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SCE Sales and Customer Forecast Work Paper

Southern California Edison

1) Introduction

SCE uses econometric models to develop its retail sales[1] forecast – a forecast of monthly retail electricity sales by customer class. Retail sales are final sales to bundled, Direct Access (DA), and Community Choice Aggregate (CCA) customers. DA and CCA sales are subtracted from the retail sales forecast to derive a forecast of SCE bundled customer sales. Retail sales exclude sales to public power customers, contractual sales, resale city sales, municipal departing load and inter-changes with other utilities.

SCE Retail Sales

The retail sales forecast represents the sum of sales in six customer classes: residential, commercial, industrial, public authority, agriculture, and street lighting. Each customer class forecast itself is the product of two separate forecasts: a forecast of electricity consumption and a forecast of the number of customers[2]. Customer class data are used because they have been defined in a consistent manner throughout the sample period used in the econometric estimation.

In addition to the categorization by customer class, residential sales are further modeled and forecasted according to geographical region. The SCE service area encompasses several distinct climate zones. Accordingly, we model residential electricity consumption in part to capture regional variation in the weather and consumption relationship.

The electricity consumption per customer or per square foot forecasts are produced by statistical models that are based upon measured historical relationships between electricity consumption and various economic factors that are thought to influence electricity consumption. The estimation procedure used to construct these statistical models is ordinary least squares (OLS). Another set of econometric equations is used to forecast customers by customer class (in most cases customer additions are modeled (the change in the number of customers in the current month and the previous month) and converted into a forecast of total customers).

The regression equations, combined with forecasts of various economic drivers, such as employment and output, along with normal weather conditions and normal number of days billed, are used in combination to predict sales by customer class. Model-generated forecasts may be modified based on current trends, judgment, and events that are not specifically modeled in the equations.

Direct Access and Community Choice Aggregators

On March 14, 2019, the Commission issued an Order Instituting Rulemaking (R.) 19-03-009, pursuant to Senate Bill (SB) 237, 3 which defined GWh limits for Direct Access (DA) transactions. In May 2019, the Commission issued Decision 19-05-043 that expanded maximum allowable kilowatt-hour annual limit for DA transactions. This decision increased SCE's portion of the cap from 11,710 GWh to 13,457 GWh. With the actual DA load expansion in 2024 in a slow phase,

[1] Retail sales represent the net sales in cooperating NEM export energy impact from customers' behind-the-meter solar PV generations.

[2] Electricity usage of residential, agriculture, commercial, and streetlights service accounts is forecasted by consumption per customers. Electricity usage of industrial and public authority (OPA) service accounts is forecasted by usage per square footage.

[3] Stats. 2018, Ch. 600, amending Public Utilities (Pub. Uitl) Code section 365.1. All further statutory references are to the Pub. Util. §§ unless otherwise specified.

SCE expects that the total DA load will continue grow but need more years to be close to cap. SCE's Community Choice Aggregation's (CCAs) are listed below:

CCAs by April of 2024

Entity	Implementation Date
Lancaster (Muni)	May-2015
Lancaster (Res & Non-res)	Aug-2015
Apple Valley	Apr-2017
Pico Rivera Ph 1 (Muni & Res)	Sep-2017
Clean Power Alliance (CPA) Ph 1 (Muni)	Feb-2018
San Jacinto	Apr-2018
Pico Rivera Ph 2 (Non-res)	May-2018
Rancho Mirage	May-2018
CPA Ph 2 (Non-res))	Jun-2018
CPA Ph 3 (Res)	Feb-2019
CPA Ph 4 (Non-res))	May-2019
Desert Community (DCE) (Palm Springs)	Apr-2020
CPA Phase 5	Jun-2020
Pomona (Res, Muni)	Oct-2020
Pomona (Non-res)	Jun-2021
Santa Barbara City Ph1 (Res & Muni)	Oct-2021
Central Coast Community Energy	Oct-2021
Santa Barbara City Ph 2 (Non-res)	Mar-2022
Orange County Public Authority (OCPA) Phase 1 (Non-res)	Apr-2022
Palmdale Phase 1 (Res)	Oct-2022
OCPA Phase 2 (res)	Oct-2022
Palmdale Phase 2 (C&I, NEM)	Mar-023
OCPA NEM	May-Dec, 2023
CPA Phase6 (all)	Mar-2024
CPA Phase7 (all)	Oct-2025
OCPA Phase3 (all)	Oct-2026

Western Choice Energy (WCE) and Baldwin Park Resident Owned Utility District (BPROUD) both started CCA service in 2020. However, WCE terminated CCA service in 2021 and BPROUD terminated CCA service in 2022, both returning their customers to SCE bundled service. The City of Huntington Beach also withdraw from OCPA and customers in Huntington Beach were back to SCE in June of 2024. SCE has incorporated its best estimate of the migrating CCA load to this forecast based on the best information SCE had received at the time that this forecast was made.

SCE conducted separate meet-and-confer meetings with CPA (on April 11th) and OCPA (on April 4th). SCE discussed with CPA and OCPA both monthly energy and peak forecasts along with other major forecast assumptions for 2026. In general, SCE reached consensus views with CPA and OCPA separately on each side's forecast without finding any major discrepancy.

2) Forecast Assumptions and Drivers

The underlying assumptions regarding the economy, weather, energy efficiency, self-generation, building electrification, and transportation electrification are all significant factors affecting the sales forecast. Each of these important variables is discussed briefly below.

Employment

Changes in employment often has some explanatory power in measuring and predicting variation in non-residential electricity consumption. Changes in employment cause both seasonal variations in electricity consumption and changes in the long-term rate of growth in consumption over the forecast period. Only government employment is used as an explanatory variable to model public authority (federal, state, or local government) customer class electricity sales.

Weather

SCE estimates future temperature by leveraging historical observed hourly temperature data from weather stations and downscaled projected daily temperature data from global climate models (GCMs)to incorporate the long-term climate impact on load. SCE calibrates the GCM projections to weather station observations using the bias-correction method of quantile mapping. Then SCE observes long-term average warming climate trend from 2024 to 2050 that aligns with future median of the distribution of monthly CDD built from the calibrated GCM temperature data. Daily actual and normal temperature data are transformed into monthly cooling degree days (CDD) from April to October, and heating degree days (HDD) from November to March. A base temperature of 70 degrees F is used to calculate monthly cooling degree days, and a base temperature of 65 degrees F is used to calculate monthly heating degree days. The CDD and HDD variables used in model estimation are based on daily temperatures that are weighed averages of ten weather stations located in the SCE service area.

An important aspect in the calculation of CDD/HDD is the weights attached to the weather stations. The weather station weights reflect the historical geographical customer distribution. SCE customer growth is increasing faster in the areas, experiencing higher temperatures in the summer and lower temperatures in the winter and thereby have a higher frequency of cooling and heating appliances. SCE has experienced decreasing HDDs and increasing CDDs over its service territory in recent decade or so.

Billing Days

We define billing days as the sum of the number of calendar days between meter reads for each of the meter read cycles. There are typically 21 meter-reading cycles to a month. The number of days for which a customer is billed can vary depending upon meter reading schedules in a month and the number of holidays and weekend days in a month. Recorded sales will therefore vary with the number of days billed. The average number of billing days in a month turns out to be a particularly important source of explanatory power in all the electricity use models. For purposes of the forecast, we assume the historical average number of billing days in each month. Like weather, billing days explain variation in use over the months in a year but does not contribute to trend growth in electricity consumption.

Electricity Prices

It is typically difficult to estimate a statistically significant relationship between changes in electricity consumption and changes in electricity prices. There are several reasons for this. First, electricity prices are regulated and therefore may vary only infrequently. Second, price signals between electric utilities and consumers can be obscured by lags in the transmission of price information and the complexities inherent in tariff structures. Finally, electricity consumption is a necessity good, which means that consumption is relatively unresponsive to changes in price, at least in the short run. In other words, the short-run residential price elasticity of demand, as derived from our forecast models, is generally insignificant with some exception[4]. For purposes of model estimation, electricity prices are derived as monthly utility revenue divided by kWh consumption (i.e., unit revenue prices) and deflated by GDP deflator to express rates in constant dollars.

Real Output

Real output serves much the same purpose in the residential electricity consumption model that employment does in the commercial and agricultural electricity consumption models: Changes in output explain a significant amount of the variation in residential electricity consumption which is due to changes in economic conditions. Although changes in real output explain some of the seasonal variation in residential electricity consumption, it is really a major determinant of the long-run growth trend in residential electricity consumption. SCE uses historical and forecast real output by metropolitan statistical area from Moody's Analytics (MA) and IHS Markit in the regional residential OLS forecasting models. In the case of Riverside and San Bernardino counties, MA's combined Inland Empire MSA real output forecast was divided using a 10-year compound average growth rate based on historical county employment data obtained from CA Employment Development Department.

Self-Generation

The forecast of customer on-site bypass self-generation is calculated from two lists of customers operating generating systems interconnected to the SCE grid for the purpose of meeting their own energy requirements: a thermal list and a solar list. Both customer lists identify those customers that have behind-the-meter systems installed. The description of each facility includes designation of customer class, nameplate capacity in kilowatts (KW), probable bypass KW, capacity factor and on-line date. Separate forecasts are developed for thermal and solar/renewable systems and then combined for use in the sales forecast. Both lists are used to estimate annual energy production by customer class, which is allocated to the months in the year.

Within the SCE service area, there were approximately total 692,602 operational residential and non-residential behind-the-meter solar PV systems as of December 2024 ranging in size from 1 kW to more than 5,000 kW. For the solar PV generation, the annual energy is calculated using an average annual capacity factor. The capacity factor reflects the updates from the latest IEPR forecast. Annual energy is distributed to the months of the year using a load shape based on hourly distribution[5].

[4] Based on SCE's updated model estimations, the price elasticity only shows up significantly in the industrial usage model.

[5] The hourly load shape for Cogeneration is from SCE internal study, the shape for solar is from Itron Study

Solar Photovoltaic

SCE models the residential adoption of solar photovoltaic through a generalized Bass diffusion model.[6] The Bass diffusion model is a standard technology adoption model originally developed in 1969.[7] The SCE model uses percentage changes in the price per Watt-AC of installation, adjusted for the extended Federal Investment Tax Credit, as its explanatory variable. SCE leverages Bloomberg New Energy Finance (BNEF)'s historical and forecast solar installation price series from 2010-2030.[8] The compound monthly growth rate was used to extend BNEF's price series from 2030 to 2035. Residential solar photovoltaic adoption history comes from SCE's internal net energy meter (NEM) database. Non-residential solar photovoltaic adoption is modeled using a simulated Bass Diffusion model calibrated to the historical installs.

As the models are essentially a regression, expected policy changes in the future that are not reflected in historical installation data require post-model adjustments. Additional post-model adjustments were made to account for future incremental PV growth driven by the Title 24 building code compliance for both residential and non-residential new constructions. Specific bill impact or bill savings analysis is performed to estimate the net impact from the net-billing tariff and SCE's near-term rate increases.

