002,410	0	0	0	0	0	0	222.19
83	2014	11	1,983,938,220	0	0	0	0	0	0	0
84	2014	12	1,715,609,838	0	0	0	0	0	0	0
85	2015	1	2,730,194,235	457.88	0	0	0	0	0	0
86	2015	2	1,678,311,753	0	0	0	0	0	0	0
87	2015	3	1,812,706,796	0	0	0	0	0	0	0
88	2015	4	1,712,755,373	0	0	0	0	0	0	0
89	2015	5	1,922,994,066	0	385.44	0	0	0	0	0
90	2015	6	2,915,391,500	0	0	527.93	0	0	0	0
91	2015	7	3,547,834,281	0	0	0	629.6	0	0	0

Exhibit AM-3

Model Data for Residential Class

92	2015	8	3,796,200,369	0	0	0	0	563.96	0	0
93	2015	9	3,225,731,340	0	0	0	0	0	416.78	0
94	2015	10	2,655,398,062	0	0	0	0	0	0	258.08
95	2015	11	1,720,225,210	0	0	0	0	0	0	0
96	2015	12	1,824,206,151	0	0	0	0	0	0	0
97	2016	1	1,957,894,426	360.21	0	0	0	0	0	0
98	2016	2	1,666,890,991	0	0	0	0	0	0	0
99	2016	3	1,592,301,426	0	0	0	0	0	0	0
100	2016	4	1,673,816,058	0	0	0	0	0	0	0
101	2016	5	2,098,626,047	0	323.97	0	0	0	0	0
102	2016	6	2,894,429,549	0	0	531.87	0	0	0	0
103	2016	7	3,622,073,947	0	0	0	659.81	0	0	0
104	2016	8	4,002,593,990	0	0	0	0	713.28	0	0
105	2016	9	3,360,458,315	0	0	0	0	0	498.76	0
106	2016	10	2,799,571,327	0	0	0	0	0	0	317.77
107	2016	11	2,031,694,522	0	0	0	0	0	0	0
108	2016	12	1,807,075,135	0	0	0	0	0	0	0
109	2017	1	2,078,149,350	176.96	0	0	0	0	0	0
110	2017	2	1,546,938,362	0	0	0	0	0	0	0
111	2017	3	1,726,483,735	0	0	0	0	0	0	0
112	2017	4	1,766,829,751	0	0	0	0	0	0	0
113	2017	5	2,326,638,110	0	330.56	0	0	0	0	0
114	2017	6	3,045,578,357	0	0	454.7	0	0	0	0
115	2017	7	3,457,311,047	0	0	0	546.7	0	0	0
116	2017	8	3,934,023,385	0	0	0	0	411.31	0	0
117	2017	9	3,072,922,036	0	0	0	0	0	427.21	0
118	2017	10	2,954,107,704	0	0	0	0	0	0	381.03
119	2017	11	1,883,733,742	0	0	0	0	0	0	0
120	2017	12	1,763,859,615	0	0	0	0	0	0	0

Exhibit AM-3
Model Data for SVS Class

SVS Customer Class

Line No.	Year	Month	Sales	HDD_Jan	CDD_Jun	CDD_Jul	CDD_Aug	CDD_Sep
1	2008	1	95,850,067	374.14	0	0	0	0
2	2008	2	89,841,738	0	0	0	0	0
3	2008	3	81,857,659	0	0	0	0	0
4	2008	4	85,294,217	0	0	0	0	0
5	2008	5	81,891,304	0	0	0	0	0
6	2008	6	92,723,484	0	568.06	0	0	0
7	2008	7	100,374,466	0	0	583.28	0	0
8	2008	8	102,026,612	0	0	0	549.85	0
9	2008	9	100,102,924	0	0	0	0	399.42
10	2008	10	46,479,636	0	0	0	0	0
11	2008	11	107,752,521	0	0	0	0	0
12	2008	12	91,797,277	0	0	0	0	0
13	2009	1	99,883,361	322.69	0	0	0	0
14	2009	2	83,968,107	0	0	0	0	0
15	2009	3	79,360,635	0	0	0	0	0
16	2009	4	83,093,191	0	0	0	0	0
17	2009	5	85,758,460	0	0	0	0	0
18	2009	6	93,157,251	0	605.45	0	0	0
19	2009	7	106,484,820	0	0	652.64	0	0
20	2009	8	111,598,409	0	0	0	587.83	0
21	2009	9	108,874,254	0	0	0	0	408.15
22	2009	10	96,040,196	0	0	0	0	0
23	2009	11	87,208,050	0	0	0	0	0
24	2009	12	89,471,180	0	0	0	0	0
25	2010	1	105,292,920	526.62	0	0	0	0
26	2010	2	95,650,155	0	0	0	0	0
27	2010	3	92,349,912	0	0	0	0	0
28	2010	4	83,959,032	0	0	0	0	0
29	2010	5	80,770,655	0	0	0	0	0
30	2010	6	95,201,150	0	561.08	0	0	0
31	2010	7	100,010,450	0	0	586.27	0	0
32	2010	8	99,692,850	0	0	0	617.78	0
33	2010	9	102,329,734	0	0	0	0	432.47
34	2010	10	96,136,317	0	0	0	0	0
35	2010	11	84,997,126	0	0	0	0	0
36	2010	12	84,560,159	0	0	0	0	0
37	2011	1	92,845,477	504.55	0	0	0	0
38	2011	2	88,829,458	0	0	0	0	0
39	2011	3	80,674,274	0	0	0	0	0
40	2011	4	74,615,619	0	0	0	0	0
41	2011	5	80,578,872	0	0	0	0	0
42	2011	6	84,261,907	0	620.75	0	0	0
43	2011	7	91,973,457	0	0	660.88	0	0
44	2011	8	91,110,459	0	0	0	683.63	0

Exhibit AM-3
Model Data for SVS Class

45	2011	9	93,923,322	0	0	0	0	491.65
46	2011	10	85,621,328	0	0	0	0	0
47	2011	11	76,197,245	0	0	0	0	0
48	2011	12	76,450,711	0	0	0	0	0
49	2012	1	82,830,753	252.38	0	0	0	0
50	2012	2	71,457,856	0	0	0	0	0
51	2012	3	67,969,506	0	0	0	0	0
52	2012	4	68,255,041	0	0	0	0	0
53	2012	5	69,445,599	0	0	0	0	0
54	2012	6	73,356,712	0	541.71	0	0	0
55	2012	7	74,980,442	0	0	558.25	0	0
56	2012	8	74,093,616	0	0	0	595.57	0
57	2012	9	77,821,368	0	0	0	0	408.73
58	2012	10	74,625,017	0	0	0	0	0
59	2012	11	69,143,487	0	0	0	0	0
60	2012	12	71,461,702	0	0	0	0	0
61	2013	1	75,459,380	314.57	0	0	0	0
62	2013	2	70,527,988	0	0	0	0	0
63	2013	3	63,965,039	0	0	0	0	0
64	2013	4	65,431,016	0	0	0	0	0
65	2013	5	63,759,387	0	0	0	0	0
66	2013	6	70,550,121	0	580.8	0	0	0
67	2013	7	75,353,227	0	0	595.58	0	0
68	2013	8	75,706,579	0	0	0	583.87	0
69	2013	9	77,792,272	0	0	0	0	489.4
70	2013	10	77,089,394	0	0	0	0	0
71	2013	11	69,528,494	0	0	0	0	0
72	2013	12	71,235,334	0	0	0	0	0
73	2014	1	79,514,674	487.26	0	0	0	0
74	2014	2	70,527,988	0	0	0	0	0
75	2014	3	67,187,323	0	0	0	0	0
76	2014	4	63,473,354	0	0	0	0	0
77	2014	5	66,660,721	0	0	0	0	0
78	2014	6	68,388,935	0	515.87	0	0	0
79	2014	7	72,636,559	0	0	555.93	0	0
80	2014	8	74,528,802	0	0	0	580.44	0
81	2014	9	77,033,390	0	0	0	0	437.47
82	2014	10	74,327,062	0	0	0	0	0
83	2014	11	69,377,248	0	0	0	0	0
84	2014	12	71,570,199	0	0	0	0	0
85	2015	1	102,257,795	457.88	0	0	0	0
86	2015	2	65,733,432	0	0	0	0	0
87	2015	3	71,274,480	0	0	0	0	0
88	2015	4	68,051,425	0	0	0	0	0
89	2015	5	64,066,519	0	0	0	0	0
90	2015	6	76,449,489	0	527.93	0	0	0
91	2015	7	79,922,211	0	0	629.6	0	0

