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Disaggregating Future Retail Electricity Rate Growth

Supplemental Information on Data and Methodology

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Introduction

We describe the data sources, methodology, and calculations to quantify and disaggregate future retail electricity rates. The study results and conclusions are described in a separate report.[1] The supplemental information is organized in two sections, specifically: 1) data (including the utility characterization and rate driver growth rate assumptions) and 2) methodology (including the financial calculations and uncertainty modeling approach).

Data

The Federal Energy Regulatory Commission (FERC) Form No. 1 ("FERC Form 1") documents financial information reported by most utilities in the U.S. annually[2] and served as the primary data source to develop inputs for the analysis. FERC Form 1 data is publicly available and uses a consistent accounting system that ensures uniform reporting of utility costs. We collected data for each of the cost-related (i.e., utilities' capital expenditures (CapEx), non-fuel operations and maintenance (O&M), and fuel and purchased power costs) and non-cost-related (i.e., retail sales and customers) retail rate drivers for the historical period of 2008-2019, which was the most recent year available. Table 1 shows the FERC Form 1 reference and calculations of FERC Form 1 data for each of the rate drivers.

From the initial set of data, we used various quality assurance filters to down-select to a final sample of utility data. Starting with 304 utilities, the dataset was filtered to only include investor-owned, regulated utilities that served retail customers. These filters ultimately left 117 utilities. From this master set, data for each rate driver were considered separately and further screens were applied. First, for each rate driver, we eliminated a utility if it had any null, negative, or infinite annual values within the time range. Second, for each rate driver, we eliminated any data point that fell outside of two standard deviations from the respective utility's mean. Finally, the ratio of maximum to minimum levels were analyzed and we eliminated any data point outside of a ratio of two (2) for retail customers and sales or outside a ratio of ten (10) for all O&M expenditure variables. Note that the screen on ratios was not applied to CapEx due to the highly variable nature of these drivers. Table 2 summarizes the number of utilities included for each variable which differ as a result of data availability (e.g., wires-only utilities were not included in generation expenditure variables), quality, and completeness.

[1] Available at: https://emp.lbl.gov/publications/disaggregating-future-retail
[2] Available publically at: https://www.ferc.gov/industries-data/electric/general-information/electric-industry-forms/form-1-electric-utility-annual, but extracted via ABB Ventyx (accessed February, 2021)

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Table 1. FERC Form 1 reference and calculation for each rate driver

Rate Driver	Equation	FERC Form 1 Ref.*
Generation CapEx [$]	$= [Total\ Prod.Plant]$	Page 204, Line 46
Distribution CapEx [$]	$= [Total\ Distribution\ Plant]$	Page 206, Line 75
Transmission CapEx [$]	$= [Total\ Transmission\ Plant]$	Page 206, Line 58
Other CapEx [$]	$= [Total\ Electric\ Plant\ in\ Service]$ $- [Total\ Prod.Plant]$ $- [Total\ Distrib.Plant]$ $- [Total\ Tx.Plant]$	Page 206, Line 104 Page 204, Line 46 Page 206, Line 75 Page 206, Line 58
Generation Non-Fuel O&M [$]	$= [Total\ Steam\ O\&M]$ $- [Steam\ Fuel]$ $+ [Total\ Nuclear\ O\&M]$ $- [Nuclear\ Fuel]$ $+ [Total\ Hydro\ O\&M]$ $- [Water\ for\ Power]$ $+ [Total\ Other\ O\&M\ Production]$ $- [Other\ Fuel\ Expenses]$	Page 320, Line 21 Page 320, Line 5 Page 320, Line 41 Page 320, Line 25 Page 320, Line 59 Page 320, Line 45 Page 321, Line 74 Page 321, Line 63
Distribution O&M [$]	$= [Total\ Distribution\ O\&M]$	Page 322, Line 156
Transmission O&M [$]	$= [Total\ Transmission\ O\&M]$	Page 321, Line 112
Other O&M [$]	$= [Total\ Electric\ O\&M]$ $- [Total\ Distribution\ O\&M]$ $- [Total\ Transmission\ O\&M]$ $- [Total\ Power\ Production\ O\&M]$	Page 323, Line 198 Page 322, Line 156 Page 321, Line 112 Page 321, Line 80
Fuel and Purchased Power [$]	$= [Steam\ Fuel]$ $+ [Nuclear\ Fuel]$ $+ [Water\ for\ Power]$ $+ [Other\ Fuel\ Expenses]$ $+ [Purchased\ Power]$	Page 320, Line 5 Page 320, Line 25 Page 320, Line 45 Page 321, Line 63 Page 321, Line 76
Retail Sales [MWh]	$= [MWh\ Sold]$	Page 304
Customers [#]	$= [Average\ Number\ of\ Customers]$	Page 304