Behind-The-Meter (BTM) Energy Storage

SCE forecasts adoption of paired solar PV and energy storage systems as well as standalone energy storage systems for residential and non-residential customers in the SCE service territory. SCE employs the System Advisor Model (SAM) by the National Energy Laboratory (NREL) to generate the key economic analysis or bill savings analysis for residential energy storage systems. The major inputs of SAM are considered such as hourly electric loads, rates, incentives, and system costs. SCE then applies internal analysis to estimate the annual adoptions. First, SCE converts the bill savings estimates from the SAM model into the maximum market potential based on SCE's internal analysis. Next, SCE runs a Bass Diffusion Model with estimated maximum market potential and other specified parameters to produce an annual adoption forecast. Additional installations are incorporated in the forecast based on the incentives offered by the SGIP Equity Resiliency Incentive Program and Energy Storage Pilot Program.

Non-residential energy storage systems are modeled separately with trend analyses based on historical adoptions. SCE specifies the representative storage system size for each customer group based on historical installation statistics. The SAM model simulates 8760 hourly storage system dispatch profile for residential customers, and the 2019 SGIP Advanced Energy Storage Impact Evaluation was used to produce non-residential paired and standalone energy storage charge/discharge profiles. SCE then aggregates all customer groups together to form a system level energy storage 8760 hourly profile.

Transportation Electrification

SCE forecasts future transportation electrification (TE) load growth for both light duty vehicle (LDV) load and non-LDV load. Non-LDV load includes medium, heavy duty, bus electric vehicles, and off-road transportation electrification.

For LDVs, policies such as CARB's (California Air Resources Board) Advanced Clean Cars II and 100% ZEV sales by 2035 were considered. The growth of transportation electrification to date has been

[6] Bass, Frank M., Trichy V. Krishnan, Dipak C. Jain. "Why the Bass Model Fits Without Decision Variables." Marketing Science. Vol. 13, No. 3, Summer 1994.
[7] Bass, Frank. "A New Product Growth for Model Consumer Durables." Management Science. Vol. 15, Issue 5, 1969.
[8] 1H 2021 U.S. PV Market Outlook data set, Bloomberg New Energy Finance.

profound, and that growth is accelerating. According to the Electric Power Research Institute (EPRI), California EV sales accounted for 25.3% of new car sales in 2024.[9] SCE expects the cumulative number of light duty EVs will continue strong growth and reach 1,250,257 in 2026.

For the Medium and Heavy-duty forecast, SCE reflects the CARB's Advanced Clean Trucks and Advanced Clean Fleet rules.

Building Electrification

SCE forecasts future building electrification (BE) load growth for residential and commercial space and water heating. In the longer term, SCE's BE forecast incorporates anticipated impacts from zero-emission appliance standards proposed by the California Air Resources Board (CARB) and local Air Quality Management Districts (AQMD). The near-term BE forecast considers the expected heat pump adoption from Title 24 standards for new buildings, estimated impacts based on approved and applied programs such as SCE BE Program Application, Building Initiative for Low-Emissions Development (BUILD), TECH, the Self-Generation Incentive Programs (SGIP), and the federal Inflation Reduction Act (IRA). We expect the total load from BE adoption to reach roughly 472 GWh in 2026.

Electricity Conservation Programs

SCE leverages the California Energy Commission's (CEC) Integrated Energy Policy Report (IEPR) Additional Achievable Energy Efficiency (AAEE) scenario forecasts to develop its EE forecast for our forecasting horizon.

3) Weather Adjustment Procedures

SCE has developed the weather and billing cycle adjustment model for the purpose of comparing recorded and weather adjusted sales on a monthly basis. Weather and the calendar have the most significant impact on the monthly and annual variations in electricity sales. The Weather Modeling System (WMS) is a SAS based program that calculates heating- and cooling-degree days (HDD/CDD) that corresponds to the monthly billing cycle schedule rather than a calendar month.

The annual billing cycle consists of 12 schedules of 21-meter reading days distributed across the year. A monthly billing cycle consists of 21-meter read days. The 12 monthly billing cycles while approximating a calendar month are not required to be coincident with the calendar month. In addition, the number of days for each meter read varies depending on the days in the month and the number of weekend days and holidays. The MWS, using daily temperatures and the number of days between each meter read, calculates the number of HDD/CDD for the 252 (12 x 21) meter read days in a year.

The electricity sales for each monthly billing cycle are disaggregated into each meter read. The electricity sales for the meter reads are statistically adjusted as a function of the difference between actual HDD/CDD for recorded number of days in the meter read. The adjusted electricity sales are then aggregated back into a monthly billing cycle.

The HDD/CDD is also adjusted for the changing distribution of customers within the service area. The WMS calculates customer-weighted average HDD/CDD using daily temperatures for the ten weather stations listed above. A further refinement is that the HDD/CDD are also adjusted according to the changing saturation of space conditioning appliances. Finally, separate sets of

[9] As of December 2024, based on EPRI analysis of Experian data (EPRI data is available via subscription).

HDD/CDD are calculated for residential and non-residential electricity sales. A corresponding set of normal HDD/CCD based on recent years of history are also calculated in the same manner.

The weather and billing day adjustment process is as follows:

Let $Y_{A,t}$ = actual billed sales per customer and $Y_{N,t}$ = adjusted sales per customer

Then $Y_{At} = \beta_0 + \beta_1 \bullet CDD_{A,t} + \beta_2 \bullet BDays_{A,t}$ and

$Y_{Nt} = \beta_0 + \beta_1 \bullet CDD_{N,t} + \beta_2 \bullet BDays_{N,t}$

Where $CDD_{A,t}$ is actual measured cooling degree days in the current time period, $BDays_{A,t}$ is actual measured billing days in the current time period, $CDD_{N,t}$ is normal cooling degree days and $BDays_{N,t}$ is normal billing days; β_1 and β_2 are coefficients that measure the relationship between a change in CDD and BDays respectively and a change in sales per customer.

The weather adjustment is:
$W_t = (Y_{A,t} - Y_{N,t}) \bullet Cust_t$ and Weather Adjusted sales are: $S_{N,t} = S_{A,t} - W_t$

SCE's recent sales forecast generally aligns with actual weather-adjusted retail sales throughout the year. In 2024, the mean absolute percentage error (MAPE) is 8.7% while the simple error is near 1.6%.

4) Model Statistics – Electricity Use Models

The statistical details of the electricity consumption models are shown below. A glossary of variable names is included at the end of the model specification. Last sample observation is August 2024, first forecast period is September 2024.

Residential Electricity Use Model – L.A. County

Dependent Variable: LAUSE
Method: Least Squares
Date: 10/20/24 Time: 13:32
Sample: 2004M01 2024M08
Included observations: 248

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.920182	0.242699	-3.791455	0.0002
RES_LACDD*SUMSEAS*LASIZE	7.70E-07	3.26E-08	23.61163	0.0000
RES_LAHDD*WINSEAS*LASIZE	2.42E-07	2.50E-08	9.692526	0.0000
CUMBDAYS	0.000675	4.96E-05	13.62576	0.0000
LOG(LAGDP(-24))	0.168244	0.046468	3.620644	0.0004
RESRATE(-6)	0.001036	0.001134	0.913835	0.3618
RESCAC	-0.183864	0.063965	-2.874453	0.0044
JAN	0.018923	0.006584	2.874284	0.0044
FEB	-0.021305	0.007895	-2.698544	0.0075
MAR	-0.018857	0.006048	-3.117707	0.0021
APR	-0.018326	0.007044	-2.601609	0.0099
MAY	0.007299	0.009610	0.759532	0.4483
JUN	0.019883	0.009641	2.062357	0.0403
JUL	0.029045	0.011797	2.462127	0.0146
AUG	0.056340	0.013009	4.330866	0.0000
SEP	0.019309	0.013173	1.465726	0.1442
OCT	0.016709	0.010558	1.582624	0.1149
NOV	0.014903	0.008441	1.765440	0.0789
DUMMY_200503	0.096955	0.019736	4.912614	0.0000
DUMMY_201308	-0.058127	0.019747	-2.943562	0.0036
DUMMY_201508	-0.066977	0.019748	-3.391580	0.0008
DUMMY_201808	0.075513	0.020526	3.678826	0.0003
DUMMY_202007	0.066992	0.019987	3.351788	0.0009
DUMMY_202009	0.067253	0.019834	3.390689	0.0008
DUMMY_202108	0.060083	0.019823	3.030963	0.0027
DUMMY_202304	0.023715	0.020120	1.178680	0.2398
DUMMY_202307	0.047803	0.020017	2.388152	0.0178
DUMMY_202407	0.070902	0.019850	3.571894	0.0004

R-squared	0.965728	Mean dependent var	0.535419
Adjusted R-squared	0.961522	S.D. dependent var	0.097003
S.E. of regression	0.019028	Akaike info criterion	-4.979819
Sum squared resid	0.079653	Schwarz criterion	-4.583142
Log likelihood	645.4976	Hannan-Quinn criter.	-4.820132
F-statistic	229.6025	Durbin-Watson stat	1.331986
Prob(F-statistic)	0.000000		

LOG(LAGDP (-24)) indicates the log of Los Angeles County GDP lagged 24 periods.

Residential Electricity Use Model – Orange County

Dependent Variable: ORUSE
Method: Least Squares
Date: 10/20/24 Time: 13:35
Sample: 2005M01 2024M08
Included observations: 236

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.755352	0.177818	-4.247905	0.0000
RES_ORCDD*SUMSEAS*ORSIZE	7.38E-07	4.23E-08	17.42535	0.0000
RES_ORHDD*WINSEAS*ORSIZE	2.19E-07	3.32E-08	6.593950	0.0000
CUMBDAYS	0.000763	6.36E-05	12.00300	0.0000
LOG(ORGDP(-9))	0.190812	0.040421	4.720605	0.0000
RESRATE(-3)	0.001597	0.001393	1.145875	0.2531
RESCAC	-0.314159	0.053753	-5.844514	0.0000
JAN	0.014765	0.008679	1.701210	0.0904
FEB	-0.030140	0.010304	-2.925083	0.0038
MAR	-0.029304	0.007919	-3.700312	0.0003
APR	-0.029166	0.008318	-3.506235	0.0006
MAY	-0.004069	0.010407	-0.390931	0.6962
JUN	0.013869	0.010192	1.360837	0.1750
JUL	0.053739	0.011236	4.782916	0.0000
AUG	0.089487	0.012317	7.265492	0.0000
SEP	0.050013	0.013683	3.655221	0.0003
OCT	0.021438	0.011566	1.853443	0.0652
NOV	0.015381	0.010343	1.487133	0.1385
DUMMY_200503	0.078999	0.024822	3.182586	0.0017
DUMMY_201408	-0.098055	0.025103	-3.906088	0.0001
DUMMY_201409	-0.068019	0.025310	-2.687433	0.0078
DUMMY_201608	0.052498	0.024645	2.130129	0.0343
DUMMY_201808	0.073030	0.025788	2.831883	0.0051
DUMMY_202007	0.040055	0.025007	1.601791	0.1107
DUMMY_202407	0.080122	0.024799	3.230891	0.0014

R-squared	0.937981	Mean dependent var	0.558241
Adjusted R-squared	0.930927	S.D. dependent var	0.090701
S.E. of regression	0.023838	Akaike info criterion	-4.535196
Sum squared resid	0.119899	Schwarz criterion	-4.168264
Log likelihood	560.1531	Hannan-Quinn criter.	-4.387282
F-statistic	132.9663	Durbin-Watson stat	1.208561
Prob(F-statistic)	0.000000		

LOG(ORGDP (-9) indicates the log of Orange County GDP lagged 9 periods.

