EXHIBIT RW-4

Georgia Public Service Commission

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Docket No: 42310 **In Re: Georgia Power Company's 2019 Integrated Resource Plan and Application for Certification of Capacity from Plant Scherer Unit 3 and Plant Goat Rock Units 9-12, Application for Decertification of Plant Hammond Units 1-4, Plant McIntosh Unit 1, Plant Estatoah Unit 1, Plant Langdale Units 5-6 and Plant Riverview Units 1-2.**

Docket No. 42311 **In Re: Georgia Power Company's 2019 Application for the Certification, Decertification, and Amended Demand-Side Management Plan.**

ORDER ADOPTING STIPULATION AS AMENDED

APPEARANCES:

On behalf of Georgia Public Service Commission:

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-and-
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On behalf of Georgia Power Company:

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ALAN R. JENKINS, Attorney

On behalf of Concerned Ratepayers of Georgia:

STEVEN PRENOVITZ
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On behalf of Emory University:

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On behalf of Georgia Association of Manufacturers and Georgia Industrial Group:

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On behalf of Georgia Distributed Generation Group, Inc.:

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On behalf of Georgia Interfaith Power & Light and Partnership for Southern Equity:

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BY THE COMMISSION:

On January 31, 2019, Georgia Power Company ("Georgia Power" or the "Company") submitted to the Georgia Public Service Commission ("Commission") an Application for Integrated Resource Plan ("IRP" or "Plan") for approval pursuant to O.C.G.A. § 46-3A-1 *et. Seq.* Included in the Company's filing was an Application for Certification Capacity from Plant Scherer Unit 3 and

Plant Goat Rock Units 9-12, Application for Decertification of Plant Hammond Units 1-4, Plant McIntosh Unit 1, Plant Estatoah Unit 1, Plant Langdale Units 5-6 and Plant Riverview Units 1-2, Docket No. 42310. The Company also simultaneously submitted an Application for the Certification, Decertification, and Amended Demand-Side Management Plan ("DSM Application") Docket No. 42311.

JURISDICTION AND AUTHORITY

Georgia Power is a public electric utility serving retail customers within the State of Georgia. Georgia Power is one of the retail operating companies of which the Southern Company system is comprised. This Commission has jurisdiction over Georgia Power's IRP and DSM Application pursuant to O.C.G.A. § 46-2-20, 46-2-21, 46-2-23 generally, and the IRP Act in particular.

The IRP Act requires the Company to file an Integrated Resource Plan at least every three years.[1] The Company's obligations with respect to the information that is filed is set forth pursuant to criteria identified in the Commission's IRP Rules. A "plan" is defined in the Act as an Integrated Resource Plan that contains the utility's electric demand and energy forecast for at least a 20-year period; program for meeting the requirements shown in its forecast in an economical and reliable manner; the analysis of all capacity resource options, including both demand-side and supply-side options; and the assumptions used and the conclusions reached with respect to the effect of each capacity resource option on the future cost and reliability of electric service. The Plan also must:

(A) Contain the size and type of facilities which are expected to be owned or operated in whole or in part by such utility and the construction of which is expected to commence during the ensuing ten years or such longer period as the Commission deems necessary and shall identify all existing facilities intended to be removed from service during such period or upon completion of such construction;

[1] O.C.G.A. § 46-3A-2.

(B) Contain practical alternatives to the fuel type and method of generation of the proposed electric generating facilities and set forth in detail the reasons for selecting the fuel type and method of generation;

(C) Contain a statement of the estimated impact of proposed and alternative generating plants on the environment and the means by which potential adverse impacts will be avoided or minimized;

(D) Indicate, in detail, the projected demand for electric energy for a 20-year period and the basis for determining the projected demand;

(E) Describe the utility's relationship to other utilities in regional associations, power pools, and networks;

(F) Identify and describe all major research projects and programs which will continue or commence in the succeeding three years and set forth the reasons for selecting specific areas of research;

(G) Identify and describe existing and planned programs and policies to discourage inefficient and excessive power use; and

(H) Provide any other information as may be required by the Commission.[2]

The Commission is required under O.C.G.A. § 46-3A-2 to make determinations as to the adequacy of the IRP and to ensure that the utility's Plan has appropriately addressed numerous matters. There must be a determination that the forecast requirements contained in the Plan are based on substantially accurate data and an adequate method of forecasting.[3] The Commission must also find that the Plan identifies and considers any present and projected reductions in the demand for energy that may result from measures to improve energy efficiency in the industrial, commercial, residential, and energy-producing sectors of the state.[4]

[2] O.C.G.A. § 46-3A-1(7).
[3] O.C.G.A. § 46-3A-2(b)(1).
[4] O.C.G.A. § 46-3A-2(b)(2).