* *Listed in order of appearance in Equation column*

Table 2: Sample size of utilities for each rate driver's compound annual growth rate

Rate Driver	Utility Sample [#]
Generation CapEx [$]	17
Distribution CapEx [$]	53
Transmission CapEx [$]	45
Other CapEx [$]	35
Generation Non-Fuel O&M [$]	50
Distribution O&M [$]	70
Transmission O&M [$]	77
Other O&M [$]	78
Fuel and Purchased Power [$]	54
Retail Sales [MWh]	69
Customers [#]	95

The Energy Information Administration (EIA) collects hourly electricity demand data from each balancing authority (BA) in the U.S. using Form 930. We collected Form 930 data from 2016-2019 via EIA's Hourly Electric Grid Monitor web portal. Our goal was to produce a robust panel dataset for analysis purposes, so we applied several data cleaning algorithms. For each BA, year, and month, we developed an average 24-hour load profile. If the load in a given hour for a unique BA, year, and month was missing or negative, then we either assigned the previous day's load for that hour, if it existed, or the associated hourly value from that month's average load profile. If the load in a given hour for a unique BA, year, and month was more than two (2) times the previous day's load or more than two (2) times the hourly value from that month's average load profile, then we either assigned the previous day's load for that hour, if it existed, or the associated hourly value from that month's average load profile.

We derived a typical utility hourly load shape based on the following criteria: 1) Had the smallest sum of squared differences from that BAs annual load factor to the mean annual load factor across all BAs; 2) Had as few hourly data values as possible that our data cleaning algorithm was applied to; and 3) Represented a summer-peaking system. This resulted in five viable BAs: ISO New England (ISO-NE), California ISO, Electric Reliability Council of Texas, New York ISO, and Southwest Power Pool. From there, we ordered the BAs first by the sum of squared load factor differences (in ascending order) and then the number of observations that had to be cleaned (in ascending order). ISO-NE had annual load factors most consistent with the overall sample annual simple average (54.6-58.6%), had only 3 hourly data points that our data cleaning algorithm was applied to, was summer peaking in all four years of the analysis period, and covered both urban and rural communities. Therefore, we used ISO-NE 2019 data to derive an hourly system load shape for our analysis.

Utility Characterization

We characterized a generic investor-owned and vertically-integrated utility using average or typical financial and load assumptions.[3] The utility characterization was used in the study to derive starting year (2019) utility revenue requirement and retail rates. The cost and load assumptions were based on the rate

[3] Although the system load shape we used to represent this utility is based on a system (ISO-NE) where the vast majority of utilities are not vertically integrated, we believe that utility ownership of generation assets should have little to no effect on the electricity consumption patterns of customers. Thus, we contend it was reasonable to apply this load shape in this context.

driver dataset described above using historical FERC Form 1 data. Specifically, we calculated a sample-weighted, 10-year moving average for each rate driver.[4] The utility average 2019 retail sales, total customers, and total average fuel and purchased power cost values ($/MWh) were used as the utility's starting year value. When the starting year retail sales level was applied to the system load shape developed for this analysis as described above, which had a 56% annual load factor, we derived the utility's starting year peak demand level. We normalized average CapEx and O&M costs by customer counts (within their respective FERC Form 1 samples) and multiplied the per-customer values by the staring year number of customers (see Table 3 "2019 Value" column) to derive starting year total budgets for these categories.