Residential Electricity Use Model – Riverside County

Dependent Variable: RVUSE
Method: Least Squares
Date: 10/20/24 Time: 13:37
Sample: 2004M01 2024M08
Included observations: 248

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.455067	0.168139	-8.653944	0.0000
RES_RVCDD*SUMSEAS*RVSIZE	8.45E-07	4.16E-08	20.28213	0.0000
RES_RVHDD*WINSEAS*RVSIZE	1.38E-07	3.61E-08	3.821836	0.0002
CUMBDAYS	0.000893	0.000100	8.895513	0.0000
LOG(RVGDP(-9))	0.387338	0.048141	8.045880	0.0000
RESRATE(-9)	0.000899	0.002232	0.402674	0.6876
RESCAC	-0.263089	0.072207	-3.643521	0.0003
JAN	0.037276	0.013414	2.778819	0.0059
FEB	-0.010898	0.015906	-0.685133	0.4940
MAR	0.008534	0.011996	0.711419	0.4776
APR	0.023015	0.014629	1.573288	0.1171
MAY	0.001456	0.019192	0.075876	0.9396
JUN	0.011301	0.020962	0.539097	0.5904
JUL	0.062897	0.029225	2.152172	0.0325
AUG	0.144465	0.033178	4.354280	0.0000
SEP	0.054379	0.031861	1.706737	0.0893
OCT	0.015507	0.022591	0.686428	0.4932
NOV	0.055374	0.017147	3.229387	0.0014
DUMMY_200508	0.132866	0.039737	3.343616	0.0010
DUMMY_200808	-0.134729	0.039925	-3.374591	0.0009
DUMMY_201508	-0.165689	0.039631	-4.180815	0.0000
DUMMY_202007	0.038226	0.039912	0.957756	0.3392
DUMMY_201408	-0.123705	0.039663	-3.118888	0.0021
DUMMY_202108	0.109552	0.039552	2.769818	0.0061
DUMMY_202205	0.077146	0.039380	1.959017	0.0514
DUMMY_202206	0.080802	0.039508	2.045198	0.0420
DUMMY_202304	0.074188	0.040398	1.836423	0.0677
DUMMY_202406	0.124951	0.039863	3.134483	0.0020
DUMMY_202407	0.135337	0.040138	3.371770	0.0009

R-squared	0.979375	Mean dependent var	0.797181
Adjusted R-squared	0.976737	S.D. dependent var	0.250131
S.E. of regression	0.038150	Akaike info criterion	-3.585062
Sum squared resid	0.318740	Schwarz criterion	-3.174217
Log likelihood	473.5476	Hannan-Quinn criter.	-3.419671
F-statistic	371.3904	Durbin-Watson stat	0.997751
Prob(F-statistic)	0.000000		

LOG (RVGDP (-9)) indicates the log of Riverside County GDP lagged 9 periods.

Residential Electricity Use Model – San Bernardino County

Dependent Variable: SBUSE
Method: Least Squares
Date: 10/20/24 Time: 13:42
Sample: 2005M01 2024M08
Included observations: 236

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.017728	0.110067	-9.246414	0.0000
RES_SBCDD*SUMSEAS*SBSIZE	7.96E-07	3.15E-08	25.25534	0.0000
RES_SBHDD*WINSEAS*SBSIZE	1.87E-07	2.51E-08	7.442304	0.0000
CUMBDAYS	0.000816	6.72E-05	12.15299	0.0000
LOG(SBGDP(-9))	0.250141	0.030626	8.167590	0.0000
RESRATE(-6)	0.000123	0.001458	0.084544	0.9327
RESCAC	-0.146939	0.045040	-3.262442	0.0013
JAN	0.016409	0.008729	1.879868	0.0616
FEB	-0.023133	0.010435	-2.216803	0.0278
MAR	-0.014601	0.007888	-1.851006	0.0656
APR	-0.007359	0.009550	-0.770606	0.4418
MAY	0.013938	0.013316	1.046767	0.2965
JUN	0.033455	0.013946	2.398832	0.0174
JUL	0.068312	0.018849	3.624237	0.0004
AUG	0.120224	0.020741	5.796398	0.0000
SEP	0.057638	0.020018	2.879220	0.0044
OCT	0.034730	0.014811	2.344944	0.0200
NOV	0.033355	0.011509	2.898277	0.0042
DUMMY_200503	0.116524	0.025156	4.631981	0.0000
DUMMY_200508	0.075071	0.025371	2.958860	0.0035
DUMMY_200808	-0.073157	0.025348	-2.886078	0.0043
DUMMY_201408	-0.075111	0.025209	-2.979597	0.0032
DUMMY_201508	-0.118260	0.025204	-4.692072	0.0000
DUMMY_201808	0.040877	0.026146	1.563425	0.1195
DUMMY_201907	-0.071374	0.025142	-2.838845	0.0050
DUMMY_202108	0.075391	0.025240	2.986990	0.0032
DUMMY_202205	0.054386	0.024978	2.177346	0.0306
DUMMY_202007	0.050335	0.025551	1.969981	0.0502
DUMMY_201906	-0.067339	0.025106	-2.682188	0.0079
DUMMY_202206	0.045456	0.025116	1.809798	0.0718
DUMMY_202304	0.044083	0.025700	1.715274	0.0878
DUMMY_202307	0.072601	0.025650	2.830415	0.0051
DUMMY_202406	0.092696	0.025404	3.648901	0.0003
DUMMY_202407	0.108234	0.025522	4.240795	0.0000

R-squared	0.985600	Mean dependent var	0.658336
Adjusted R-squared	0.983248	S.D. dependent var	0.186538
S.E. of regression	0.024144	Akaike info criterion	-4.477001
Sum squared resid	0.117751	Schwarz criterion	-3.977974
Log likelihood	562.2861	Hannan-Quinn criter.	-4.275839
F-statistic	418.9645	Durbin-Watson stat	1.267926
Prob(F-statistic)	0.000000		

LOG (SBGDP (-9)) indicates the log of San Bernardino County GDP lagged 9 periods.

Residential Electricity Use Model – Ventura/Santa Barbara Counties

Dependent Variable: VSBUSE
Method: Least Squares
Date: 10/20/24 Time: 13:58
Sample: 2005M01 2024M08
Included observations: 236

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.537536	0.151014	-3.559515	0.0005
RES_VSBCDD*SUMSEAS*VSBSIZE	5.17E-07	2.96E-08	17.47994	0.0000
RES_VSBHDD*WINSEAS*VSBSIZE	1.95E-07	1.95E-08	10.00513	0.0000
CUMBDAYS	0.000733	4.76E-05	15.41045	0.0000
LOG(VSBGDP(-6))	0.189894	0.043588	4.356572	0.0000
RESRATE(-6)	9.43E-05	0.001094	0.086239	0.9314
RESCAC	-0.247639	0.038024	-6.512650	0.0000
JAN	0.019018	0.006049	3.143927	0.0019
FEB	-0.028909	0.007458	-3.876358	0.0001
MAR	-0.026521	0.005636	-4.705361	0.0000
APR	-0.034672	0.006185	-5.605813	0.0000
MAY	-0.011722	0.008366	-1.401137	0.1627
JUN	-0.006659	0.008314	-0.800964	0.4241
JUL	-0.000248	0.009701	-0.025610	0.9796
AUG	0.009240	0.010495	0.880413	0.3797
SEP	-0.005165	0.010982	-0.470267	0.6387
OCT	-0.005384	0.009187	-0.586073	0.5585
NOV	0.003263	0.007559	0.431646	0.6665
DUMMY_200503	0.072891	0.017663	4.126753	0.0001
DUMMY_201309	-0.049673	0.017814	-2.788492	0.0058
DUMMY_201411	-0.009308	0.017657	-0.527157	0.5987
DUMMY_201601	-0.026529	0.017659	-1.502265	0.1346
DUMMY_201708	0.034589	0.017547	1.971283	0.0501
DUMMY_201808	0.085870	0.018262	4.702190	0.0000
DUMMY_201812	-0.029823	0.017660	-1.688698	0.0929
DUMMY_202001	-0.048190	0.017464	-2.759345	0.0063
DUMMY_202005	0.049617	0.017566	2.824582	0.0052
DUMMY_202006	0.043473	0.017568	2.474525	0.0142
DUMMY_202007	0.043996	0.017967	2.448684	0.0152
DUMMY_202009	0.062871	0.017689	3.554294	0.0005
DUMMY_202105	0.037424	0.017650	2.120329	0.0352
DUMMY_202108	0.051635	0.017526	2.946128	0.0036
DUMMY_202304	0.038738	0.017981	2.154334	0.0324
DUMMY_202307	0.056598	0.017805	3.178864	0.0017
DUMMY_202308	0.078103	0.017705	4.411276	0.0000
DUMMY_202310	0.055906	0.017687	3.160845	0.0018
DUMMY_202406	0.078866	0.017732	4.447776	0.0000
DUMMY_202407	0.069321	0.017634	3.931075	0.0001

R-squared	0.944231	Mean dependent var	0.561460
Adjusted R-squared	0.933810	S.D. dependent var	0.065601
S.E. of regression	0.016877	Akaike info criterion	-5.179209
Sum squared resid	0.056400	Schwarz criterion	-4.621473
Log likelihood	649.1466	Hannan-Quinn criter.	-4.954380
F-statistic	90.60507	Durbin-Watson stat	1.607218
Prob(F-statistic)	0.000000		

Residential Electricity Use Model – Other (Rural) Counties

Dependent Variable: OTHUSE
Method: Least Squares
Date: 10/20/24 Time: 14:08
Sample: 2005M01 2024M08
Included observations: 236