Exhibit AM-3
Model Data for SVS Class

92	2015	8	76,959,643	0	0	0	563.96	0
93	2015	9	76,788,865	0	0	0	0	416.78
94	2015	10	76,067,504	0	0	0	0	0
95	2015	11	63,581,167	0	0	0	0	0
96	2015	12	75,169,931	0	0	0	0	0
97	2016	1	73,434,713	360.21	0	0	0	0
98	2016	2	67,984,660	0	0	0	0	0
99	2016	3	70,366,063	0	0	0	0	0
100	2016	4	69,189,789	0	0	0	0	0
101	2016	5	68,957,321	0	0	0	0	0
102	2016	6	79,589,603	0	531.87	0	0	0
103	2016	7	77,952,326	0	0	659.81	0	0
104	2016	8	87,789,221	0	0	0	713.28	0
105	2016	9	81,712,085	0	0	0	0	498.76
106	2016	10	77,617,088	0	0	0	0	0
107	2016	11	71,384,147	0	0	0	0	0
108	2016	12	74,546,389	0	0	0	0	0
109	2017	1	79,252,789	176.96	0	0	0	0
110	2017	2	62,400,336	0	0	0	0	0
111	2017	3	78,461,611	0	0	0	0	0
112	2017	4	64,915,263	0	0	0	0	0
113	2017	5	76,284,157	0	0	0	0	0
114	2017	6	81,628,981	0	454.7	0	0	0
115	2017	7	79,096,056	0	0	546.7	0	0
116	2017	8	90,679,158	0	0	0	411.31	0
117	2017	9	77,285,058	0	0	0	0	427.21
118	2017	10	82,718,257	0	0	0	0	0
119	2017	11	70,832,128	0	0	0	0	0
120	2017	12	72,205,990	0	0	0	0	0

Exhibit AM-3
Model Data for SVL AMS Class

SVL AMS Customer Class

Line No.	Year	Month	Sales	HDD_Jan	CDD_May	CDD_Jun	CDD_Jul	CDD_Aug	CDD_Sep	CDD_Oct
1	2008	1	1,244,685,451	374.14	0	0	0	0	0	0
2	2008	2	1,146,899,222	0	0	0	0	0	0	0
3	2008	3	1,105,795,870	0	0	0	0	0	0	0
4	2008	4	1,213,838,567	0	0	0	0	0	0	0
5	2008	5	1,234,089,127	0	406.65	0	0	0	0	0
6	2008	6	1,443,460,377	0	0	568.06	0	0	0	0
7	2008	7	1,550,319,811	0	0	0	583.28	0	0	0
8	2008	8	1,561,356,236	0	0	0	0	549.85	0	0
9	2008	9	1,537,665,890	0	0	0	0	0	399.42	0
10	2008	10	660,377,426	0	0	0	0	0	0	183.1
11	2008	11	1,365,523,110	0	0	0	0	0	0	0
12	2008	12	1,301,843,247	0	0	0	0	0	0	0
13	2009	1	1,407,477,214	322.69	0	0	0	0	0	0
14	2009	2	1,108,543,306	0	0	0	0	0	0	0
15	2009	3	1,094,623,833	0	0	0	0	0	0	0
16	2009	4	1,127,040,724	0	0	0	0	0	0	0
17	2009	5	1,219,627,045	0	396.02	0	0	0	0	0
18	2009	6	1,389,315,405	0	0	605.45	0	0	0	0
19	2009	7	1,539,918,586	0	0	0	652.64	0	0	0
20	2009	8	1,586,733,987	0	0	0	0	587.83	0	0
21	2009	9	1,601,633,170	0	0	0	0	0	408.15	0
22	2009	10	1,392,047,042	0	0	0	0	0	0	218.16
23	2009	11	1,242,567,250	0	0	0	0	0	0	0
24	2009	12	1,160,522,747	0	0	0	0	0	0	0
25	2010	1	1,273,046,075	526.62	0	0	0	0	0	0
26	2010	2	1,155,706,171	0	0	0	0	0	0	0
27	2010	3	1,176,504,798	0	0	0	0	0	0	0
28	2010	4	1,126,536,947	0	0	0	0	0	0	0
29	2010	5	1,170,014,231	0	422.36	0	0	0	0	0
30	2010	6	1,444,065,873	0	0	561.08	0	0	0	0
31	2010	7	1,534,105,561	0	0	0	586.27	0	0	0
32	2010	8	1,532,753,728	0	0	0	0	617.78	0	0
33	2010	9	1,596,814,091	0	0	0	0	0	432.47	0
34	2010	10	1,466,907,291	0	0	0	0	0	0	223.45
35	2010	11	1,266,647,793	0	0	0	0	0	0	0
36	2010	12	1,201,212,945	0	0	0	0	0	0	0
37	2011	1	1,236,537,515	504.55	0	0	0	0	0	0
38	2011	2	1,175,273,679	0	0	0	0	0	0	0
39	2011	3	1,191,679,032	0	0	0	0	0	0	0
40	2011	4	1,177,040,673	0	0	0	0	0	0	0
41	2011	5	1,344,231,349	0	440.91	0	0	0	0	0
42	2011	6	1,471,300,369	0	0	620.75	0	0	0	0
43	2011	7	1,642,609,617	0	0	0	660.88	0	0	0
44	2011	8	1,654,208,601	0	0	0	0	683.63	0	0

Exhibit AM-3
Model Data for SVL AMS Class

45	2011	9	1,723,133,788	0	0	0	0	0	491.65	0
46	2011	10	1,546,786,666	0	0	0	0	0	0	232.45
47	2011	11	1,306,305,073	0	0	0	0	0	0	0
48	2011	12	1,250,603,835	0	0	0	0	0	0	0
49	2012	1	1,286,314,926	252.38	0	0	0	0	0	0
50	2012	2	1,168,288,588	0	0	0	0	0	0	0
51	2012	3	1,157,817,294	0	0	0	0	0	0	0
52	2012	4	1,248,956,744	0	0	0	0	0	0	0
53	2012	5	1,347,570,909	0	411.71	0	0	0	0	0
54	2012	6	1,503,962,637	0	0	541.71	0	0	0	0
55	2012	7	1,611,048,392	0	0	0	558.25	0	0	0
56	2012	8	1,600,252,514	0	0	0	0	595.57	0	0
57	2012	9	1,678,609,139	0	0	0	0	0	408.73	0
58	2012	10	1,539,253,132	0	0	0	0	0	0	227.67
59	2012	11	1,339,381,977	0	0	0	0	0	0	0
60	2012	12	1,273,889,789	0	0	0	0	0	0	0
61	2013	1	1,311,968,135	314.57	0	0	0	0	0	0
62	2013	2	1,240,982,880	0	0	0	0	0	0	0
63	2013	3	1,144,263,371	0	0	0	0	0	0	0
64	2013	4	1,209,561,192	0	0	0	0	0	0	0
65	2013	5	1,235,392,145	0	348.46	0	0	0	0	0
66	2013	6	1,470,685,477	0	0	580.8	0	0	0	0
67	2013	7	1,666,112,372	0	0	0	595.58	0	0	0
68	2013	8	1,658,539,070	0	0	0	0	583.87	0	0
69	2013	9	1,699,355,964	0	0	0	0	0	489.4	0
70	2013	10	1,615,613,751	0	0	0	0	0	0	200.86
71	2013	11	1,336,974,546	0	0	0	0	0	0	0
72	2013	12	1,303,569,482	0	0	0	0	0	0	0
73	2014	1	1,428,004,665	487.26	0	0	0	0	0	0
74	2014	2	1,315,201,208	0	0	0	0	0	0	0
75	2014	3	1,285,867,851	0	0	0	0	0	0	0
76	2014	4	1,200,201,020	0	0	0	0	0	0	0
77	2014	5	1,329,922,606	0	339.54	0	0	0	0	0
78	2014	6	1,465,191,574	0	0	515.87	0	0	0	0
79	2014	7	1,630,346,345	0	0	0	555.93	0	0	0
80	2014	8	1,670,976,160	0	0	0	0	580.44	0	0
81	2014	9	1,730,318,549	0	0	0	0	0	437.47	0
82	2014	10	1,582,505,388	0	0	0	0	0	0	222.19
83	2014	11	1,381,532,135	0	0	0	0	0	0	0
84	2014	12	1,307,045,691	0	0	0	0	0	0	0
85	2015	1	1,829,979,709	457.88	0	0	0	0	0	0
86	2015	2	1,216,431,121	0	0	0	0	0	0	0
87	2015	3	1,342,777,894	0	0	0	0	0	0	0
88	2015	4	1,315,669,633	0	0	0	0	0	0	0
89	2015	5	1,306,042,657	0	385.44	0	0	0	0	0
90	2015	6	1,633,265,112	0	0	527.93	0	0	0	0
91	2015	7	1,764,823,003	0	0	0	629.6	0	0	0