We also made several assumptions about the utility's financial characteristics. Specifically, we assumed a 56:44 debt-to-equity ratio and 4% debt service cost based on the EEI 2019 Financial Review.[5] We also assumed an authorized return on equity (ROE) of 9.65% based on the amount the typical U.S. electric utility received in 2019 as reported by S&P Global Market Intelligence.[6] We assumed an accumulated deferred income tax (ADIT) value of 95%, based on previous FINDER analysis results.

Rate Driver Growth Rates

In order to estimate future retail rates, we assumed compound annual growth rates (CAGRs) for each of the rate drivers and bounded them with a range of Low, Medium, and High values to characterize the potential variability (see Table 3). We first calculated three samples for each rate driver that corresponded to the respective Low, Medium, and High categories. Specifically, the 2nd quintile (i.e., 20-40th percentile of utilities) represented the Low value, all utilities in the sample were used to derive the Medium value, and the 4th quintile (i.e., 60-80th percentile) represented the High value. For each sample, we developed an annual 10-year sample-weighted moving average of the aggregate annual value and then developed annual growth rates for each year in the sample.[7] The 2019 10-year moving average growth rate for each sample was then assigned as the Low, Medium, and High CAGR.

We then compared the Low, Medium, and High CAGRs to publicly available literature describing historical and future trends in each rate driver to inform whether the use of historical data for future projections was reasonable. For retail sales, the Low CAGR value of -0.2% was directionally consistent with other historical analyses and regional forecasts. For example, a Texas regional study forecasted -0.6%[8] growth while a California regional study forecasted -1.6%.[9] The Medium CAGR of 0.3% was also consistent with several national and regional studies that spanned retail sales growth between 0% and 1%.[10] Finally, the selected

[4] Specifically, the sum of that particular driver across all utilities in the sample over a 10-year period ending at time *t* was divided by 10 to produce a sample-weighted 10-year average value at time *t*.

[5] EEI. (2020) 2019 Financial Review: Annual Report of the U.S. Investor-Owned Electric Utility Industry. Washington, D.C. July 19. https://www.eei.org/issuesandpolicy/Finance%20and%20Tax/Financial_Review/FinancialReview_2019.pdf

[6] Fontanella, L. (2020) Electric Roe Authorizations Drift Lower in H1'20 as Virus Worries Continue. Retrieved December 21, 2020. https://www.spglobal.com/marketintelligence/en/news-insights/research/electric-roe-authorizations-drift-lower-in-h1-20-as-virus-worries-continue.

[7] Applying a moving average is a simple yet effective way to capture trends over time in data that is highly variable from year to year. Hanke, J. E., & Reitsch, A. G. (1995). Business Forecasting (Fifth Edition). Englewood Cliffs, NJ: Prentice Hall, Inc.

[8] Electric Reliability Council of Texas (ERCOT) (2019). 2020 Long-Term Load Forecast Report (accessed July 23, 2020). Available at: http://www.ercot.com/gridinfo/load/forecast.

[9] California Energy Commission (2020). 2019 Integrated Energy Policy Report. Docket # 19-IEPR-01.