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.782801	0.115859	-6.756492	0.0000
RES_OTHCDD*SUMSEAS*OTHSIZE	7.27E-07	3.47E-08	20.96127	0.0000
RES_OTHHDD*WINSEAS*OTHSIZE	2.17E-07	3.05E-08	7.105974	0.0000
CUMBDAYS	0.000893	7.76E-05	11.51180	0.0000
LOG(OTHGDP(-6))	0.206630	0.044814	4.610863	0.0000
RESRATE(-12)	0.000385	0.001741	0.221313	0.8251
RESCAC	-0.004818	0.057488	-0.083801	0.9333
JAN	0.025436	0.010566	2.407385	0.0170
FEB	-0.005504	0.011994	-0.458923	0.6468
MAR	0.000404	0.010873	0.037142	0.9704
APR	0.024611	0.015820	1.555675	0.1214
MAY	0.066323	0.023585	2.812118	0.0054
JUN	0.088811	0.025275	3.513773	0.0005
JUL	0.101323	0.031680	3.198352	0.0016
AUG	0.127173	0.032917	3.863455	0.0002
SEP	0.087287	0.030010	2.908591	0.0040
OCT	0.079617	0.024296	3.276885	0.0012
NOV	0.042851	0.016954	2.527420	0.0123
DUMMY_200502	0.085106	0.028970	2.937771	0.0037
DUMMY_200503	0.154354	0.029075	5.308780	0.0000
DUMMY_201712	-0.050592	0.028767	-1.758710	0.0801
DUMMY_202007	0.079917	0.029054	2.750604	0.0065
DUMMY_202105	0.070038	0.028928	2.421096	0.0164
DUMMY_202108	0.067850	0.028918	2.346289	0.0199
DUMMY_202205	0.068268	0.028729	2.376298	0.0184
DUMMY_202303	0.026190	0.030023	0.872331	0.3841
DUMMY_202304	0.077578	0.029674	2.614310	0.0096
DUMMY_202306	0.076722	0.029133	2.633469	0.0091
DUMMY_202307	0.117445	0.029208	4.020953	0.0001
DUMMY_202310	0.098462	0.028993	3.396103	0.0008
DUMMY_202403	0.115547	0.029444	3.924347	0.0001
DUMMY_202404	0.093791	0.029477	3.181881	0.0017
DUMMY_202405	0.129897	0.029115	4.461477	0.0000
DUMMY_202406	0.173005	0.029234	5.917854	0.0000
DUMMY_202407	0.107227	0.030594	3.504880	0.0006

R-squared	0.983505	Mean dependent var	0.694116
Adjusted R-squared	0.980715	S.D. dependent var	0.199558
S.E. of regression	0.027713	Akaike info criterion	-4.197780
Sum squared resid	0.154365	Schwarz criterion	-3.684076
Log likelihood	530.3380	Hannan-Quinn criter.	-3.990701
F-statistic	352.4931	Durbin-Watson stat	1.167703
Prob(F-statistic)	0.000000		

LOG (OTHGDP (-6)) indicates the log of other/rurals Counties GDP lagged 6 periods.

Commercial Electricity Use Model

Dependent Variable: COMUSE
Method: Least Squares
Date: 10/20/24 Time: 14:11
Sample: 2010M01 2024M08
Included observations: 176

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-13.08409	3.438828	-3.804810	0.0002
COM_CDD*SUMSEAS*COMSIZE	0.000827	0.000108	7.651779	0.0000
CUMBDAYS	0.007911	0.000464	17.03575	0.0000
LOG(SCEGDP(-3))	2.380045	0.705221	3.374895	0.0009
COMRATE(-24)	0.014465	0.020333	0.711382	0.4780
NONRESCAC	-3.299841	1.594723	-2.069225	0.0403
JAN	-0.062642	0.058207	-1.076198	0.2836
FEB	0.030551	0.073005	0.418481	0.6762
MAR	0.107134	0.058011	1.846799	0.0668
APR	0.143763	0.062266	2.308839	0.0223
MAY	0.296391	0.063146	4.693756	0.0000
JUN	0.394559	0.063950	6.169829	0.0000
JUL	0.397836	0.093063	4.274933	0.0000
AUG	0.612910	0.111005	5.521469	0.0000
SEP	0.376046	0.117728	3.194207	0.0017
OCT	0.556708	0.081726	6.811841	0.0000
NOV	0.377258	0.067607	5.580151	0.0000
DUMMY_201504	0.438917	0.159218	2.756697	0.0066
DUMMY_202004	-0.643805	0.160828	-4.003068	0.0001
DUMMY_202005	-0.940626	0.161925	-5.809035	0.0000
DUMMY_202006	-0.524829	0.159013	-3.300544	0.0012
DUMMY_202103	0.415462	0.159825	2.599479	0.0103
DUMMY_202102	-0.889707	0.158772	-5.603689	0.0000
DUMMY_202108	0.655210	0.160486	4.082651	0.0001
DUMMY_202205	0.453696	0.159923	2.836963	0.0052
DUMMY_202208	0.510657	0.162162	3.149057	0.0020
DUMMY_202308	0.497942	0.161251	3.087993	0.0024
DUMMY_202310	0.604493	0.162106	3.729006	0.0003
DUMMY_202401	0.602956	0.161188	3.740708	0.0003

R-squared	0.954528	Mean dependent var	6.148642
Adjusted R-squared	0.945867	S.D. dependent var	0.654498
S.E. of regression	0.152279	Akaike info criterion	-0.776711
Sum squared resid	3.408766	Schwarz criterion	-0.254302
Log likelihood	97.35057	Hannan-Quinn criter.	-0.564824
F-statistic	110.2060	Durbin-Watson stat	2.089083
Prob(F-statistic)	0.000000		

LOG (SCEGDP (-3)) indicates the log of SCE GDP lagged 3 periods.

Industrial Electricity Use Model

Dependent Variable: INDUSE
Method: Least Squares
Date: 10/20/24 Time: 14:23
Sample: 2011M01 2024M08
Included observations: 164

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.964255	3.266116	0.601404	0.5485
COM_CDD*SUMSEAS	0.000260	0.000352	0.739828	0.4606
INDRATE(-6)	-0.080772	0.009757	-8.278114	0.0000
LOG(SCEGDP(-3))	0.534025	0.522605	1.021852	0.3086
CUMBDAYS	0.001598	0.000366	4.363669	0.0000
INDTREND	-0.112354	0.013640	-8.236895	0.0000
JAN	-0.058786	0.044872	-1.310080	0.1923
FEB	-0.050875	0.056821	-0.895349	0.3721
MAR	0.064335	0.045824	1.403951	0.1625
APR	0.028422	0.047714	0.595667	0.5523
MAY	0.090289	0.048291	1.869672	0.0636
JUN	0.112619	0.050748	2.219200	0.0280
JUL	0.095905	0.075942	1.262864	0.2087
AUG	0.213104	0.091825	2.320766	0.0217
SEP	0.033892	0.096876	0.349853	0.7270
OCT	0.063592	0.065317	0.973583	0.3319
NOV	0.081432	0.053531	1.521221	0.1304
DUMMY_201103	-0.378576	0.123741	-3.059416	0.0026
DUMMY_201409	0.299004	0.121694	2.457010	0.0152
DUMMY_201410	0.277110	0.122326	2.265332	0.0250
DUMMY_201810	0.299009	0.123106	2.428876	0.0164

R-squared	0.939409	Mean dependent var	2.109394
Adjusted R-squared	0.930935	S.D. dependent var	0.440868
S.E. of regression	0.115861	Akaike info criterion	-1.353779
Sum squared resid	1.919591	Schwarz criterion	-0.956845
Log likelihood	132.0099	Hannan-Quinn criter.	-1.192639
F-statistic	110.8552	Durbin-Watson stat	0.882283
Prob(F-statistic)	0.000000		

INDTREND is a time trend variable designed to counteract the recent decline in industrial usage.

Other Public Authority Electricity Use Model

Dependent Variable: OPAUSE
Method: Least Squares
Date: 10/20/24 Time: 14:26
Sample: 2010M01 2024M08
Included observations: 176

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.222225	1.173095	-1.894326	0.0602
COM_CDD	0.000383	0.000151	2.539621	0.0122
NONRESCAC	-1.522966	0.106331	-14.32291	0.0000
OPARATE(-15)	-0.009801	0.005752	-1.703904	0.0906
LOG(SCEGOVEMP(-24))	0.561663	0.161594	3.475772	0.0007
CUMBDAYS	0.001741	0.000163	10.69804	0.0000
JAN	-0.022999	0.020453	-1.124476	0.2627
FEB	0.003522	0.025349	0.138927	0.8897
MAR	0.020507	0.020847	0.983688	0.3269
APR	0.051316	0.021847	2.348836	0.0202
MAY	0.128339	0.022342	5.744266	0.0000
JUN	0.159868	0.022376	7.144656	0.0000
JUL	0.198671	0.031488	6.309406	0.0000
AUG	0.273311	0.037296	7.328071	0.0000
SEP	0.272375	0.039453	6.903769	0.0000
OCT	0.254889	0.027605	9.233509	0.0000
NOV	0.112316	0.023958	4.687987	0.0000
DUMMY_201508	-0.102038	0.054247	-1.880995	0.0620
DUMMY_201712	0.160780	0.053373	3.012411	0.0031
DUMMY_201801	-0.167966	0.053406	-3.145085	0.0020
DUMMY_201910	0.062136	0.053953	1.151668	0.2514
DUMMY_202004	-0.158587	0.053466	-2.966160	0.0035
DUMMY_202010	-0.167635	0.055448	-3.023307	0.0030
DUMMY_202108	0.168863	0.054331	3.108075	0.0023
DUMMY_202203	0.064207	0.054343	1.181527	0.2393
DUMMY_202208	0.166886	0.054855	3.042311	0.0028
DUMMY_202301	0.142398	0.054394	2.617911	0.0098
DUMMY_202303	0.039771	0.054503	0.729709	0.4668
DUMMY_202304	0.106706	0.054917	1.943045	0.0540
DUMMY_202305	0.091888	0.054213	1.694943	0.0922
DUMMY_202307	0.114583	0.054792	2.091222	0.0383
DUMMY_202308	0.112329	0.054270	2.069811	0.0403

R-squared	0.921894	Mean dependent var	1.237890
Adjusted R-squared	0.905080	S.D. dependent var	0.166117
S.E. of regression	0.051179	Akaike info criterion	-2.944005
Sum squared resid	0.377179	Schwarz criterion	-2.367554
Log likelihood	291.0725	Hannan-Quinn criter.	-2.710199
F-statistic	54.82772	Durbin-Watson stat	1.272865
Prob(F-statistic)	0.000000		

LOG(SCEGOVEMP(-24)) indicates a log of SCE government employment lagged 24 months.