Further, the Commission must determine whether the Plan adequately demonstrates the economic, environmental, and other benefits to the state and to customers of the utilities, associated with the following possible measures and sources of supply:

(A) Improvements in energy efficiency;

(B) Pooling of power;

(C) Purchases of power from neighboring states;

(D) Facilities that operate on alternative sources of energy;

(E) Facilities that operate on the principle of cogeneration or hydro-generation; and

(F) Other generation facilities and demand-side options.[5]

After hearings have been conducted on a Plan, the Commission may approve the IRP; approve it subject to stated conditions; approve it with modifications; approve it in part and reject it in part; reject the plan as filed; or provide an alternate plan, upon determining that this is in the public interest.[6]

An electric utility is entitled to recover the approved or actual cost, whichever is less, of any certificated demand-side capacity option in rates, along with an additional sum.[7] In determining the additional sum, the Commission "shall consider lost revenues, if any, changed risks, and an equitable sharing of benefits between the utility and its retail customer."[8]

BACKGROUND AND STATEMENT OF PROCEEDINGS

On February 2, 2019, the Commission issued its Procedural and Scheduling Order in both Dockets setting forth the dates for filing of testimony and briefs, as well as the dates for the hearings in this matter. These proceedings were declared to be contested cases as the term is defined in O.C.G.A. § 50-13-13 and were also held to encompass complex litigation pursuant to O.C.G.A. §

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[5] O.C.G.A. § 46-3A-2 (b)(3).

[6] GPSC Utility Rule 515-3-4-.01(2).

[7] O.C.G.A. § 46-3A-9

[8] *Id.*

9-11-33(a). The two proceedings were assigned Docket Numbers 42310 and 42311, respectively, and combined for purposes of administrative efficiency and convenience.

Pursuant to O.C.G.A. § 46-3A-5(c), the Commission established the fee for review of the IRP within sixty days of the filing of the applications. On March 16, 2019, the Commission concluded that six hundred eighteen thousand three hundred eighty-five dollars ($618,385.00) was the appropriate fee for review and analysis of the Company's filing.

On April 8, 2019, in accordance with the Procedural and Scheduling Order, the Commission heard direct testimony of Georgia Power's two panels of witnesses: (1) Jeffery R. Grubb, Narin Smith, Michael A. Bush and Jeffrey B. Weathers; and (2) Mark S. Berry and Aaron D. Mitchell.

The Commission conducted hearings on the direct cases of the Public Interest Advocacy Staff ("PIA Staff") and intervening parties in both Dockets on April 13 – 15, 2019. The PIA Staff sponsored several witnesses and witness panels: a panel consisting of Ralph Smith and Robert Trokey; panel witnesses Philip Hayet, Tom Newsome and Stephen Baron; individual testimony of John Hutts and John Chiles; panel witnesses Jamie Barber, John Kaduk, Richard Spellman and John Athas; and lastly, a panel consisting of Jamie Barber, Nick Cooper and Richard Spellman.

The Intervening parties testified as follows: Commercial Group - Steve Chriss; Concerned Ratepayers of Georgia - Steven C. Prenovitz; Emory University - panel Joan Kowal and Edward T. Borer, Jr.; Georgia Center for Energy Solutions - Peter J. Hubbard; Georgia Distributed Generation Group - panel Dr. Ben Johnson and Ryan Sanders: Georgia Interfaith Power & Light and Partnership for Southern Equity - James Wilson; Georgia Interfaith Power & Light and Partnership for Southern Equity, Southface Energy Institute and Vote Solar - William M. Cox; Georgia Large Scale Solar Association - panel John Sterling, Lynnae Willette, John Vanhoe and Arne Olson; Georgia Solar Energy Industries Association, Inc. - panel William M. Cox and Karl R. Rabago; Georgia Solar Energy Association, Inc. - panel Casey M. Busch, Steve A. Chiarello, George N. Mori and Thatcher R. Young; Georgia Watch - panel of Charles Harak and Lindsey Robbins; Sierra Club - Rachel S. Wilson; Southern Alliance for Clean Energy and

Southern Renewable Energy Assoc. - Mark Detsky; Southern Alliance for Clean Energy - panel Theresa Perry, Brendan J. Kirby and Forest Bradley - Wright and panel John D. Wilson and Bryan A. Jacob; and Southern Renewable Energy Assoc. - Michael Goggin and Joshua D. Rhodes.