Exhibit AM-3
Model Data for SVL AMS Class

92	2015	8	1,777,892,049	0	0	0	0	563.96	0	0
93	2015	9	1,689,515,175	0	0	0	0	0	416.78	0
94	2015	10	1,599,220,226	0	0	0	0	0	0	258.08
95	2015	11	1,218,557,188	0	0	0	0	0	0	0
96	2015	12	1,331,346,985	0	0	0	0	0	0	0
97	2016	1	1,288,141,727	360.21	0	0	0	0	0	0
98	2016	2	1,220,550,099	0	0	0	0	0	0	0
99	2016	3	1,277,743,791	0	0	0	0	0	0	0
100	2016	4	1,286,140,083	0	0	0	0	0	0	0
101	2016	5	1,358,604,622	0	323.97	0	0	0	0	0
102	2016	6	1,616,513,040	0	0	531.87	0	0	0	0
103	2016	7	1,699,242,956	0	0	0	659.81	0	0	0
104	2016	8	1,905,240,200	0	0	0	0	713.28	0	0
105	2016	9	1,710,951,531	0	0	0	0	0	498.76	0
106	2016	10	1,568,729,300	0	0	0	0	0	0	317.77
107	2016	11	1,336,731,146	0	0	0	0	0	0	0
108	2016	12	1,292,335,067	0	0	0	0	0	0	0
109	2017	1	1,375,709,405	176.96	0	0	0	0	0	0
110	2017	2	1,162,924,930	0	0	0	0	0	0	0
111	2017	3	1,338,650,090	0	0	0	0	0	0	0
112	2017	4	1,228,004,142	0	0	0	0	0	0	0
113	2017	5	1,500,258,310	0	330.56	0	0	0	0	0
114	2017	6	1,648,511,337	0	0	454.7	0	0	0	0
115	2017	7	1,665,094,988	0	0	0	546.7	0	0	0
116	2017	8	1,894,178,973	0	0	0	0	411.31	0	0
117	2017	9	1,520,723,583	0	0	0	0	0	427.21	0
118	2017	10	1,664,734,445	0	0	0	0	0	0	381.03
119	2017	11	1,288,940,897	0	0	0	0	0	0	0
120	2017	12	1,250,512,567	0	0	0	0	0	0	0

Exhibit AM-3
Model Data for SVL IDR Class

SVL IDR Customer Class

Line No.	Year	Month	Sales	CDD_Jun	CDD_Jul	CDD_Aug	CDD_Sep	CDD_Oct
1	2008	1	987,037,923	0	0	0	0	0
2	2008	2	1,022,756,996	0	0	0	0	0
3	2008	3	992,558,250	0	0	0	0	0
4	2008	4	1,019,060,794	0	0	0	0	0
5	2008	5	1,066,103,855	0	0	0	0	0
6	2008	6	1,175,777,111	568.53	0	0	0	0
7	2008	7	1,206,076,560	0	591.43	0	0	0
8	2008	8	1,247,298,320	0	0	546.38	0	0
9	2008	9	1,220,163,501	0	0	0	358.51	0
10	2008	10	933,253,576	0	0	0	0	133.56
11	2008	11	1,197,274,022	0	0	0	0	0
12	2008	12	984,940,248	0	0	0	0	0
13	2009	1	1,025,599,187	0	0	0	0	0
14	2009	2	973,653,783	0	0	0	0	0
15	2009	3	972,037,554	0	0	0	0	0
16	2009	4	986,766,729	0	0	0	0	0
17	2009	5	1,059,567,902	0	0	0	0	0
18	2009	6	1,134,489,048	633.21	0	0	0	0
19	2009	7	1,194,635,806	0	657.95	0	0	0
20	2009	8	1,251,771,711	0	0	566.12	0	0
21	2009	9	1,208,001,928	0	0	0	373.96	0
22	2009	10	1,184,575,852	0	0	0	0	153.85
23	2009	11	1,062,728,757	0	0	0	0	0
24	2009	12	1,009,647,759	0	0	0	0	0
25	2010	1	1,013,401,368	0	0	0	0	0
26	2010	2	957,058,186	0	0	0	0	0
27	2010	3	958,554,667	0	0	0	0	0
28	2010	4	1,057,075,962	0	0	0	0	0
29	2010	5	1,039,275,281	0	0	0	0	0
30	2010	6	1,164,051,176	566.82	0	0	0	0
31	2010	7	1,242,387,352	0	602.6	0	0	0
32	2010	8	1,215,624,985	0	0	601.41	0	0
33	2010	9	1,297,844,273	0	0	0	384.34	0
34	2010	10	1,208,918,740	0	0	0	0	203.08
35	2010	11	1,071,601,466	0	0	0	0	0
36	2010	12	1,039,326,152	0	0	0	0	0
37	2011	1	1,024,233,209	0	0	0	0	0
38	2011	2	990,349,278	0	0	0	0	0
39	2011	3	987,912,894	0	0	0	0	0
40	2011	4	1,101,104,783	0	0	0	0	0
41	2011	5	1,122,054,676	0	0	0	0	0
42	2011	6	1,204,051,499	628.16	0	0	0	0
43	2011	7	1,309,453,795	0	693.07	0	0	0
44	2011	8	1,225,605,083	0	0	662.13	0	0