Agriculture Electricity Use Model

Dependent Variable: AGUSE
Method: Least Squares
Date: 10/15/24 Time: 05:10
Sample: 2010M01 2024M08
Included observations: 176

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-29.87827	3.105953	-9.619677	0.0000
CUMBDAYS	0.008949	0.001754	5.103610	0.0000
LOG(SCEGDP(-6))	3.879711	0.403996	9.603333	0.0000
PDSI_10	-0.361790	0.017414	-20.77632	0.0000
JAN	-0.472400	0.216043	-2.186598	0.0303
FEB	0.007654	0.273821	0.027953	0.9777
MAR	0.610871	0.215358	2.836536	0.0052
APR	1.664613	0.236188	7.047835	0.0000
MAY	2.756010	0.232782	11.83945	0.0000
JUN	4.456479	0.221894	20.08386	0.0000
JUL	5.639364	0.224485	25.12139	0.0000
AUG	5.893458	0.224704	26.22765	0.0000
SEP	4.638266	0.237971	19.49092	0.0000
OCT	3.175562	0.223673	14.19733	0.0000
NOV	1.345155	0.259900	5.175670	0.0000
DUMMY_201507	1.176331	0.600822	1.957870	0.0521
DUMMY_201705	4.428994	0.601197	7.366956	0.0000
DUMMY_201706	1.463963	0.599070	2.443726	0.0157
DUMMY_201804	-1.603977	0.600196	-2.672422	0.0083
DUMMY_202004	-1.360628	0.601362	-2.262576	0.0251
DUMMY_202108	2.118624	0.604220	3.506378	0.0006
DUMMY_202111	-1.314769	0.602708	-2.181435	0.0307
DUMMY_202208	2.279317	0.604069	3.773273	0.0002

R-squared	0.960515	Mean dependent var	6.599971
Adjusted R-squared	0.954837	S.D. dependent var	2.715173
S.E. of regression	0.577017	Akaike info criterion	1.859427
Sum squared resid	50.94109	Schwarz criterion	2.273751
Log likelihood	-140.6295	Hannan-Quinn criter.	2.027475
F-statistic	169.1756	Durbin-Watson stat	1.288043
Prob(F-statistic)	0.000000		

Street Light Electricity Use Model

Dependent Variable: STLUSE
Method: Least Squares
Date: 10/20/24 Time: 14:30
Sample: 2008M01 2024M08
Included observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.235333	0.328466	3.760918	0.0002
CUMBDAYS	0.000489	0.000121	4.025272	0.0001
DAYHRS	-0.000471	8.85E-05	-5.321930	0.0000
LIGHTINDEX	-0.786543	0.067030	-11.73424	0.0000
RESPRSTL	0.007699	0.002545	3.025005	0.0029
DUMMY_201702	0.029891	0.068732	0.434891	0.6642
DUMMY_201703	0.269789	0.062954	4.285496	0.0000
DUMMY_201704	0.330005	0.069229	4.766879	0.0000
DUMMY_201706	0.145613	0.062915	2.314448	0.0218
DUMMY_201707	0.082440	0.065718	1.254454	0.2113
DUMMY_201902	-0.170574	0.059415	-2.870879	0.0046
DUMMY_202006	-0.148119	0.058983	-2.511197	0.0129
DUMMY_202007	-0.151821	0.059365	-2.557424	0.0114
DUMMY_202008	-0.179188	0.058958	-3.039246	0.0027
DUMMY_202009	-0.183092	0.058833	-3.112049	0.0022
DUMMY_202102	-0.234859	0.059602	-3.940460	0.0001
DUMMY_202103	0.377265	0.059100	6.383486	0.0000
DUMMY_202203	0.398824	0.059220	6.734607	0.0000
DUMMY_202210	0.176661	0.058952	2.996707	0.0031
DUMMY_202303	-0.037308	0.059288	-0.629263	0.5300
DUMMY_202308	-0.096200	0.059473	-1.617550	0.1075
DUMMY_202309	-0.153170	0.059152	-2.589437	0.0104

R-squared	0.929824	Mean dependent var	1.171865
Adjusted R-squared	0.921545	S.D. dependent var	0.208319
S.E. of regression	0.058350	Akaike info criterion	-2.741257
Sum squared resid	0.606036	Schwarz criterion	-2.378442
Log likelihood	296.1257	Hannan-Quinn criter.	-2.594431
F-statistic	112.3092	Durbin-Watson stat	1.045819
Prob(F-statistic)	0.000000		

Electricity Use Model Variable Description

Residential Electricity Use Model

ResUse	Recorded residential class monthly electricity consumption in kWh per customer. Source: SCE.
CDD	Cooling degree-days. Sources: SCE, Cal-Adapt, and National Weather Service
HDD	Heating degree-days. Sources: SCE, Cal-Adapt, and National Weather Service
ResRate	Residential constant $2012 dollar price of electricity in cents per kWh. Sources: SCE and IHS Markit
RESCAC	An index measuring the average efficiency of residential air conditioning equipment. Compiled from Energy Information Administration data.
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
GeoGDP	Regional output in 2017 dollars. Compiled from Moody's Analytics and IHS Markit.
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise.
GeoSIZE	Average residential household size in square feet. Compiled from Dodge Data & Analytics data.
SUMSEAS	A binary equal to 1 during the summer months May to October and zero otherwise.
WINSEAS	A binary equal to 1 during the winter months November to April and zero otherwise.
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.
LA	Prefix in front of variable name to denote Los Angeles County.
OR	Prefix in front of variable name to denote Orange County.
SB	Prefix in front of variable name to denote San Bernardino County.
RIV	Prefix in front of variable name to denote Riverside County.
VEN	Prefix in front of variable name to denote Ventura and Santa Barbara Counties.
OTH	Prefix in front of variable name to denote Rural Counties (Fresno, Inyo, Kern Kings, Mono and Tulare)

Commercial Electricity Use Model

COMUSE	Recorded commercial class monthly electricity consumption in MWh per commercial customer. Source: SCE
COMCDD	Non-residential cooling degree-days, dynamic population share weighted. Sources: SCE, Cal-Adapt, and National Weather Service
SCEGDP	SCE regional output in 2017 dollars. Compiled from Moody's Analytics and IHS Markit.
COMSIZE	Average commercial building size in square feet. Sources: Dodge Data & Analytics and SCE
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise.
SUMSEAS	A binary equal to 1 during the summer months May to October and zero otherwise
NONRESCAC	An index measuring the average efficiency of commercial air conditioning equipment. Compiled from Energy Information Administration data.
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.

Industrial Electricity Use Model

INDUSE	Recorded industrial class monthly electricity consumption in kWh per industrial building square feet. Sources: SCE and Dodge Data & Analytics
COMCDD	Non-residential cooling degree-days static population weighting. Sources: SCE, Cal-Adapt, and National Weather Service
INDRATE	Industrial class constant $2012 dollar price of electricity in cents per kWh. Sources: SCE and IHS Markit
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in a month. Source: SCE
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise.
SUMSEAS	A binary equal to 1 during the summer months May to October and zero otherwise
INDTREND	Linear counter variable designed to capture secular trend in industrial class electricity consumption not otherwise captured in the model.
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.

Other Public Authority Electricity Use Model

OPAUSE	Recorded other public authority class monthly electricity consumption in kWh per government building square feet. Sources: SCE and Dodge Data & Analytics
COMCDD	Non-residential cooling degree-days, static population weighted. Sources: SCE, Cal-Adapt, and National Weather Service
OPARATE	Other public authority class constant $2012 dollar price of electricity in cents per kWh. Sources: SCE and IHS Markit
SCEGOVEMP	Government employment. Compiled from Moody's Analytics and IHS Markit.
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise.
NONRESCAC	An index measuring the average efficiency of commercial air conditioning equipment. Compiled from Energy Information Administration data.
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.

Agriculture Electricity Use Model

AGRUSE	Recorded agriculture class monthly electricity consumption in MWh per agriculture customer. Source: SCE
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
SCEGDP	SCE regional output in 2017 dollars. Compiled from Moody's Analytics and IHS Markit.
PDSI	Palmer Drought Severity Index measure of relative dryness based on temperature and precipitation data ranging from -7 (dry) to +7 (wet)
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise.
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.

Street Light Electricity Use Model

STLUSE	Recorded Street light class electricity monthly consumption in MWh per street light customer. Source: SCE
RESPRSTLT	Number of residential customers per street lighting customer. Source: SCE.
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE.
DAYHRS	Number of hours of daylight in a month in Southern California (a proxy for office lighting use). Source: SCE

5) Model Statistics – Customer Models

The statistical details of the residential and non-residential customer models are shown below, while a glossary of terms follows in Section 14. The residential customer models are constructed on the basis that new customers are determined mainly by housing starts (with a lag extending from zero up to 12 months depending upon the region). The housing start forecast is a blended forecast derived from Moody's Analytics and Information Handling Service (IHS) Markit.

Residential new customers are closely tied to activity in the residential construction sector, with lags of up to 12 months, meaning that a change in the number of new customers is typically a result of a change in the number of housing starts that occurred up to 12 months earlier.

Note that in the case of the industrial and other public authority (OPA) customer classes, the sales forecasts are constructed as the product of electricity consumption per square foot and total building square feet. Thus, the forecasts of Industrial class customers and OPA customers are independent of industrial and OPA customer class sales. An independent forecast of building square feet by building type is provided by Dodge Data & Analytics.

Last sample observation is September 2024, first forecast period is October 2024.

Residential Electricity Customer Model – Los Angeles County

Dependent Variable: D(LACUS)
Method: Least Squares
Date: 10/18/24 Time: 10:11
Sample: 2010M01 2024M09
Included observations: 177

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-651.4561	257.9658	-2.525358	0.0127
LASTRT_ADJ(-6)	0.045737	0.021260	2.151293	0.0332
JAN	1084.962	273.5597	3.966088	0.0001
FEB	1376.941	278.1820	4.949784	0.0000
MAR	695.9027	297.2334	2.341267	0.0207
APR	693.4126	283.6049	2.444995	0.0158
MAY	961.1806	283.5776	3.389480	0.0009
JUN	969.1035	278.1003	3.484727	0.0007
JUL	854.5917	278.0981	3.072987	0.0026
AUG	508.3954	273.3553	1.859834	0.0651
SEP	1159.479	269.3036	4.305471	0.0000
OCT	960.7402	289.6236	3.317202	0.0012
NOV	769.5490	289.3366	2.659701	0.0088
DUMMY_201312	1404.532	710.7770	1.976051	0.0502
DUMMY_201510	-1987.153	711.3579	-2.793465	0.0060
DUMMY_201703	-1780.382	714.2092	-2.492802	0.0139
DUMMY_201707	-3662.792	704.7625	-5.197200	0.0000
DUMMY_201708	3513.317	702.3696	5.002092	0.0000
DUMMY_201803	-4950.803	712.0812	-6.952582	0.0000
DUMMY_201804	3463.072	706.3132	4.903025	0.0000
DUMMY_201810	-2372.078	711.4004	-3.334378	0.0011
DUMMY_201811	2583.846	710.9056	3.634585	0.0004
DUMMY_201903	-1879.198	712.8628	-2.636128	0.0094
DUMMY_201911	1931.258	708.7281	2.724963	0.0073
DUMMY_201912	-1648.077	708.6113	-2.325785	0.0215
DUMMY_202002	1723.588	704.0929	2.447955	0.0156
DUMMY_202003	-2832.014	711.8292	-3.978502	0.0001
DUMMY_202006	-2456.057	705.9224	-3.479217	0.0007
DUMMY_202007	1978.642	707.6534	2.796062	0.0059
DUMMY_201704	2824.596	708.7545	3.985295	0.0001
DUMMY_201705	-4570.928	708.5446	-6.451151	0.0000
DUMMY_202010	-2233.574	710.3443	-3.144354	0.0020
DUMMY_202011	3264.602	708.5833	4.607224	0.0000
DUMMY_202105	-2595.292	706.9634	-3.671041	0.0003
DUMMY_202106	-2056.052	704.9637	-2.916536	0.0041
DUMMY_202204	-2503.318	708.2559	-3.534482	0.0006
DUMMY_202201	1931.472	704.5270	2.741516	0.0069
DUMMY_202202	4569.306	706.2900	6.469447	0.0000
DUMMY_202203	-4072.354	714.4550	-5.699945	0.0000
DUMMY_202205	2196.936	707.9726	3.103137	0.0023
DUMMY_202312	2050.971	710.2062	2.887852	0.0045