On June 6, 2019, Georgia Power and PIA Staff executed and submitted a Stipulation designed to resolve all the issues that were raised in these two dockets. (See Attachment A) Subsequently, on June 11, 2019, The Commercial Group, Georgia Industrial Group ("GIG") and Georgia Association of Manufacturers ("GAM") signed the Stipulation; Georgia Watch signed the Stipulation on June 18, 2019; and the Georgia Distributed Generation Group signed the Stipulation thereafter. The Stipulation along with the Company's rebuttal testimony were addressed by Georgia Power's witness panel Jeffrey R. Grubb, Narian Smith, Michael A. Bush and Jeffrey B. Weathers on June 11, 2019.

The Stipulation contains 43 provisions. There are twenty-seven provisions pertaining to the Supply Side Plan and sixteen provisions pertaining to the Demand Side Plan as outlined in Attachment A.

On June 24, 2019 briefs and/or proposed orders were filed by parties in the case. Five signing parties filed briefs in support of the Stipulation and nine non-signing parties filed brief and/or proposed orders making the following recommendations.

NON-SIGNING PARTIES' POSITIONS

<u>Georgia Interfaith Power & Light and Partnership for Southern Equity – GIPL & PSE ("GIPL")</u>

GIPL recommended that the Commission amend the Stipulation to include and require the Company to: (1) model a scenario in which energy efficiency measures are allowed to compete against supply-side measures. Additionally, the DSM Plan must demonstrate optimization of DSM resources, including program budget and details concerning how the Plan balances economic efficiency and rate impacts; (2) develop its 2022 IRP, to allow demand-side resources to compete with supply-side resources; (3) collaborate with Staff and interested stakeholders, over the next year, to model ways to meet a 1% energy efficiency savings target by 2025; (4) continue offering the Automated Benchmarking Tool and to promote the tool; (5) increase funding of its low-income energy efficiency program to $400,000 in 2020, and $500,000 in each of the two subsequent years so that by 2022 the total funding reaches $4 million; (6) work with Staff and interested stakeholders to conduct a data-driven and collaborative conversation over the next year. The group will submit a report to the Commission by January 31, 2021 to inform 2022 IRP planning; (7) add a total of 3,000 MW of renewable energy, over the next three years, including 250 MW of distributed generation. The DG portion must include at least 100 MW of a standard offer, buy-all/sell-all program, with a fixed price levelized over thirty years set at 5 percent below avoided cost; (8) reevaluate and update as appropriate the avoided cost methodology used in Docket 4822, over the next year, while allowing for participation by interested stakeholders; (9) designate at least 100 MW of utility-scale solar capacity to a municipal subscription program designed for government customers; (10) dedicate 10 MW of its approved storage capacity to be deployed in resilience hubs in underserved and vulnerable rural and urban communities for critical emergency services. The Company and Staff will work together to identify and gather input from interested communities on their needs; (11) eliminate winter declining block rates in the upcoming 2019 rate case and, before the 2022 IRP, investigate scaling up the Company's residential thermostat demand-response program to address winter reliability concerns; (12) approve its coal ash clean-up strategy only for those methods that comply with the federal and state CCR Rules; and (13) continue operating its MATS controls to control emission of mercury and other air toxins irrespective of any state or federal attempts to weaken existing standards for the control of mercury and other air toxins. (GIPL/PSE Brief at pp. 2-4).

Georgia Large Scale Solar Association

Georgia Large Scale Solar Association recommended that the Commission adopt the Stipulation with the following changes: (1) Increase by 1,000 MWs from the stipulated agreement, utility scale solar program. The procurement(s) shall be completed by 2021 with all procurements accepting commercial operations dates of 2023 (1500 to 2500). (2) Hold a break out session between PSC Staff and interested Intervenors at the conclusion of this IRP to update the Renewable Cost-Benefit Framework ("RCB") and develop a methodology to value solar + storage in an all source procurement prior to the 2022-2023 capacity-based RFP and prior to the onset of the Company's 2022 resource planning. (GLSSA Brief at pp. 1-2).