Exhibit AM-3
Model Data for SVL IDR Class

45	2011	9	1,346,623,545	0	0	0	454.43	0
46	2011	10	1,264,167,662	0	0	0	0	200.76
47	2011	11	1,103,712,813	0	0	0	0	0
48	2011	12	1,074,339,757	0	0	0	0	0
49	2012	1	1,042,715,113	0	0	0	0	0
50	2012	2	1,021,859,606	0	0	0	0	0
51	2012	3	1,034,444,583	0	0	0	0	0
52	2012	4	1,131,402,936	0	0	0	0	0
53	2012	5	1,112,877,861	0	0	0	0	0
54	2012	6	1,248,157,844	556.88	0	0	0	0
55	2012	7	1,251,093,814	0	575.55	0	0	0
56	2012	8	1,237,963,836	0	0	574.32	0	0
57	2012	9	1,359,271,739	0	0	0	369.2	0
58	2012	10	1,175,228,533	0	0	0	0	194.54
59	2012	11	1,191,289,094	0	0	0	0	0
60	2012	12	1,106,140,576	0	0	0	0	0
61	2013	1	1,036,115,159	0	0	0	0	0
62	2013	2	1,067,504,081	0	0	0	0	0
63	2013	3	1,005,801,297	0	0	0	0	0
64	2013	4	1,054,110,042	0	0	0	0	0
65	2013	5	1,154,419,447	0	0	0	0	0
66	2013	6	1,211,895,396	591.69	0	0	0	0
67	2013	7	1,264,369,680	0	599.36	0	0	0
68	2013	8	1,310,567,352	0	0	585.32	0	0
69	2013	9	1,318,875,994	0	0	0	440.04	0
70	2013	10	1,258,738,974	0	0	0	0	148.7
71	2013	11	1,160,946,566	0	0	0	0	0
72	2013	12	1,066,176,380	0	0	0	0	0
73	2014	1	1,088,618,661	0	0	0	0	0
74	2014	2	1,087,478,884	0	0	0	0	0
75	2014	3	1,029,463,084	0	0	0	0	0
76	2014	4	1,045,698,306	0	0	0	0	0
77	2014	5	1,148,791,558	0	0	0	0	0
78	2014	6	1,196,757,322	525.52	0	0	0	0
79	2014	7	1,261,841,249	0	567.43	0	0	0
80	2014	8	1,327,257,278	0	0	578.26	0	0
81	2014	9	1,334,387,619	0	0	0	409.17	0
82	2014	10	1,254,715,258	0	0	0	0	179.48
83	2014	11	1,230,685,380	0	0	0	0	0
84	2014	12	1,034,180,690	0	0	0	0	0
85	2015	1	1,415,755,586	0	0	0	0	0
86	2015	2	1,044,467,371	0	0	0	0	0
87	2015	3	1,089,089,585	0	0	0	0	0
88	2015	4	1,152,112,104	0	0	0	0	0
89	2015	5	1,124,236,653	0	0	0	0	0
90	2015	6	1,253,891,724	540.44	0	0	0	0
91	2015	7	1,339,890,781	0	654.54	0	0	0

Exhibit AM-3
Model Data for SVL IDR Class

92	2015	8	1,317,630,236	0	0	548.24	0	0
93	2015	9	1,325,950,914	0	0	0	393.21	0
94	2015	10	1,245,165,579	0	0	0	0	214.86
95	2015	11	1,056,607,942	0	0	0	0	0
96	2015	12	1,163,864,539	0	0	0	0	0
97	2016	1	1,078,712,996	0	0	0	0	0
98	2016	2	1,006,870,491	0	0	0	0	0
99	2016	3	1,043,672,141	0	0	0	0	0
100	2016	4	1,133,797,466	0	0	0	0	0
101	2016	5	1,123,748,282	0	0	0	0	0
102	2016	6	1,293,013,853	588.63	0	0	0	0
103	2016	7	1,306,814,893	0	628.98	0	0	0
104	2016	8	1,266,946,682	0	0	516.61	0	0
105	2016	9	1,369,894,682	0	0	0	458.56	0
106	2016	10	1,283,873,192	0	0	0	0	268.19
107	2016	11	1,183,618,364	0	0	0	0	0
108	2016	12	1,077,466,365	0	0	0	0	0
109	2017	1	1,122,405,053	0	0	0	0	0
110	2017	2	1,053,652,906	0	0	0	0	0
111	2017	3	1,060,581,783	0	0	0	0	0
112	2017	4	1,174,646,308	0	0	0	0	0
113	2017	5	1,147,027,190	0	0	0	0	0
114	2017	6	1,304,146,089	593.25	0	0	0	0
115	2017	7	1,302,788,739	0	639	0	0	0
116	2017	8	1,115,257,063	0	0	534.88	0	0
117	2017	9	1,461,683,802	0	0	0	472.32	0
118	2017	10	1,246,292,771	0	0	0	0	234.53
119	2017	11	1,130,577,382	0	0	0	0	0
120	2017	12	1,053,223,155	0	0	0	0	0

Exhibit AM-3
Model Data for PVS AMS Class

PVS AMS Customer Class

Line No.	Year	Month	Sales	HDD_Jan	CDD_Jun	CDD_Jul	CDD_Aug	CDD_Sep	CDD_Oct
1	2008	1	24,175,758	374.14	0	0	0	0	0
2	2008	2	22,753,013	0	0	0	0	0	0
3	2008	3	24,617,801	0	0	0	0	0	0
4	2008	4	18,837,712	0	0	0	0	0	0
5	2008	5	19,091,112	0	0	0	0	0	0
6	2008	6	24,168,515	0	568.06	0	0	0	0
7	2008	7	26,356,775	0	0	583.28	0	0	0
8	2008	8	25,766,868	0	0	0	549.85	0	0
9	2008	9	24,525,160	0	0	0	0	399.42	0
10	2008	10	10,195,012	0	0	0	0	0	183.1
11	2008	11	17,172,870	0	0	0	0	0	0
12	2008	12	19,372,026	0	0	0	0	0	0
13	2009	1	19,425,105	322.69	0	0	0	0	0
14	2009	2	17,144,066	0	0	0	0	0	0
15	2009	3	14,195,407	0	0	0	0	0	0
16	2009	4	15,871,186	0	0	0	0	0	0
17	2009	5	15,716,711	0	0	0	0	0	0
18	2009	6	18,514,079	0	605.45	0	0	0	0
19	2009	7	24,464,263	0	0	652.64	0	0	0
20	2009	8	21,613,942	0	0	0	587.83	0	0
21	2009	9	21,457,947	0	0	0	0	408.15	0
22	2009	10	19,165,194	0	0	0	0	0	218.16
23	2009	11	14,677,247	0	0	0	0	0	0
24	2009	12	20,884,461	0	0	0	0	0	0
25	2010	1	19,724,381	526.62	0	0	0	0	0
26	2010	2	16,925,106	0	0	0	0	0	0
27	2010	3	16,043,153	0	0	0	0	0	0
28	2010	4	14,695,809	0	0	0	0	0	0
29	2010	5	18,111,006	0	0	0	0	0	0
30	2010	6	18,379,549	0	561.08	0	0	0	0
31	2010	7	20,401,266	0	0	586.27	0	0	0
32	2010	8	20,378,061	0	0	0	617.78	0	0
33	2010	9	21,637,777	0	0	0	0	432.47	0
34	2010	10	19,710,999	0	0	0	0	0	223.45
35	2010	11	17,697,353	0	0	0	0	0	0
36	2010	12	16,266,372	0	0	0	0	0	0
37	2011	1	15,648,247	504.55	0	0	0	0	0
38	2011	2	15,610,620	0	0	0	0	0	0
39	2011	3	16,382,393	0	0	0	0	0	0
40	2011	4	15,002,346	0	0	0	0	0	0
41	2011	5	18,161,498	0	0	0	0	0	0
42	2011	6	19,098,392	0	620.75	0	0	0	0
43	2011	7	22,272,824	0	0	660.88	0	0	0
44	2011	8	22,133,345	0	0	0	683.63	0	0