R-squared	0.797640	Mean dependent var	472.8456
Adjusted R-squared	0.738123	S.D. dependent var	1325.701
S.E. of regression	678.4134	Akaike info criterion	16.07717
Sum squared resid	62593287	Schwarz criterion	16.81289
Log likelihood	-1381.830	Hannan-Quinn criter.	16.37555
F-statistic	13.40177	Durbin-Watson stat	2.207748
Prob(F-statistic)	0.000000		

Residential Electricity Customer Model – Orange County

Dependent Variable: D(ORCUS)
Method: Least Squares
Date: 10/20/24 Time: 12:42
Sample: 2010M01 2024M09
Included observations: 177

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-162.1269	227.4413	-0.712830	0.4771
ORSTRT_ADJ(-6)	0.041999	0.021053	1.994921	0.0479
JAN	538.8814	243.9812	2.208701	0.0287
FEB	831.4979	244.2838	3.403819	0.0009
MAR	-101.4177	248.8910	-0.407479	0.6842
APR	213.2295	259.0530	0.823111	0.4118
MAY	585.1735	253.2680	2.310492	0.0222
JUN	383.2841	253.4509	1.512262	0.1326
JUL	693.3576	253.3336	2.736935	0.0070
AUG	125.8026	252.8343	0.497569	0.6195
SEP	581.7588	252.8371	2.300923	0.0228
OCT	180.0710	247.9442	0.726256	0.4688
NOV	762.5885	252.6487	3.018375	0.0030
DUMMY_201704	2895.929	684.2209	4.232448	0.0000
DUMMY_201705	-3370.958	682.7378	-4.937413	0.0000
DUMMY_201706	944.2422	683.7051	1.381067	0.1693
DUMMY_201707	-2592.381	682.8980	-3.796146	0.0002
DUMMY_201708	2592.652	681.3854	3.804972	0.0002
DUMMY_201803	-2731.648	679.8848	-4.017811	0.0001
DUMMY_201804	2265.775	683.7129	3.313927	0.0012
DUMMY_201908	-667.7928	681.8220	-0.979424	0.3290
DUMMY_201909	1026.270	681.4751	1.505954	0.1342
DUMMY_202006	-2483.072	684.8998	-3.625453	0.0004
DUMMY_202007	942.0349	684.8321	1.375571	0.1710
DUMMY_202011	2114.961	681.4551	3.103595	0.0023
DUMMY_202104	-365.4109	682.8826	-0.535101	0.5934
DUMMY_202105	-1641.920	680.6964	-2.412117	0.0171
DUMMY_202109	700.4641	681.5875	1.027695	0.3058

R-squared	0.552588	Mean dependent var	504.8568
Adjusted R-squared	0.471514	S.D. dependent var	902.2809
S.E. of regression	655.9316	Akaike info criterion	15.95417
Sum squared resid	64106689	Schwarz criterion	16.45661
Log likelihood	-1383.944	Hannan-Quinn criter.	16.15794
F-statistic	6.815804	Durbin-Watson stat	2.677036
Prob(F-statistic)	0.000000		

ORSTRT_ADJ(-6) indicates Orange County's total housing starts lagging 6 months.

Residential Electricity Customer Model – Riverside County

Dependent Variable: D(ORCUS)
Method: Least Squares
Date: 10/20/24 Time: 12:42
Sample: 2010M01 2024M09
Included observations: 177

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-162.1269	227.4413	-0.712830	0.4771
ORSTRT_ADJ(-6)	0.041999	0.021053	1.994921	0.0479
JAN	538.8814	243.9812	2.208701	0.0287
FEB	831.4979	244.2838	3.403819	0.0009
MAR	-101.4177	248.8910	-0.407479	0.6842
APR	213.2295	259.0530	0.823111	0.4118
MAY	585.1735	253.2680	2.310492	0.0222
JUN	383.2841	253.4509	1.512262	0.1326
JUL	693.3576	253.3336	2.736935	0.0070
AUG	125.8026	252.8343	0.497569	0.6195
SEP	581.7588	252.8371	2.300923	0.0228
OCT	180.0710	247.9442	0.726256	0.4688
NOV	762.5885	252.6487	3.018375	0.0030
DUMMY_201704	2895.929	684.2209	4.232448	0.0000
DUMMY_201705	-3370.958	682.7378	-4.937413	0.0000
DUMMY_201706	944.2422	683.7051	1.381067	0.1693
DUMMY_201707	-2592.381	682.8980	-3.796146	0.0002
DUMMY_201708	2592.652	681.3854	3.804972	0.0002
DUMMY_201803	-2731.648	679.8848	-4.017811	0.0001
DUMMY_201804	2265.775	683.7129	3.313927	0.0012
DUMMY_201908	-667.7928	681.8220	-0.979424	0.3290
DUMMY_201909	1026.270	681.4751	1.505954	0.1342
DUMMY_202006	-2483.072	684.8998	-3.625453	0.0004
DUMMY_202007	942.0349	684.8321	1.375571	0.1710
DUMMY_202011	2114.961	681.4551	3.103595	0.0023
DUMMY_202104	-365.4109	682.8826	-0.535101	0.5934
DUMMY_202105	-1641.920	680.6964	-2.412117	0.0171
DUMMY_202109	700.4641	681.5875	1.027695	0.3058

R-squared	0.552588	Mean dependent var	504.8568
Adjusted R-squared	0.471514	S.D. dependent var	902.2809
S.E. of regression	655.9316	Akaike info criterion	15.95417
Sum squared resid	64106689	Schwarz criterion	16.45661
Log likelihood	-1383.944	Hannan-Quinn criter.	16.15794
F-statistic	6.815804	Durbin-Watson stat	2.677036
Prob(F-statistic)	0.000000		

Residential Electricity Customer Model – San Bernardino County

Dependent Variable: D(SBCUS)
Method: Least Squares
Date: 10/18/24 Time: 09:59
Sample: 2010M01 2024M09
Included observations: 177

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.142376	90.94066	-0.012562	0.9900
SBSTRT_ADJ(-6)	0.041440	0.010630	3.898294	0.0001
JAN	301.2426	103.4490	2.911991	0.0042
FEB	390.7501	101.7847	3.838986	0.0002
MAR	132.9525	103.4487	1.285202	0.2008
APR	343.8060	105.3599	3.263158	0.0014
MAY	216.4682	107.5314	2.013069	0.0460
JUN	157.2600	107.8270	1.458447	0.1469
JUL	114.1523	110.0489	1.037287	0.3014
AUG	92.56738	105.4883	0.877513	0.3817
SEP	229.5508	103.6876	2.213870	0.0284
OCT	99.63160	107.5387	0.926472	0.3558
NOV	98.36018	107.5272	0.914747	0.3619
DUMMY_201206	-1256.057	281.5450	-4.461300	0.0000
DUMMY_201207	1101.175	281.9332	3.905802	0.0001
DUMMY_201705	-1923.424	279.5887	-6.879474	0.0000
DUMMY_201706	1056.419	279.5762	3.778645	0.0002
DUMMY_201707	-880.6567	280.5189	-3.139384	0.0021
DUMMY_201708	1285.390	278.7652	4.611014	0.0000
DUMMY_201803	-1271.893	278.3585	-4.569261	0.0000
DUMMY_201804	1400.869	278.8212	5.024257	0.0000
DUMMY_201908	-738.1438	278.7893	-2.647676	0.0090
DUMMY_201811	1065.107	280.6126	3.795648	0.0002
DUMMY_202007	943.5414	281.5061	3.351761	0.0010
DUMMY_202105	-1424.270	282.5980	-5.039916	0.0000
DUMMY_202011	864.9146	279.5755	3.093671	0.0024
DUMMY_201704	789.7761	278.7176	2.833607	0.0053
DUMMY_201209	-694.4781	280.1876	-2.478618	0.0144
DUMMY_201410	573.6431	279.9644	2.048986	0.0423
DUMMY_202205	1300.430	280.8095	4.631007	0.0000
DUMMY_201306	-591.8286	280.7677	-2.107894	0.0368
DUMMY_202201	451.6170	278.4125	1.622115	0.1070
DUMMY_202310	-2210.649	281.4140	-7.855503	0.0000
DUMMY_202312	3091.246	283.1017	10.91921	0.0000
DUMMY_202407	909.1648	283.3663	3.208444	0.0016

R-squared	0.802696	Mean dependent var	419.8491
Adjusted R-squared	0.755454	S.D. dependent var	543.1098
S.E. of regression	268.5763	Akaike info criterion	14.19930
Sum squared resid	10242918	Schwarz criterion	14.82736
Log likelihood	-1221.638	Hannan-Quinn criter.	14.45402
F-statistic	16.99123	Durbin-Watson stat	1.998757
Prob(F-statistic)	0.000000		

Residential Electricity Customer Model – Ventura/Santa Barbara Counties

Dependent Variable: D(VSBCUS)
Method: Least Squares
Date: 10/20/24   Time: 12:47
Sample: 2010M01 2024M09
Included observations: 177

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-39.93009	52.55678	-0.759751	0.4486
VSBSTRT_ADJ(-12)	0.044927	0.022570	1.990536	0.0484
JAN	170.7869	62.08490	2.750860	0.0067
FEB	170.8114	62.08856	2.751093	0.0067
MAR	-20.36297	63.22708	-0.322061	0.7479
APR	116.5360	63.24568	1.842592	0.0674
MAY	127.0880	64.56028	1.968517	0.0509
JUN	-143.8473	64.52652	-2.229275	0.0273
JUL	258.2782	64.54450	4.001553	0.0001
AUG	75.17931	63.23238	1.188937	0.2364
SEP	282.3283	61.08257	4.622077	0.0000
OCT	41.70670	62.08109	0.671810	0.5028
NOV	162.8392	64.54591	2.522843	0.0127
DUMMY_201406	474.9682	168.3043	2.822080	0.0054
DUMMY_201503	620.8171	167.3171	3.710422	0.0003
DUMMY_201707	-1182.308	168.0685	-7.034675	0.0000
DUMMY_201708	944.7682	167.3322	5.646063	0.0000
DUMMY_201712	-660.9335	167.6937	-3.941315	0.0001
DUMMY_201803	-1153.562	167.5285	-6.885769	0.0000
DUMMY_201804	987.6857	167.8667	5.883749	0.0000
DUMMY_201907	-485.8015	167.8327	-2.894559	0.0044
DUMMY_201908	-1055.074	167.3610	-6.304184	0.0000
DUMMY_202002	529.0781	166.9458	3.169161	0.0019
DUMMY_202006	-477.5719	168.2382	-2.838665	0.0052
DUMMY_202007	446.6359	168.2039	2.655325	0.0088
DUMMY_202011	555.3413	167.7747	3.310042	0.0012
DUMMY_202104	679.1956	167.6217	4.051954	0.0001
DUMMY_201906	754.2110	167.7766	4.495328	0.0000
DUMMY_201811	629.1930	170.2089	3.696593	0.0003
DUMMY_201705	-721.9729	168.4888	-4.284990	0.0000
DUMMY_202105	-638.9058	167.8713	-3.805927	0.0002
DUMMY_202201	446.9777	166.9383	2.677502	0.0083
DUMMY_202205	471.6014	168.7096	2.795343	0.0059