Georgia Solar Energy Assoc., Inc. & Georgia Solar Energy Industries Assoc., Inc. (GSEA & GSEIA)

Georgia Solar recommended that the following directives be included in the Stipulation: (1) Direct the Company to develop and implement a Customer-Sited BA/SA tariff. (2) Revise the program guidelines for customer-sited program following the precedent of the Customer-Sited BA/SA program in REDI. (3) Expand the RNR tariff to include small and medium business customers with solar DG needs between 250 kW to 3 MW. (4) Revise the RCB to properly consider the geographic benefit and cost savings to the Company from deployment of solar generation at or near load. And (5) Modification of PURPA avoided costs and RCB for application to basic QFs. (GSEA & GSEIA Brief at p. 17)

Resource Supply Management - ("RSM")

RSM recommended that participation in DSM programs be voluntary for all customers and that customers should be allowed to opt-out of Demand Side Measures along with the associated surcharges on customer bills. (RSM Brief at p. 1).

Sierra Club

Sierra Club recommended that the Commission direct Georgia Power to (1) significantly expand its procurement of renewable resources, (2) retire Plant Bowen or lower the caps on expenditures in line with those placed on Hammond and McIntosh in the 2016 IRP and that the Commission state that exceedances of the caps are not recoverable from ratepayers and (3) in future IRP dockets, employ resource dispatch modeling that analyzes all resource types head-to-head. (Sierra Club Brief at p. 1).

Southern Alliance for Clean Energy, Inc. ("SACE")

SACE recommended the following: (1) the amount of renewable energy generation be increased to a minimum of 3,000 MW; (2) the amount of distributed generation be expanded to 450 MW and any amount of distributed generation not under development or contract by January 1, 2022, automatically be allocated to either the CRSP or REDI II programs; (3) the Company be ordered to update its analysis of technical feasibility of renewable energy factoring in the flexible operating mode of solar; (4) the DSM Advocacy Program be adopted or double the amount of energy efficiency savings in the DSM plan and make the Manufactured Homes Program a pilot program; (5) the Company be directed to use an All-Source Bidding process in future RFPs that does not exclude any type of generation resource; (6) Plant Wansley be included in the 2022-23 capacity RFP; (7) the seven critical improvements and additional enhancement to the CRSP program recommended by SACE witness Perry be adopted; (8) the Company be directed to reexamine the generation remix cost method, the support capacity, the winter reserve requirements in the RCB Framework and recalculate the reserve margins and capacity worth factor tables prior to issuing any RFPs; (9) the Company's additional sum proposal be redesigned to ensure risk and equitable sharing of benefits are considered; and (10) all parties may intervene and fully participate in any proceedings regarding the RCB Framework, the RFPs for all renewable energy generation and all semi-annual reviews of the Company's coal combustion residual compliance efforts. (SACE Brief at pp. 16-17).

<u>Southern Renewable Energy Association ("SREA")</u>

SREA recommended that the IRP be rejected for not providing for a sufficiently sized, nor suitably timed, renewable energy request for proposal ("RFP") process. SREA requested that the Commission consider the following findings and recommendations: (1) Determine that the 1,500 MW solicitation for large scale renewables as part of the Customer Renewable Supply Procurement (CRSP) program is too small and fails to incorporate of the benefits of various renewable resources. (2) The Commission modify CRSP to include a competitive solicitation of at least 3,000 MW's of renewable energy. (3) Within CRSP, 1,000 MW's of large-scale renewable energy resources should be dedicated for customer subscription for new and existing customers with a minimum of 3 MW's of aggregated load. (4) The remaining 2,000 MW's (or greater) of large-scale renewable energy resources within CRSP should be provided for the entire customer base. (5) Before ITC tax incentives begin to phase out, the Company needs to develop a RFP process that produces proposals, evaluates results, and allows the Commission to review and approve proposals in a much more expedient manner. (6) The Company should be required to include fuel hedging as a placeholder in the Renewable Cost Benefit (RCB) Framework. This Framework should also consider the benefits of solar energy, wind power, and energy storage as long-term price hedges for volatile fossil fuel pricing. (7) The Commission should modify the proposed "Capacity Requests for Proposals" (RFPs) to become "All-Source" RFPs. And (8) The Commission should order that intervening parties in this docket will be formally included in discussions regarding the proposed CRSP program, the updated RCB Framework, Capacity RFP's, and the Battery Energy Storage System RFP. (SREA Brief at pp. 3-4).