[10] See, e.g., EIA AEO 2020. Available at: https://www.eia.gov/outlooks/archive/aeo20/. Gotham et al. (2019). 2019 MISO Energy and Peak Demand Forecasting for System Planning. Available at: https://www.misoenergy.org/planning/policy-studies/system-forecasting-for-

High CAGR of 1.7% is far higher than FERC Form 1's 4th quintile value of 0.6% due to literature forecasting retail sales growth between 1.5% and 2.0%.[11] Low and Medium fuel and purchased power (FPP) cost CAGR values were taken directly from the ten-year moving averages, however, the selected High CAGR value of 1.7% was much higher than the FERC Form 1 4th quintile value of -1.8%. This was changed to allow possible positive growth consistent with higher end EIA Annual Energy Outlook's 2019-2030 fuel cost forecasts in the 1.5% - 2.2% range.[12] There were no changes to remaining rate driver CAGRs from the FERC Form 1 moving averages due to either insufficient literature, noncomparable studies, or literature that confirmed the reasonableness of the FERC Form 1 moving averages. In several cases, literature was also inconsistent. For example, recent short-term CapEx forecasts based on utility filings, EEI, and S&P Global[13] predicted flat growth, but EEI[14] notes that short-term forecasting has historically underestimated spending, suggesting increasing CapEx growth.

Table 3: Starting year values and CAGR assumptions for rate drivers: These data were derived from FERC Form 1 and serve as inputs into the FINDER model

Rate Driver	2019 Value	Low CAGR	Medium CAGR	High CAGR
Generation CapEx	$563M	-5.3%	4.7%	8.4%
Distribution CapEx	$258M	6.1%	7.1%	7.9%
Transmission CapEx	$298M	7.1%	7.9%	8.3%
Other CapEx	$79M	3.3%	7.0%	10.3%
Gen. Non-Fuel O&M	$311M	0.0%	0.9%	3.1%
Distribution O&M	$120M	1.8%	3.5%	4.4%
Transmission O&M	$202M	3.4%	5.1%	7.5%
Other O&M	$298M	0.5%	1.5%	3.7%
Fuel and Purchased Power	$753M	-5.8%	-3.0%	1.7%
Retail Sales*	20,092 GWh	-0.2%	0.3%	1.7%
Customers*	962,851	-0.2%	0.3%	1.7%
Peak Demand*	4,072 MW	-0.2%	0.3%	1.7%

*** Retail sales and customers were strongly correlated (ρ=0.94) in the FERC Form 1 dataset. Consequently, a constant use-per-customer was assumed over the entire analysis period. Since we also assumed a constant system load shape with a load factor of 56% that simply adjusted uniformly in all hours with changes in annual retail sales, all three non-cost-related rate drivers (i.e., retail sales, system peak, customers) were assigned identical CAGRs.**

energy-planning/. Northwest Power Planning Council (2016). Seventh Power Plan. Available at: https://www.nwcouncil.org/reports/seventh-power-plan.

[11] See, e.g., Mai, Trieu, Paige Jadun, Jeffrey Logan, Colin McMillan, Matteo Muratori, Daniel Steinberg, Laura Vimmerstedt, Ryan Jones, Benjamin Haley, and Brent Nelson. 2018. Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-71500; Weiss, J., Hledik, R., Hagerty, M., and Gorman, W. (2017). Electrification: Emerging opportunities for utility growth. January.

[12] EIA (2019) Annual Energy Outlook 2019 with Projections to 2050. Energy Information Administration, Washington, D.C. January 24.

[13] Available at: https://www.statista.com/statistics/217018/capital-expenditure-of-us-shareholder-owned-electric-utilities/

[14] Available at: https://www.eei.org/issuesandpolicy/Finance%20and%20Tax/EEI_Industry_Capex_Functional_2020.pdf

Methodology

The Financial Impacts of Distributed Energy Resources (FINDER) pro forma financial model quantifies the utility's annual costs and revenues over a pre-defined analysis period. For this analysis, the FINDER model calculated all costs and revenues at the total utility level and without allocation to individual rate classes.

Financial Calculations

One of the first, and most important, steps in utility ratemaking is to determine the utility's annual revenue requirement. The revenue requirement is comprised of all the capitalized and expensed costs incurred by a utility in a given year. We mapped our rate drivers to the utility revenue requirement in two ways. First, expensed cost-related rate drivers (i.e., FPP and O&M) mapped exactly to corresponding revenue requirement elements (see Figure 1).