R-squared	0.777270	Mean dependent var	125.6535
Adjusted R-squared	0.727774	S.D. dependent var	308.9215
S.E. of regression	161.1806	Akaike info criterion	13.16947
Sum squared resid	3741004.	Schwarz criterion	13.76164
Log likelihood	-1132.498	Hannan-Quinn criter.	13.40963
F-statistic	15.70381	Durbin-Watson stat	2.240932
Prob(F-statistic)	0.000000		

Residential Electricity Customer Model – Other (Rural) Counties

Dependent Variable: D(OTHCUS)
Method: Least Squares
Date: 10/10/24 Time: 07:43
Sample: 2008M01 2024M09
Included observations: 201

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-19.08470	41.87202	-0.455786	0.6491
OTHSTRT_ADJ(-9)	0.055342	0.017541	3.154969	0.0019
JAN	89.96512	42.39508	2.122065	0.0353
FEB	92.48433	42.38386	2.182065	0.0305
MAR	21.34849	42.97638	0.496749	0.6200
APR	90.22844	44.38339	2.032932	0.0436
MAY	106.2110	44.36152	2.394216	0.0178
JUN	92.79533	42.95269	2.160408	0.0321
JUL	17.44571	43.61515	0.399992	0.6897
AUG	69.35765	43.62995	1.589680	0.1138
SEP	88.99335	42.97043	2.071037	0.0399
OCT	-16.70075	44.36034	-0.376479	0.7070
NOV	122.2249	44.37003	2.754673	0.0065
DUMMY_201411	-335.7166	121.5850	-2.761169	0.0064
DUMMY_201704	541.1981	121.4859	4.454822	0.0000
DUMMY_201705	-739.1715	121.5231	-6.082559	0.0000
DUMMY_201706	331.0451	121.0696	2.734337	0.0069
DUMMY_201708	280.9132	121.3598	2.314714	0.0218
DUMMY_201803	-821.3884	121.0596	-6.784991	0.0000
DUMMY_201804	819.3906	121.5509	6.741129	0.0000
DUMMY_201908	-447.8652	121.2708	-3.693100	0.0003
DUMMY_202007	371.6818	121.8142	3.051218	0.0026
DUMMY_202105	1901.968	121.4946	15.65475	0.0000
DUMMY_202109	-2333.713	121.1329	-19.26572	0.0000
DUMMY_202110	347.1860	121.7041	2.852707	0.0049
DUMMY_202112	-912.0104	121.6965	-7.494139	0.0000
DUMMY_202104	1019.226	121.6256	8.380032	0.0000
DUMMY_202107	-697.3311	121.3507	-5.746410	0.0000
DUMMY_202205	456.3070	121.5273	3.754769	0.0002
DUMMY_202310	3882.626	122.0987	31.79909	0.0000
DUMMY_202311	-322.6028	121.6353	-2.652213	0.0088
DUMMY_202312	-3078.714	121.5214	-25.33474	0.0000

R-squared	0.944833	Mean dependent var	138.1597
Adjusted R-squared	0.934713	S.D. dependent var	459.3373
S.E. of regression	117.3664	Akaike info criterion	12.51348
Sum squared resid	2327953.	Schwarz criterion	13.03938
Log likelihood	-1225.605	Hannan-Quinn criter.	12.72628
F-statistic	93.36825	Durbin-Watson stat	2.136606
Prob(F-statistic)	0.000000		

Commercial Customer Model

Dependent Variable: D(COMCUS)
Method: Least Squares
Date: 10/10/24 Time: 10:08
Sample: 2008M01 2024M09
Included observations: 201

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	588.0806	240.6167	2.444056	0.0155
D(SCERESCUSF(-9))	0.041288	0.024076	1.714922	0.0881
JAN	-677.2303	342.3147	-1.978385	0.0495
FEB	-879.3161	336.4500	-2.613512	0.0097
MAR	581.6753	336.6313	1.727930	0.0858
APR	-269.8068	354.8466	-0.760348	0.4481
MAY	-612.4380	343.6449	-1.782183	0.0765
JUN	-463.1991	341.2339	-1.357424	0.1764
JUL	-532.8983	338.2762	-1.575335	0.1170
AUG	-417.8677	343.6004	-1.216144	0.2256
SEP	-714.3928	330.3920	-2.162258	0.0320
OCT	-41.15620	341.4809	-0.120523	0.9042
NOV	-919.2077	350.4750	-2.622748	0.0095
DUMMY_201701	-1322.121	963.1186	-1.372750	0.1716
DUMMY_201702	-3408.100	962.6363	-3.540382	0.0005
DUMMY_201704	-4108.363	972.1834	-4.225913	0.0000
DUMMY_201705	-1203.078	968.7875	-1.241839	0.2160
DUMMY_201706	4093.019	960.7070	4.260424	0.0000
DUMMY_201708	5840.641	960.6537	6.079861	0.0000
DUMMY_201903	-3154.968	961.1083	-3.282635	0.0012
DUMMY_201904	3499.285	967.0845	3.618386	0.0004
DUMMY_201905	2410.631	962.7178	2.503985	0.0132
DUMMY_202011	-3355.664	969.2415	-3.462154	0.0007
DUMMY_202012	3371.880	968.6003	3.481189	0.0006
DUMMY_202104	206.9624	981.0851	0.210953	0.8332
DUMMY_202107	1339.024	967.0440	1.384657	0.1679
DUMMY_202004	-975.1575	968.1956	-1.007191	0.3152

R-squared	0.528003	Mean dependent var	273.7652
Adjusted R-squared	0.457474	S.D. dependent var	1265.204
S.E. of regression	931.9032	Akaike info criterion	16.63674
Sum squared resid	1.51E+08	Schwarz criterion	17.08047
Log likelihood	-1644.993	Hannan-Quinn criter.	16.81629
F-statistic	7.486388	Durbin-Watson stat	2.698145
Prob(F-statistic)	0.000000		

The D_ indicates the first difference. SCERESCUSF(-9) indicates number of SCE residential customer lagging 9 months.

Industrial Customer Model

Dependent Variable: D(INDCUS)
Method: Least Squares
Date: 10/20/24 Time: 12:51
Sample: 2008M01 2024M09
Included observations: 201

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-96.32412	23.38977	-4.118216	0.0001
D(SCEMFGEMP(-9))	1.481883	0.861971	1.719179	0.0874
JAN	21.58776	14.99717	1.439456	0.1518
FEB	30.14162	13.59275	2.217477	0.0279
MAR	-0.787441	13.82148	-0.056972	0.9546
APR	28.43183	14.36986	1.978574	0.0494
MAY	28.14382	13.78054	2.042287	0.0426
JUN	39.91851	15.71345	2.540404	0.0119
JUL	19.33940	13.69444	1.412208	0.1597
AUG	19.33121	13.82838	1.397937	0.1639
SEP	43.96518	14.99189	2.932598	0.0038
OCT	-10.80642	22.48167	-0.480677	0.6313
NOV	34.59658	14.21688	2.433486	0.0160
DUMMY_200910	-161.2401	40.87952	-3.944276	0.0001
DUMMY_200911	126.6702	41.46037	3.055212	0.0026
DUMMY_201701	-125.3646	40.33097	-3.108396	0.0022
DUMMY_201705	-292.2286	40.25047	-7.260253	0.0000
DUMMY_201706	205.4174	40.31114	5.095797	0.0000
DUMMY_201708	202.1848	40.24664	5.023643	0.0000
DUMMY_201903	-364.8082	40.29905	-9.052526	0.0000
DUMMY_201904	172.6876	40.47632	4.266387	0.0000
DUMMY_202104	-21.25555	41.17043	-0.516282	0.6063
DUMMY_202106	-197.6506	41.44115	-4.769428	0.0000
DUMMY_202201	-75.83067	40.95536	-1.851545	0.0658
DUMMY_202204	-336.1733	41.00676	-8.197997	0.0000
INDTREND	1.428032	0.645867	2.211031	0.0283
CSRP	-55.64384	9.423019	-5.905097	0.0000

R-squared	0.719426	Mean dependent var	-41.59388
Adjusted R-squared	0.677501	S.D. dependent var	68.62641
S.E. of regression	38.97224	Akaike info criterion	10.28798
Sum squared resid	264277.4	Schwarz criterion	10.73171
Log likelihood	-1006.942	Hannan-Quinn criter.	10.46753
F-statistic	17.15989	Durbin-Watson stat	1.437143
Prob(F-statistic)	0.000000		

The D_ indicates the first difference. SCEMFGEMP(-9) indicates SCE manufacturing employment lagging 9 months.