Exhibit AM-3
Model Data for PVS AMS Class

45	2011	9	23,522,958	0	0	0	0	491.65	0
46	2011	10	20,555,858	0	0	0	0	0	232.45
47	2011	11	17,136,460	0	0	0	0	0	0
48	2011	12	17,488,456	0	0	0	0	0	0
49	2012	1	19,103,211	252.38	0	0	0	0	0
50	2012	2	20,697,109	0	0	0	0	0	0
51	2012	3	20,298,326	0	0	0	0	0	0
52	2012	4	17,687,148	0	0	0	0	0	0
53	2012	5	18,563,184	0	0	0	0	0	0
54	2012	6	20,750,859	0	541.71	0	0	0	0
55	2012	7	21,244,194	0	0	558.25	0	0	0
56	2012	8	22,013,547	0	0	0	595.57	0	0
57	2012	9	22,106,837	0	0	0	0	408.73	0
58	2012	10	19,840,754	0	0	0	0	0	227.67
59	2012	11	16,715,027	0	0	0	0	0	0
60	2012	12	15,811,250	0	0	0	0	0	0
61	2013	1	17,040,437	314.57	0	0	0	0	0
62	2013	2	16,384,204	0	0	0	0	0	0
63	2013	3	14,730,815	0	0	0	0	0	0
64	2013	4	15,307,975	0	0	0	0	0	0
65	2013	5	15,570,813	0	0	0	0	0	0
66	2013	6	19,396,103	0	580.8	0	0	0	0
67	2013	7	22,053,595	0	0	595.58	0	0	0
68	2013	8	22,902,562	0	0	0	583.87	0	0
69	2013	9	23,600,400	0	0	0	0	489.4	0
70	2013	10	24,891,620	0	0	0	0	0	200.86
71	2013	11	20,043,267	0	0	0	0	0	0
72	2013	12	17,116,341	0	0	0	0	0	0
73	2014	1	21,251,085	487.26	0	0	0	0	0
74	2014	2	21,254,414	0	0	0	0	0	0
75	2014	3	26,337,247	0	0	0	0	0	0
76	2014	4	17,826,895	0	0	0	0	0	0
77	2014	5	17,278,380	0	0	0	0	0	0
78	2014	6	20,015,176	0	515.87	0	0	0	0
79	2014	7	23,345,062	0	0	555.93	0	0	0
80	2014	8	24,345,673	0	0	0	580.44	0	0
81	2014	9	24,144,670	0	0	0	0	437.47	0
82	2014	10	20,729,680	0	0	0	0	0	222.19
83	2014	11	17,363,008	0	0	0	0	0	0
84	2014	12	15,847,041	0	0	0	0	0	0
85	2015	1	25,479,894	457.88	0	0	0	0	0
86	2015	2	15,975,037	0	0	0	0	0	0
87	2015	3	16,913,049	0	0	0	0	0	0
88	2015	4	16,689,403	0	0	0	0	0	0
89	2015	5	18,278,206	0	0	0	0	0	0
90	2015	6	20,509,701	0	527.93	0	0	0	0
91	2015	7	25,063,543	0	0	629.6	0	0	0

Exhibit AM-3
Model Data for PVS AMS Class

92	2015	8	23,800,382	0	0	0	563.96	0	0
93	2015	9	21,049,312	0	0	0	0	416.78	0
94	2015	10	19,778,593	0	0	0	0	0	258.08
95	2015	11	15,672,710	0	0	0	0	0	0
96	2015	12	17,272,259	0	0	0	0	0	0
97	2016	1	16,977,110	360.21	0	0	0	0	0
98	2016	2	15,290,429	0	0	0	0	0	0
99	2016	3	15,369,888	0	0	0	0	0	0
100	2016	4	15,667,903	0	0	0	0	0	0
101	2016	5	16,534,883	0	0	0	0	0	0
102	2016	6	20,839,112	0	531.87	0	0	0	0
103	2016	7	25,222,574	0	0	659.81	0	0	0
104	2016	8	31,155,787	0	0	0	713.28	0	0
105	2016	9	27,492,235	0	0	0	0	498.76	0
106	2016	10	24,565,654	0	0	0	0	0	317.77
107	2016	11	21,394,385	0	0	0	0	0	0
108	2016	12	19,795,427	0	0	0	0	0	0
109	2017	1	21,979,216	176.96	0	0	0	0	0
110	2017	2	21,083,212	0	0	0	0	0	0
111	2017	3	29,356,995	0	0	0	0	0	0
112	2017	4	33,385,300	0	0	0	0	0	0
113	2017	5	23,059,725	0	0	0	0	0	0
114	2017	6	27,867,611	0	454.7	0	0	0	0
115	2017	7	26,484,390	0	0	546.7	0	0	0
116	2017	8	30,833,590	0	0	0	411.31	0	0
117	2017	9	24,103,924	0	0	0	0	427.21	0
118	2017	10	24,216,431	0	0	0	0	0	381.03
119	2017	11	20,039,149	0	0	0	0	0	0
120	2017	12	19,453,293	0	0	0	0	0	0
			24,107,131						
			20,436,035						
			19,306,326						
			20,728,274						
			22,054,650						
			27,686,293						
			28,488,783						
			32,515,909						
			26,966,410						
			28,154,370						
			22,876,891						
			20,751,719						

Exhibit AM-3
Model Data for PVS IDR Class

PVS IDR Customer Class

Line No.	Year	Month	Sales	CDD_Jun	CDD_Jul	CDD_Aug	CDD_Sep	CDD_Oct
1	2008	1	254,422,081	0	0	0	0	0
2	2008	2	263,910,260	0	0	0	0	0
3	2008	3	261,281,368	0	0	0	0	0
4	2008	4	281,026,378	0	0	0	0	0
5	2008	5	287,119,472	0	0	0	0	0
6	2008	6	312,248,362	568.53	0	0	0	0
7	2008	7	327,557,522	0	591.43	0	0	0
8	2008	8	323,858,162	0	0	546.38	0	0
9	2008	9	343,821,882	0	0	0	358.51	0
10	2008	10	242,897,388	0	0	0	0	133.56
11	2008	11	293,647,565	0	0	0	0	0
12	2008	12	252,389,779	0	0	0	0	0
13	2009	1	263,297,393	0	0	0	0	0
14	2009	2	241,281,892	0	0	0	0	0
15	2009	3	246,028,788	0	0	0	0	0
16	2009	4	249,442,866	0	0	0	0	0
17	2009	5	258,728,902	0	0	0	0	0
18	2009	6	281,161,003	633.21	0	0	0	0
19	2009	7	299,997,369	0	657.95	0	0	0
20	2009	8	327,675,527	0	0	566.12	0	0
21	2009	9	304,128,164	0	0	0	373.96	0
22	2009	10	296,535,585	0	0	0	0	153.85
23	2009	11	267,991,882	0	0	0	0	0
24	2009	12	253,889,417	0	0	0	0	0
25	2010	1	255,421,274	0	0	0	0	0
26	2010	2	245,968,570	0	0	0	0	0
27	2010	3	249,776,190	0	0	0	0	0
28	2010	4	270,290,763	0	0	0	0	0
29	2010	5	264,538,253	0	0	0	0	0
30	2010	6	299,034,042	566.82	0	0	0	0
31	2010	7	319,944,440	0	602.6	0	0	0
32	2010	8	320,289,053	0	0	601.41	0	0
33	2010	9	334,354,342	0	0	0	384.34	0
34	2010	10	307,812,427	0	0	0	0	203.08
35	2010	11	270,838,062	0	0	0	0	0
36	2010	12	262,469,162	0	0	0	0	0
37	2011	1	261,381,141	0	0	0	0	0
38	2011	2	260,588,961	0	0	0	0	0
39	2011	3	252,708,165	0	0	0	0	0
40	2011	4	281,628,958	0	0	0	0	0
41	2011	5	285,968,518	0	0	0	0	0
42	2011	6	303,862,526	628.16	0	0	0	0
43	2011	7	318,810,571	0	693.07	0	0	0
44	2011	8	311,562,416	0	0	662.13	0	0