Second, capitalized cost-related rate drivers (i.e., CapEx) are associated with the utility's rate base that is inclusive of depreciation, equity return, debt service, and taxes (see Figure 2). In the first year of the analysis, the utility's existing rate base was derived by normalizing each utility's FERC Form 1 2019 start of year plant in service by their total customer count and taking a simple average across the data sample. The same method was applied to derive a utility average accumulated depreciation expenses on a per-customer basis in 2019, as well as a depreciation provision on a per-customer basis in 2019. The average asset lifetime of the utility's rate base was developed by taking the utility average normalized rate base and dividing it by the utility average annual depreciation provision. The three normalized capital-related inputs were multiplied by the starting year customer count for our modeled utility to derive starting year utility-level values for start of year rate base, accumulated depreciation, and annual depreciation expense. We then allocated the utility's start of year rate base to the four CapEx categories (i.e., generation, transmission, distribution, and other) based on each categories' share of starting year total CapEx budget. For each CapEx category, we derived the revenue requirement elements based on assumptions of typical utility capital structure and federal and state tax rates (see utility characterization above for specific assumptions).

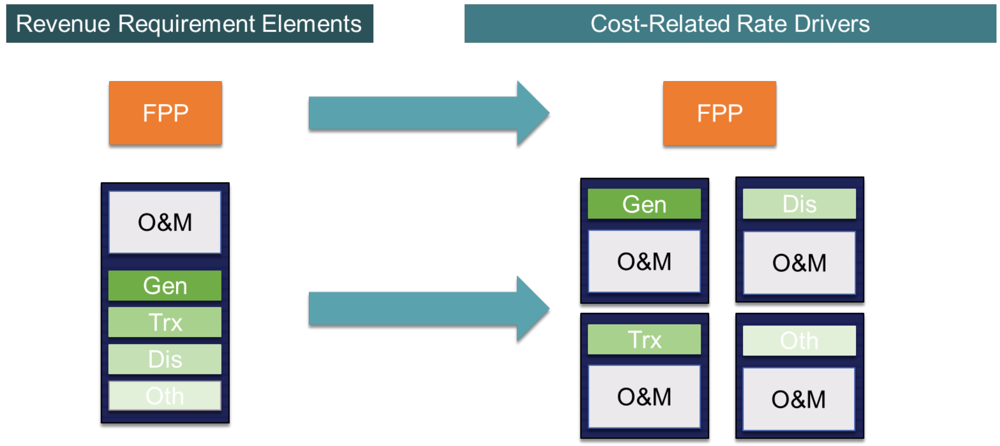

Figure 1. Mapping of FPP and O&M rate drivers to the utility revenue requirement

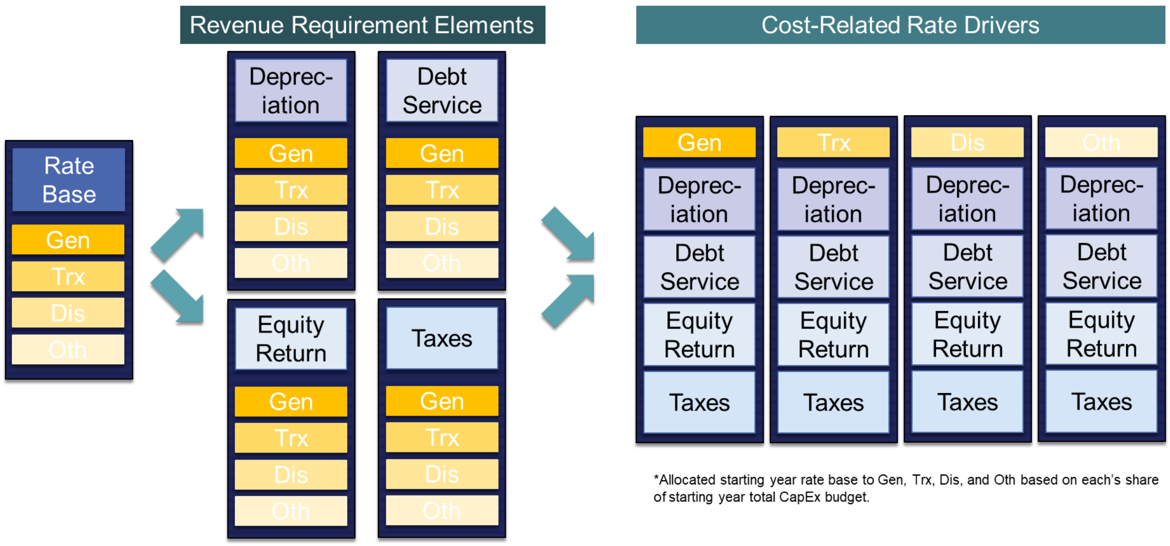

Figure 2. Mapping of CapEx rate drivers to the utility revenue requirement

Uncertainty Modeling

We represented uncertainty of rate driver growth in the analysis in two ways: 1) uncertainty in isolation and 2) joint uncertainty. Both representations used triangular distributions of CAGRs (i.e. Low, Medium, and High) for each rate driver. In order to explore uncertainty in isolation, we ran the model iteratively with 100 random draws of an independent triangular distribution for one rate driver while holding all other rate drivers constant at their median values. This produced a distribution of outcomes that represented the uncertainty associated with that single rate driver in isolation.