Other Public Authority Customer Model

Dependent Variable: D(OPACUS)
Method: Least Squares
Date: 10/20/24 Time: 12:52
Sample: 2010M01 2024M09
Included observations: 177

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-66.58600	77.13646	-0.863223	0.3897
D(SCEGOVEMP(-15))	3.362822	3.139398	1.071168	0.2862
JAN	-61.47977	85.38758	-0.720008	0.4729
FEB	8.062838	79.05865	0.101986	0.9189
MAR	10.65028	127.6584	0.083428	0.9336
APR	-54.48908	76.24155	-0.714690	0.4761
MAY	11.53934	79.13368	0.145821	0.8843
JUN	11.63082	80.56006	0.144375	0.8854
JUL	39.60767	92.67086	0.427402	0.6698
AUG	38.89452	88.94002	0.437312	0.6626
SEP	293.0141	101.9664	2.873633	0.0048
OCT	250.1508	278.2206	0.899110	0.3703
NOV	168.6362	100.0910	1.684829	0.0945
DUMMY_201607	681.9027	183.4158	3.717797	0.0003
DUMMY_201608	-728.9052	183.5134	-3.971945	0.0001
DUMMY_201610	700.3252	186.0773	3.763626	0.0003
DUMMY_201611	39.90332	184.1761	0.216659	0.8288
DUMMY_201612	-843.3916	184.9089	-4.561119	0.0000
DUMMY_201701	-777.1517	183.3181	-4.239361	0.0000
DUMMY_201702	1323.226	183.9337	7.194039	0.0000
DUMMY_201703	-1292.709	184.7050	-6.998777	0.0000
DUMMY_201704	1361.281	182.7562	7.448615	0.0000
DUMMY_201705	-2764.285	183.3350	-15.07778	0.0000
DUMMY_201706	1075.414	183.9546	5.846086	0.0000
DUMMY_201707	804.8757	183.3292	4.390330	0.0000
DUMMY_201708	370.3080	183.3860	2.019282	0.0456
DUMMY_201710	-682.8077	186.0219	-3.670578	0.0004
DUMMY_201712	-722.9163	185.2357	-3.902683	0.0002
DUMMY_201802	1474.221	183.9338	8.014956	0.0000
DUMMY_201803	-1386.099	184.6830	-7.505285	0.0000
DUMMY_201809	-35.08722	183.3990	-0.191316	0.8486
DUMMY_201810	-1187.121	185.6135	-6.395662	0.0000
DUMMY_201901	-707.6169	183.4957	-3.856313	0.0002
DUMMY_201902	1493.559	184.0428	8.115277	0.0000
DUMMY_201903	-1827.952	184.6953	-9.897123	0.0000
DUMMY_201904	114.4433	182.7429	0.626253	0.5323
DUMMY_201905	267.1155	183.2786	1.457429	0.1475
DUMMY_201906	888.7852	183.9185	4.832494	0.0000
DUMMY_201907	-776.3028	183.2969	-4.235220	0.0000
DUMMY_201910	-656.5811	185.6343	-3.536960	0.0006
DUMMY_201911	1363.910	183.9878	7.413045	0.0000
DUMMY_201912	-1502.195	184.8999	-8.124369	0.0000
DUMMY_202002	1474.004	184.0627	8.008162	0.0000
DUMMY_202003	-1379.820	184.6939	-7.470848	0.0000
DUMMY_202005	793.9084	183.2792	4.331689	0.0000
DUMMY_202006	-768.4173	183.9178	-4.178047	0.0001
DUMMY_202010	-737.6004	186.0093	-3.965396	0.0001
DUMMY_202011	1202.281	183.9753	6.535010	0.0000
DUMMY_202012	-1339.918	184.6993	-7.254591	0.0000
DUMMY_202101	793.7376	183.2964	4.330350	0.0000

DUMMY_202103	-803.1027	185.1111	-4.338490	0.0000
DUMMY_202106	-244.2411	184.0848	-1.326786	0.1870

R-squared	0.927140	Mean dependent var	-34.96741
Adjusted R-squared	0.897413	S.D. dependent var	549.7719
S.E. of regression	176.0878	Akaike info criterion	13.41958
Sum squared resid	3875865.	Schwarz criterion	14.35268
Log likelihood	-1135.633	Hannan-Quinn criter.	13.79801
F-statistic	31.18848	Durbin-Watson stat	1.868771
Prob(F-statistic)	0.000000		

The D_ indicates the first difference. SCEGOVEMP(-15) indicates SCE government employment lagging 15 months.

Agriculture Customer Model

Dependent Variable: D(AGCUS)
Method: Least Squares
Date: 02/04/25 Time: 19:17
Sample: 2004M01 2024M09
Included observations: 249

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-21.77925	5.640126	-3.861483	0.0001
D(AGEMP_SA(-18))	7.152789	5.503443	1.299694	0.1951
JAN	0.428919	7.866050	0.054528	0.9566
FEB	20.98769	7.755428	2.706193	0.0073
MAR	7.851390	7.951423	0.987419	0.3245
APR	21.65439	8.331359	2.599142	0.0100
MAY	26.09249	7.949072	3.282457	0.0012
JUN	18.87896	7.952686	2.373910	0.0185
JUL	9.356008	7.950048	1.176849	0.2405
AUG	7.957558	7.950402	1.000900	0.3180
SEP	12.06657	7.751590	1.556657	0.1210
OCT	-3.850700	7.949632	-0.484387	0.6286
NOV	-1.328889	7.843942	-0.169416	0.8656
DUMMY_200707	69.51747	25.47380	2.728979	0.0069
DUMMY_201304	-137.9789	25.57011	-5.396100	0.0000
DUMMY_201607	-299.9663	25.46877	-11.77781	0.0000
DUMMY_201608	295.4033	25.46961	11.59827	0.0000
DUMMY_201703	-139.8586	25.46874	-5.491383	0.0000
DUMMY_201705	-9716.071	25.47594	-381.3822	0.0000
DUMMY_201706	5491.250	25.46702	215.6220	0.0000
DUMMY_201708	4368.287	25.47203	171.4935	0.0000
DUMMY_201903	-729.6651	25.46420	-28.65455	0.0000
DUMMY_201904	-3796.339	25.57383	-148.4462	0.0000
DUMMY_201905	4486.301	25.46787	176.1553	0.0000
DUMMY_202104	17.43222	25.99940	0.670486	0.5033
DUMMY_202106	-121.9599	25.84733	-4.718470	0.0000
DUMMY_202110	-413.3541	25.92277	-15.94560	0.0000
DUMMY_202201	-32.45149	27.02659	-1.200724	0.2312
DUMMY_202204	-97.08226	26.32638	-3.687642	0.0003
DUMMY_202404	-84.77488	25.61695	-3.309328	0.0011
CSRP	-29.49279	5.032433	-5.860544	0.0000

R-squared	0.999251	Mean dependent var	-18.13338
Adjusted R-squared	0.999148	S.D. dependent var	849.9866
S.E. of regression	24.80460	Akaike info criterion	9.375973
Sum squared resid	134128.5	Schwarz criterion	9.813889
Log likelihood	-1136.309	Hannan-Quinn criter.	9.552242
F-statistic	9699.847	Durbin-Watson stat	1.720679
Prob(F-statistic)	0.000000		

The D_ indicates the first difference. AGEMP(-18) indicates SCE agricultural employment lagging 18 months.

Street Light Customer Model

Dependent Variable: D(STLCUS)
Method: Least Squares
Date: 10/18/24 Time: 13:50
Sample: 2008M01 2024M09
Included observations: 201

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	92.39759	171.5340	0.538655	0.5908
D(SCERESCUSF(-6))	0.044087	0.016997	2.593849	0.0103
JAN	-188.1421	231.3702	-0.813165	0.4173
FEB	-93.36857	239.4713	-0.389895	0.6971
MAR	319.9907	235.7400	1.357388	0.1765
APR	-64.20798	231.3866	-0.277492	0.7817
MAY	-219.4703	229.5672	-0.956017	0.3404
JUN	-63.67164	225.6384	-0.282184	0.7781
JUL	-255.1434	225.9450	-1.129228	0.2604
AUG	-198.3972	236.7847	-0.837880	0.4033
SEP	-515.5127	226.8855	-2.272127	0.0243
OCT	64.21413	231.5653	0.277305	0.7819
NOV	-553.7748	231.4654	-2.392474	0.0178
DUMMY_201612	1110.324	633.6038	1.752394	0.0815
DUMMY_201701	-5659.012	633.8564	-8.927908	0.0000
DUMMY_201702	-2617.240	637.6763	-4.104339	0.0001
DUMMY_201704	-2863.406	631.6015	-4.533565	0.0000
DUMMY_201705	2743.611	629.3729	4.359278	0.0000
DUMMY_201708	7328.982	634.6334	11.54837	0.0000
DUMMY_201802	-3516.601	658.1480	-5.343176	0.0000
DUMMY_201803	2658.070	632.5119	4.202403	0.0000
DUMMY_201809	-54.04449	634.0667	-0.085235	0.9322
DUMMY_201810	1943.521	654.6894	2.968615	0.0034
DUMMY_201901	1797.477	630.5944	2.850449	0.0049
DUMMY_201902	-3155.940	633.9373	-4.978316	0.0000
DUMMY_201903	2448.307	632.4124	3.871377	0.0002
DUMMY_201912	2890.069	635.1381	4.550301	0.0000
DUMMY_202003	2544.493	634.2577	4.011765	0.0001
DUMMY_202104	674.4211	635.1770	1.061784	0.2899
DUMMY_202108	9.706729	632.0591	0.015357	0.9878
DUMMY_202002	-2912.700	640.0650	-4.550632	0.0000
DUMMY_202012	3065.164	640.1670	4.788069	0.0000
DUMMY_202011	-2602.185	633.3948	-4.108315	0.0001

R-squared	0.776903	Mean dependent var	63.27363
Adjusted R-squared	0.734408	S.D. dependent var	1184.676
S.E. of regression	610.5298	Akaike info criterion	15.81555
Sum squared resid	62621445	Schwarz criterion	16.35788
Log likelihood	-1556.463	Hannan-Quinn criter.	16.03500
F-statistic	18.28234	Durbin-Watson stat	2.533775
Prob(F-statistic)	0.000000		

The D_ indicates the first difference. SCERESCUSF(-6) indicates SCE residential customer lagging 6 months.

Customer Model Variable Description

Residential Customer Models

RESCUS	Recorded number of residential class customers. Source: SCE
LA	Prefix in front of variable name to denote Los Angeles County
OR	Prefix in front of variable name to denote Orange County.
SB	Prefix in front of variable name to denote San Bernardino County.
RV	Prefix in front of variable name to denote Riverside County.
VSB	Prefix in front of variable name to denote Ventura and Santa Barbara Counties.
OTH	Prefix in front of variable name to denote Rural Counties (Fresno, Inyo, Kern Kings, Mono and Tulare)
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture irregularities in customer count data.
GEOSTRT	SCE housing starts. Compiled from Moody's Analytics and IHS Markit.

Commercial Customer Models

ComCus	Recorded number of commercial class customers. Source: SCE
SCERESCUS	Total SCE residential customers. Source: SCE
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture irregularities in customer count data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.

Industrial Customer Model

INDCUS	Recorded number of industrial class customers. Source: SCE
SCEMFGEMP	SCE manufacturing employment. Compiled from Moody's Analytics and IHS Markit.
INDTREND	Linear counter variable designed to capture secular trend growth not otherwise captured in the model.

DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture irregularities in customer count data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.
CSRP	Binary variable set equal to 1 for the designated month and zero otherwise for the period April 2021 to December 2023.

Other Public Authorities Customer Model

OPACUS	Recorded number of other public authority class customers. Source: SCE
SCEGOVEMP	SCE regional government employment. Compiled from Moody's Analytics and IHS Markit.
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture irregularities in customer count data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.
OPATREND	Linear counter variable designed to capture secular trend growth not otherwise captured in the model.

Agriculture Customer Model

AGCUS	Recorded number of agriculture class customers. Source: SCE
AGEMP	Number of persons employed in agriculture. Source: SCE estimates
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DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture irregularities in customer count data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.
CSRP	Binary variable set equal to 1 for the designated month and zero otherwise for the period April 2021 to December 2023.

Street Light Customer Model

STRCUS	Recorded number of street lighting customers. Source: SCE
SCERESCUS	Total SCE residential customers. Source: SCE
DUMMY_YYYYMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture irregularities in customer count data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.