Exhibit AM-3
Model Data for PVS IDR Class

45	2011	9	334,530,461	0	0	0	454.43	0
46	2011	10	313,505,089	0	0	0	0	200.76
47	2011	11	280,557,929	0	0	0	0	0
48	2011	12	268,489,924	0	0	0	0	0
49	2012	1	260,609,451	0	0	0	0	0
50	2012	2	258,038,014	0	0	0	0	0
51	2012	3	258,071,394	0	0	0	0	0
52	2012	4	289,523,010	0	0	0	0	0
53	2012	5	284,118,716	0	0	0	0	0
54	2012	6	308,570,161	556.88	0	0	0	0
55	2012	7	320,465,741	0	575.55	0	0	0
56	2012	8	315,380,733	0	0	574.32	0	0
57	2012	9	334,222,556	0	0	0	369.2	0
58	2012	10	294,853,031	0	0	0	0	194.54
59	2012	11	299,561,749	0	0	0	0	0
60	2012	12	271,863,820	0	0	0	0	0
61	2013	1	258,472,357	0	0	0	0	0
62	2013	2	262,178,802	0	0	0	0	0
63	2013	3	253,880,368	0	0	0	0	0
64	2013	4	268,403,863	0	0	0	0	0
65	2013	5	292,356,882	0	0	0	0	0
66	2013	6	302,929,945	591.69	0	0	0	0
67	2013	7	319,232,861	0	599.36	0	0	0
68	2013	8	336,659,812	0	0	585.32	0	0
69	2013	9	336,867,001	0	0	0	440.04	0
70	2013	10	318,926,083	0	0	0	0	148.7
71	2013	11	299,804,098	0	0	0	0	0
72	2013	12	277,219,266	0	0	0	0	0
73	2014	1	276,587,662	0	0	0	0	0
74	2014	2	288,559,072	0	0	0	0	0
75	2014	3	273,744,543	0	0	0	0	0
76	2014	4	287,793,802	0	0	0	0	0
77	2014	5	306,143,858	0	0	0	0	0
78	2014	6	322,555,281	525.52	0	0	0	0
79	2014	7	339,453,175	0	567.43	0	0	0
80	2014	8	346,353,153	0	0	578.26	0	0
81	2014	9	356,913,117	0	0	0	409.17	0
82	2014	10	340,689,291	0	0	0	0	179.48
83	2014	11	331,840,910	0	0	0	0	0
84	2014	12	288,213,001	0	0	0	0	0
85	2015	1	410,085,996	0	0	0	0	0
86	2015	2	266,710,969	0	0	0	0	0
87	2015	3	294,156,520	0	0	0	0	0
88	2015	4	297,320,443	0	0	0	0	0
89	2015	5	282,284,169	0	0	0	0	0
90	2015	6	312,078,873	540.44	0	0	0	0
91	2015	7	347,548,770	0	654.54	0	0	0

Exhibit AM-3
Model Data for PVS IDR Class

92	2015	8	334,645,335	0	0	548.24	0	0
93	2015	9	334,586,578	0	0	0	393.21	0
94	2015	10	309,266,337	0	0	0	0	214.86
95	2015	11	255,265,221	0	0	0	0	0
96	2015	12	306,415,097	0	0	0	0	0
97	2016	1	264,175,057	0	0	0	0	0
98	2016	2	263,433,636	0	0	0	0	0
99	2016	3	263,076,794	0	0	0	0	0
100	2016	4	290,881,729	0	0	0	0	0
101	2016	5	283,738,130	0	0	0	0	0
102	2016	6	326,256,150	588.63	0	0	0	0
103	2016	7	329,102,976	0	628.98	0	0	0
104	2016	8	315,452,636	0	0	516.61	0	0
105	2016	9	343,315,019	0	0	0	458.56	0
106	2016	10	318,115,766	0	0	0	0	268.19
107	2016	11	304,779,302	0	0	0	0	0
108	2016	12	276,364,750	0	0	0	0	0
109	2017	1	277,798,383	0	0	0	0	0
110	2017	2	273,856,839	0	0	0	0	0
111	2017	3	284,711,734	0	0	0	0	0
112	2017	4	305,620,101	0	0	0	0	0
113	2017	5	302,173,314	0	0	0	0	0
114	2017	6	343,149,871	593.25	0	0	0	0
115	2017	7	338,570,111	0	639	0	0	0
116	2017	8	275,944,995	0	0	534.88	0	0
117	2017	9	380,207,671	0	0	0	472.32	0
118	2017	10	323,746,107	0	0	0	0	234.53
119	2017	11	300,789,169	0	0	0	0	0
120	2017	12	274,332,998	0	0	0	0	0
			331,048,287					
			256,781,906					
			304,529,372					
			322,314,960					
			342,338,500					
			357,828,989					
			367,700,549					
			373,364,503					
			316,477,371					
			357,084,253					
			284,342,343					
			270,178,825					

Exhibit AM-4
Statistical Output for Residential Class

Residential Model

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:15
Sample: 2008M01 2017M12
Included observations: 120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.69E+09	37699150	44.77663	0
HDD_JAN	859013.3	236659.4	3.629746	0.0004
CDD_MAY	366043.3	244590.9	1.496553	0.1373
CDD_JUN	1633783	169382.9	9.6455	0
CDD_JUL	2670666	154921.1	17.23888	0
CDD_AUG	2942372	157540.9	18.67687	0
CDD_SEP	3670627	211578.1	17.3488	0
CDD_OCT	3700626	368927.7	10.03076	0

R-squared	0.874833	Mean dependent va	2.29E+09
Adjusted R-squared	0.86701	S.D. dependent var	7.44E+08
S.E. of regression	2.71E+08	Akaike info criterion	41.7386
Sum squared resid	8.23E+18	Schwarz criterion	41.92443
Log likelihood	-2496.32	Hannan-Quinn criter	41.81406
F-statistic	111.8289	Durbin-Watson stat	1.414476
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for Residential Class

Residential Model with Autoregressive Term

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:16
Sample (adjusted): 2008M02 2017M12
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.84E+08	1.27E+08	7.724136	0
HDD_JAN	1214256	222369.3	5.460539	0
CDD_MAY	769275.2	226705.1	3.393286	0.001
CDD_JUN	1727927	150122.3	11.51013	0
CDD_JUL	2295922	151238.6	15.18079	0
CDD_AUG	2148177	195939.1	10.96349	0
CDD_SEP	2470545	280061.1	8.821451	0
CDD_OCT	1872269	454993.3	4.114938	0.0001
SALES(-1)	0.357225	0.062284	5.735389	0

R-squared	0.904161	Mean dependent va	2.30E+09
Adjusted R-squared	0.897191	S.D. dependent var	7.45E+08
S.E. of regression	2.39E+08	Akaike info criterion	41.49316
Sum squared resid	6.28E+18	Schwarz criterion	41.70335
Log likelihood	-2459.84	Hannan-Quinn criter	41.57851
F-statistic	129.7195	Durbin-Watson stat	2.276012
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for SVS Class

SVS Model

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:22
Sample: 2008M01 2017M12
Included observations: 120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	75934450	1291830	58.78051	0
HDD_JAN	35070.94	9310.686	3.766741	0.0003
CDD_JUN	10584.94	6654.64	1.590611	0.1145
CDD_JUL	16910.11	6086.249	2.778412	0.0064
CDD_AUG	20825.09	6190.602	3.363984	0.001
CDD_SEP	25198.23	8312.364	3.031415	0.003

R-squared	0.217068	Mean dependent va	80321614
Adjusted R-squared	0.182729	S.D. dependent var	12051391
S.E. of regression	10894825	Akaike info criterion	35.29418
Sum squared resid	1.35E+16	Schwarz criterion	35.43356
Log likelihood	-2111.65	Hannan-Quinn criter	35.35078
F-statistic	6.321305	Durbin-Watson stat	0.838166
Prob(F-statistic)	0.000032		

Exhibit AM-4
Statistical Output for SVS Class

SVS Model with Autoregressive Term

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:23
Sample (adjusted): 2008M02 2017M12
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	32531905	5681313	5.726124	0
HDD_JAN	33759.63	7875.383	4.286729	0
CDD_JUN	15835.68	5443.169	2.909275	0.0044
CDD_JUL	14821.72	4947.402	2.995859	0.0034
CDD_AUG	14776.87	5084.905	2.906027	0.0044
CDD_SEP	14421.58	6888.413	2.093599	0.0386
SALES(-1)	0.54664	0.07034	7.771445	0

R-squared	0.48603	Mean dependent va	80191122
Adjusted R-squared	0.458496	S.D. dependent var	12016912
S.E. of regression	8842881	Akaike info criterion	34.88515
Sum squared resid	8.76E+15	Schwarz criterion	35.04862
Log likelihood	-2068.67	Hannan-Quinn criter	34.95153
F-statistic	17.65192	Durbin-Watson stat	2.470871
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for SLV AMS Class