The joint uncertainty analysis used 100 random draws from all rate drivers' triangular distributions, while imposing correlations among the distributions (see Figure 3). Spearman correlation coefficients were derived from a natural log transform for every FERC Form 1 data point, by rate driver.[15] We found that retail sales were highly positively correlated with distribution CapEx, distribution O&M, and other O&M, and retail sales were more modestly correlated with transmission CapEx, transmission O&M, and generation CapEx. Generally, there tended to be strong positive correlation across categories (e.g., generation CapEx with generation O&M) and weaker correlation across types of CapEx or O&M. Finally, FPP costs were poorly correlated with any other rate driver.

[15] Both Spearman and Pearson methods for deriving correlation coefficients were applied first to untransformed data points, which resulted in different results. This suggests that the assumptions embodied in the Pearson method, that one is evaluating a linear relationship between two normally distributed variables, is rather weak. When the log transform of the data points was undertaken, the correlation coefficients produced were much more consistent. This supports the assumptions embodied in the Spearman method that the data elements have a non-linear relationship that are not normally distributed. As such, we elected to report and use the Spearman method applied to a natural log transformed dataset.

	GenCapEx	TxCapEx	DCapEx	OtherCapEx	GenOM	TxOM	DOM	OtherOM	FPP	Sales
GenCapEx	1.00									
TxCapEx	0.50	1.00								
DCapEx	0.60	0.75	1.00							
OtherCapEx	0.65	0.60	0.74	1.00						
GenOM	0.80	0.63	0.75	0.71	1.00					
TxOM	0.38	0.65	0.66	0.55	0.47	1.00				
DOM	0.64	0.74	0.93	0.72	0.77	0.70	1.00			
OtherOM	0.67	0.72	0.90	0.75	0.85	0.59	0.88	1.00		
FPP	-0.04	0.09	0.10	0.01	-0.02	0.01	0.06	0.05	1.00	
Sales	0.70	0.75	0.90	0.75	0.85	0.62	0.93	0.91	0.06	1.00
Customers	0.70	0.75	0.90	0.75	0.85	0.62	0.93	0.91	0.06	1.00
CP	0.70	0.75	0.90	0.75	0.85	0.62	0.93	0.91	0.06	1.00

-1.0 0.0 1.0

Spearman Correlation Coefficient

Figure 3. Spearman correlation amongst rate driver growth

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