Southface & Vote Solar

Southface and Vote Solar contend that there are several deficiencies in the proposed Stipulation and recommended that the Commission:

Supply Side Plan:

(1) Increase total renewable energy procurement in this IRP to at least 3,000 MW. (2) Expand the 150 MW DG procurement proposed in the Stipulation to 250 MW of capacity, including 150 MW of competitively bid DG and 100 MW of fixed price DG to be set at 5% below avoided cost. (3) Increase the overall utility-scale solar procurement by up to 100 MW and dedicate this capacity to a municipal customer subscription program open to existing government customer load. (4) Open a proceeding under Dockets 4822 and 16573 to examine Georgia Power's calculation of avoided cost. (5) Proposed continuation of negotiations between the Company and PIA Staff on the RCB Framework include interested Intervenors that were party to the 2019 IRP. (6) Dedicate at least 10 MW of the approved energy storage capacity to projects that both demonstrate and support local resilience. (7) Consider support for implementation of the Emory Micro-Grid project.

Demand Side Plan

(1) Require higher energy savings performance for Georgia Power's DSM portfolio now. In addition, requested the Commission direct the 2020-2021 DSM Work Group to thoroughly

explore the option of adopting a DSM performance target for Georgia Power that provides the backdrop for a 2022 DSM program portfolio that will achieve savings equal to one percent of prior year retail sales by 2025. (2) Direct the DSM Work Group to produce a DSM policy framework that clarifies the Commission's perspective on the costs and benefits of DSM resources and outlines positions of agreement among the DSM Work Group participants. (3) Support implementation of a modest industrial DSM pilot program targeting small and medium industrial customers. (4) Support the Stipulation provision aimed at capping the dramatic growth in DSM program non-incentive costs. (5) Support the Stipulation provision to further reduce administrative costs for the Income Qualified Tariff Based proposed pilot program and ensure the Company continues to seek input of interested stakeholders on Pilot program design and implementation specifics. (6) Support continued operation of Automated Benchmarking Tool by Georgia Power for the next three years. And (7) Expand the Stipulation provision regarding final DSM program plans to include a requirement that Georgia Power publish the Final Program Plans in the docket. (Southface & Vote Solar Brief at pp. 25-27).

Emory University

Emory University filed testimony promoting the proposal that Georgia Power and Emory University work together to develop microgrid technologies for use around the state, specifically around Emory's campuses. In the Stipulation, Supply Side Plan provision 27 specifically states that neither the PIA Staff nor the Company recommended the Emory microgrid project. However, if the Commission decided that it is appropriate to move forward with the project, both the PIA Staff and Company recommended that it be done so only on the condition that, if the project costs exceed the benefits to other ratepayers, Emory agrees to pay the difference. Emory University was silent on provision 27 deciding not to file a brief on the matter. However, during witness testimony, they stated that the university would not pursue the microgrid with Georgia Power if the cost burden to other customers outweighed the benefits. (Tr.1789).

Other Parties of Record

Testimony was not filed by the following non-signing parties: McFinney, LLC and Resource Supply Management. Briefs were not filed by the following non-signing parties: Concerned Ratepayers of Georgia, Emory University, Georgia Center for Energy Solutions, and McFinney, LLC.

FINDINGS OF FACT AND CONCLUSIONS OF LAW

1.

To ensure that the competing interests of all parties were properly considered, the Commission carefully considered the Stipulation, Attachment A, entered into by the Stipulating Parties of record including the testimony given and the various exhibits entered by all of the parties. The Commission finds and concludes that the terms of the Stipulation are supported by the evidence in the record and is a fair and reasonable resolution which appropriately strikes the balance of the interest of all Parties while ensuring system reliability and providing energy at a reasonable cost. Therefore, the Commission approves and adopts the Stipulation as amended below.

2.