SVL AMS Model

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:26
Sample: 1 120
Included observations: 120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.24E+09	17156055	72.2684	0
HDD_JAN	329379.9	107698.5	3.058353	0.0028
CDD_MAY	156870.8	111308	1.40934	0.1615
CDD_JUN	475242.8	77082.46	6.165382	0
CDD_JUL	646094.9	70501.17	9.164315	0
CDD_AUG	737927.5	71693.43	10.29282	0
CDD_SEP	929507.8	96284.55	9.653759	0
CDD_OCT	982383.4	167890.9	5.85132	0

R-squared	0.676649	Mean dependent va	1.40E+09
Adjusted R-squared	0.656439	S.D. dependent var	2.11E+08
S.E. of regression	1.23E+08	Akaike info criterion	40.16402
Sum squared resid	1.71E+18	Schwarz criterion	40.34986
Log likelihood	-2401.84	Hannan-Quinn criter	40.23949
F-statistic	33.4818	Durbin-Watson stat	1.5078
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for SLV AMS Class

SVL AMS Model with Autoregressive Term

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:27
Sample (adjusted): 2 120
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.36E+08	1.06E+08	8.79314	0
HDD_JAN	389971.8	108948.7	3.579408	0.0005
CDD_MAY	219090.3	109955	1.992545	0.0488
CDD_JUN	481393.9	74679.58	6.446124	0
CDD_JUL	572071.7	72872.75	7.850283	0
CDD_AUG	615919.6	81183.79	7.586732	0
CDD_SEP	734908.2	114902.5	6.395928	0
CDD_OCT	687445.4	191790.3	3.584359	0.0005
SALES(-1)	0.231113	0.079948	2.890782	0.0046

R-squared	0.700815	Mean dependent va	1.40E+09
Adjusted R-squared	0.679056	S.D. dependent var	2.11E+08
S.E. of regression	1.19E+08	Akaike info criterion	40.10802
Sum squared resid	1.57E+18	Schwarz criterion	40.3182
Log likelihood	-2377.43	Hannan-Quinn criter	40.19337
F-statistic	32.20824	Durbin-Watson stat	2.112584
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for SLV IDR Class

SVL IDR Model

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:30
Sample: 2008M01 2017M12
Included observations: 120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.07E+09	8438087	127.1649	0
CDD_JUN	249571.3	41276.77	6.046289	0
CDD_JUL	314508.5	38494.4	8.170238	0
CDD_AUG	311276.2	41819.97	7.443243	0
CDD_SEP	617068.7	57933.16	10.65139	0
CDD_OCT	717803.1	121270.9	5.919005	0

R-squared	0.651302	Mean dependent va	1.15E+09
Adjusted R-squared	0.636008	S.D. dependent var	1.18E+08
S.E. of regression	70899866	Akaike info criterion	39.04014
Sum squared resid	5.73E+17	Schwarz criterion	39.17952
Log likelihood	-2336.41	Hannan-Quinn criter	39.09674
F-statistic	42.58603	Durbin-Watson stat	1.708514
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for SLV IDR Class

SVL IDR Model with Autoregressive Term

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:31
Sample (adjusted): 2008M02 2017M12
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.47E+08	87394667	9.688166	0
CDD_JUN	240045.9	40296.86	5.956938	0
CDD_JUL	268936.1	41025.13	6.5554	0
CDD_AUG	243926.9	47748.49	5.108578	0
CDD_SEP	532971.8	64380.37	8.278483	0
CDD_OCT	456151.4	153260.5	2.976315	0.0036
SALES(-1)	0.209002	0.079904	2.615666	0.0101

R-squared	0.67038	Mean dependent va	1.15E+09
Adjusted R-squared	0.652722	S.D. dependent var	1.17E+08
S.E. of regression	68984646	Akaike info criterion	38.99369
Sum squared resid	5.33E+17	Schwarz criterion	39.15717
Log likelihood	-2313.12	Hannan-Quinn criter	39.06007
F-statistic	37.96416	Durbin-Watson stat	2.242988
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for PVS AMS Class

PVS AMS Model

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:33
Sample (adjusted): 2008M01 2017M12
Included observations: 120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18284897	427769.2	42.74477	0
HDD_JAN	4355.539	2895.069	1.504468	0.1353
CDD_JUN	4518.756	2070.41	2.182542	0.0311
CDD_JUL	8940.058	1893.599	4.721199	0
CDD_AUG	10178.17	1925.879	5.284949	0
CDD_SEP	11630.53	2586.168	4.497204	0
CDD_OCT	10045.75	4511.691	2.226604	0.028

R-squared	0.331792	Mean dependent va	20211706
Adjusted R-squared	0.296312	S.D. dependent var	4003112
S.E. of regression	3358055	Akaike info criterion	32.94818
Sum squared resid	1.27E+15	Schwarz criterion	33.11079
Log likelihood	-1969.89	Hannan-Quinn criter	33.01422
F-statistic	9.351495	Durbin-Watson stat	0.839992
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for PVS AMS Class

PVS AMS Model with Autoregressive Term

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:34
Sample (adjusted): 2 120
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7948301	1513783	5.25062	0
HDD_JAN	5072.333	2524.534	2.009216	0.0469
CDD_JUN	5657.419	1732.116	3.266189	0.0015
CDD_JUL	7363.807	1593.494	4.621169	0
CDD_AUG	6124.243	1705.535	3.590804	0.0005
CDD_SEP	4965.887	2354.99	2.108666	0.0372
CDD_OCT	808.6719	3983.067	0.203027	0.8395
SALES(-1)	0.541412	0.07711	7.021302	0

R-squared	0.540729	Mean dependent va	20178394
Adjusted R-squared	0.511766	S.D. dependent var	4003301
S.E. of regression	2797257	Akaike info criterion	32.59104
Sum squared resid	8.69E+14	Schwarz criterion	32.77787
Log likelihood	-1931.17	Hannan-Quinn criter	32.6669
F-statistic	18.66961	Durbin-Watson stat	2.160025
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for PVS IDR Class

PVS IDR Model

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:38
Sample (adjusted): 2008M01 2017M12
Included observations: 120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.76E+08	2655992	104.0349	0
CDD_JUN	59418.97	12992.37	4.573373	0
CDD_JUL	79617.02	12116.59	6.570911	0
CDD_AUG	77783.17	13163.35	5.90907	0
CDD_SEP	156370.5	18235.18	8.575211	0
CDD_OCT	163319	38171.52	4.278556	0

R-squared	0.539466	Mean dependent va	2.95E+08
Adjusted R-squared	0.519267	S.D. dependent var	32186687
S.E. of regression	22316607	Akaike info criterion	36.72827
Sum squared resid	5.68E+16	Schwarz criterion	36.86764
Log likelihood	-2197.7	Hannan-Quinn criter	36.78487
F-statistic	26.70775	Durbin-Watson stat	1.503079
Prob(F-statistic)	0		

Exhibit AM-4
Statistical Output for PVS IDR Class

PVS IDR Model with Autoregressive Term

Dependent Variable: SALES
Method: Least Squares
Date: 05/28/19 Time: 10:38
Sample (adjusted): 2008M02 2017M12
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.03E+08	23350129	8.70051	0
CDD_JUN	56944.48	12530.12	4.544609	0
CDD_JUL	66110.06	12373.12	5.343037	0
CDD_AUG	56387.37	14287.93	3.946503	0.0001
CDD_SEP	130447	19280.37	6.765793	0
CDD_OCT	81365.72	44684.53	1.820893	0.0713
SALES(-1)	0.262291	0.08285	3.16585	0.002

R-squared	0.575192	Mean dependent va	2.95E+08
Adjusted R-squared	0.552435	S.D. dependent var	32104406
S.E. of regression	21477949	Akaike info criterion	36.65997
Sum squared resid	5.17E+16	Schwarz criterion	36.82345
Log likelihood	-2174.27	Hannan-Quinn criter	36.72636
F-statistic	25.27479	Durbin-Watson stat	2.219809
Prob(F-statistic)	0		

Exhibit AM-5
Weather Adjustments to Sales

BES												
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Heating Degree days 10 year normal	348.24	221.28	82.44	14.19	0.71	0.00	0.00	0.00	1.64	44.39	203.28	344.18
Heating Degree Days Actual	375.42	112.11	46.34	28.75	0.00	0.00	0.00	0.00	1.56	51.26	245.74	291.88
Variance from normal	27.18	-109.17	-36.10	14.56	-0.71	0.00	0.00	0.00	-0.08	6.87	42.46	-52.30
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cooling Degree days 10 year normal	22.49	43.75	103.40	236.49	412.47	579.31	620.09	571.37	411.37	193.15	59.80	31.84
Cooling Degree Days Actual	20.83	84.85	130.45	202.93	474.62	582.65	628.72	593.68	465.77	206.81	53.89	10.73
Variance from normal	-1.66	41.10	27.05	-33.57	62.15	3.33	8.63	22.31	54.39	13.66	-5.91	-21.11

CIS												
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Heating Degree days 10 year normal	377.72	242.02	99.93	19.20	1.27	0.00	0.00	0.00	0.61	22.77	144.88	479.69
Heating Degree Days Actual	448.84	133.69	49.37	29.94	0.18	0.00	0.00	0.00	1.04	43.25	243.18	315.17
Variance from normal	71.12	-108.33	-50.55	10.74	-1.09	0.00	0.00	0.00	0.44	20.48	98.30	-164.52
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cooling Degree days 10 year normal	23.88	38.50	93.10	201.35	380.56	550.82	602.90	588.75	441.00	246.48	83.24	52.84
Cooling Degree Days Actual	16.40	92.38	136.09	192.95	457.40	580.47	626.00	599.86	477.58	225.97	58.37	16.08
Variance from normal	-7.48	53.89	42.99	-8.40	76.83	29.65	23.11	11.11	36.57	-20.51	-24.87	-36.76

Exhibit AM-5
Weather Adjustments to Sales

Monthly Weather Adjustments by Customer Class

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Residential	33,003,299	0	0	0	59,106,241	51,232,293	53,050,354	23,869,978	90,360,029	-38,395,186	0	0	272,227,008
Secondary <= 10	2,400,838	0	0	0	0	469,521	342,476	164,197	527,468	0	0	0	3,904,500
Secondary >10 AMS	27,733,102	0	0	0	0	14,273,122	13,218,483	6,843,937	26,879,222	-14,097,651	0	0	74,850,215
Secondary >10 IDR	0	0	0	0	0	800,035	2,320,386	5,442,400	28,988,809	6,230,711	0	0	43,782,341
Primary AMS	360,722	0	0	0	0	167,740	170,151	68,051	181,627	-16,584	0	0	931,707
Primary IDR	0	0	0	0	0	189,787	570,399	1,258,093	7,095,128	1,111,399	0	0	10,224,806
Total	63,497,962	0	0	0	59,106,241	67,132,499	69,672,248	37,646,654	154,032,284	-45,167,310	0	0	405,920,577

Residential (CIS)

HDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	27.18	-109.17	-36.10	14.56	-0.71	0.00	0.00	0.00	-0.08	6.87	42.46	-52.30	
HDD weather coefficients	1214256												
HDD adjustment	33003299	0	0	0	0	0	0	0	0	0	0	0	33003299.3
CDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	-7.48	53.89	42.99	-8.40	76.83	29.65	23.11	11.11	36.57	-20.51	-24.87	-36.76	
CDD weather coefficients					769275.2	1727927	2295922	2148177	2470545	1872269			
CDD adjustment	0	0	0	0	59106241	51232293.1	53050354	23869978	90360029.2	-38395186	0	0	239223708.4
Total weather adjustment	33003299	0	0	0	59106241	51232293.1	53050354	23869978	90360029.2	-38395186	0	0	272227007.7

Secondary <=10 (CIS)

HDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	71.12	-108.33	-50.55	10.74	-1.09	0.00	0.00	0.00	0.44	20.48	98.30	-164.52	0.00
HDD weather coefficients	33759.63												
HDD adjustment	2400838.4	0	0	0	0	0	0	0	0	0	0	0	2400838.396
CDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	-7.48	53.89	42.99	-8.40	76.83	29.65	23.11	11.11	36.57	-20.51	-24.87	-36.76	0.00
CDD weather coefficients						15835.68	14821.72	14776.87	14421.58				
CDD adjustment	0	0	0	0	0	469521.108	342475.7	164196.69	527468.389	0	0	0	1503661.887
Total weather adjustment	2400838.4	0	0	0	0	469521.108	342475.7	164196.69	527468.389	0	0	0	3904500.284

Exhibit AM-5
Weather Adjustments to Sales

Secondary > 10 AMS (CIS)													
HDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	71.12	-108.33	-50.55	10.74	-1.09	0.00	0.00	0.00	0.44	20.48	98.30	-164.52	0.00
HDD weather coefficients	389971.8												
HDD adjustment	27733102	0	0	0	0	0	0	0	0	0	0	0	27733102.26
CDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	-7.48	53.89	42.99	-8.40	76.83	29.65	23.11	11.11	36.57	-20.51	-24.87	-36.76	0.00
CDD weather coefficients					219090.3	481393.9	572071.7	615919.6	734908.2	687445.4			
CDD adjustment	0	0	0	0		14273122.3	13218483	6843936.6	26879221.6	-14097651	0	0	47117112.98
Total weather adjustment	27733102	0	0	0	0	14273122.3	13218483	6843936.6	26879221.6	-14097651	0	0	74850215.24

Secondary >10 IDR (BES)													
HDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	27.18	-109.17	-36.10	14.56	-0.71	0.00	0.00	0.00	-0.08	6.87	42.46	-52.30	0.00
HDD weather coefficients													
HDD adjustment	0	0	0	0	0	0	0	0	0	0	0	0	0
CDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	-1.66	41.10	27.05	-33.57	62.15	3.33	8.63	22.31	54.39	13.66	-5.91	-21.11	0.00
CDD weather coefficients						240045.9	268936.1	243926.9	532971.8	456151.4			
CDD adjustment	0	0	0	0	0	800035.323	2320385.8	5442399.8	28988809.2	6230710.8	0	0	43782340.92
Total weather adjustment	0	0	0	0	0	800035.323	2320385.8	5442399.8	28988809.2	6230710.8	0	0	43782340.92

Primary AMS (CIS)													
HDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	71.12	-108.33	-50.55	10.74	-1.09	0.00	0.00	0.00	0.44	20.48	98.30	-164.52	0.00
HDD weather coefficients	5072.33												
HDD adjustment	360722.1	0	0	0	0	0	0	0	0	0	0	0	360722.0998
CDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	-7.48	53.89	42.99	-8.40	76.83	29.65	23.11	11.11	36.57	-20.51	-24.87	-36.76	0.00
CDD weather coefficients						5657.42	7363.81	6124.24	4965.89	808.67			
CDD adjustment	0	0	0	0	0	167740.072	170150.7	68050.944	181627.117	-16583.64	0	0	570985.1888
Total weather adjustment	360722.1	0	0	0	0	167740.072	170150.7	68050.944	181627.117	-16583.64	0	0	931707.2886

Exhibit AM-5
Weather Adjustments to Sales

Primary IDR (BES)													
HDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	27.18	-109.17	-36.10	14.56	-0.71	0.00	0.00	0.00	-0.08	6.87	42.46	-52.30	0.00
HDD weather coefficients													
HDD adjustment	0	0	0	0	0	0	0	0	0	0	0	0	0
CDD calculation	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Variance from normal	-1.66	41.10	27.05	-33.57	62.15	3.33	8.63	22.31	54.39	13.66	-5.91	-21.11	0.00
CDD weather coefficients						56944.48	66110.06	56387.37	130447	81365.72			
CDD adjustment	0	0	0	0	0	189787.018	570398.86	1258092.5	7095128.11	1111399.1	0	0	10224805.64
Total weather adjustment	0	0	0	0	0	189787.018	570398.86	1258092.5	7095128.11	1111399.1	0	0	10224805.64