Paragraph 3 of the Stipulation states that:

The Company shall procure 1,500 MW alternating current ("AC") of new utility scale renewable resources, defined as projects greater than 3 MW AC. 500 MW of these new resources shall be dedicated to all retail customers. The Customer Renewable Supply Procurement Program ("CRSP") is approved and shall be increased such that it will procure energy from 1,000 MW (600 MW of utility scale renewable resources for subscription by existing CRSP eligible customers, and 400 MW for subscription by CRSP eligible customers adding new load). The Utility scale procurement shall take place through two separate Requests For Proposals ("RFP"). The first RFP is expected to be issued in 2020 and will seek 250 MW of renewables with in-service dates of 2022 and 2023 for all retail customers, 300 MW for subscription by existing CRSP eligible customers, and up to 400 MW for subscription by CRSP eligible customers adding new load. The second RFP is expected to be issued in 2021 and will seek 250 MW of renewables with in-service dates of 2023 and 2024 for all retail customers, 300 MW for subscription by existing CRSP eligible customers and 0 to 400 MW for subscription by CRSP eligible customers adding new load (0 MW to 400 MW represents the remainder of any resources not procured for subscription by CRSP eligible customers adding new load in the first RFP). Any capacity for new load that remains unsubscribed at the end of the second RFP would be offered to any existing CRSP eligible customers whose Notice of Intent ("NOI") capacity request had not been fully met. Any remaining amounts *procured through the RFPs for CRSP but unsubscribed by CRSP participants will be used to serve all retail customers.*

The Commission finds and concludes it is more reasonable and appropriate to increase the amount of the utility scale renewable procurement to 2000 megawatts alternating current. The amount procured by the Customer Renewable Supply Procurement Program will remain at 1000 megawatts with the additional 500 megawatts going to the retail customers. Each of the two proposed Requests for Proposals ("RFP") will increase by 250 megawatts.

3.

Paragraph 5 of the Stipulation discusses an RFP concerning distributed generation which reads in part:

The Company shall issue an RFP to procure energy from up to 150 MW AC of distributed generation solar resources ("DG") greater than 1 kW but not more than 3 MW AC.[9]

The Commission finds that the amount of the distributed generation (DG) procurement shall be increased to 210 megawatt alternating current, which includes 160 megawatts of DG Requests for Proposal and a 50 megawatt customer-sited DG program. The Commission concludes that it is appropriate that projects for the customer-sited program shall be greater than one kilowatt but not more than three megawatts. Procurement shall be done through an application process, and if oversubscribed, a lottery shall be conducted. The Commission has determined that the customer-sited projects shall be paid avoided costs as calculated by the Renewable Cost Benefit Framework.

4.

The Commission recognizes the benefits of biomass as a renewable resource and finds and concludes that increased inclusion should be considered in the future development of the Company's Integrated Resource Plan. Noting that, the Commission directs the Company and Staff to work together on a proposal to procure an additional 50 megawatts of new biomass

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[9] Stipulation - Supply Side Plan, p. 3.

generation to serve Georgia Power's customers. This generation will utilize the competitive solicitation model that allows the Company to recover all of its program costs and grants the Company an additional sum.

The Company and Staff are directed to return to this Commission no later than the end of second quarter 2020 with a proposed biomass procurement strategy for the Commission's consideration and approval.

5.

The Commission finds that it is reasonable and appropriate to further advance the educational feature of integrated resource planning going forward. Therefore, the Commission concludes that the education initiative, Learning Power[10] budget shall be increased to $4 million annually for 2020 through 2022.

6.

The Commission finds and concludes that the record reflects the necessity and need for further development for energy storage capability. Further, witness's testimony noted that the cost associated with battery technology continues to decline. (Tr. Pp. 2448, 2792) Therefore, the Commission directs Georgia Power to develop a pilot project utilizing used lithium ion batteries for a grid-connected charging system for electric vehicles. The goal for the pilot shall include keeping charging of clean electric vehicles affordable and insulating the grid from spikes in electricity demand. The cost of the pilot shall not exceed $250,000. Georgia Power shall work with the Staff in designing the project to ensure that the project has a public benefit.

7.

[10] Stipulation – Demand Side Plan, Paragraph 11, p.10.

The Commission finds that the record in this proceeding established that the Automated Benchmarking Tool ("ABT") provides current value to customers and that demand for the ABT will continue to grow. The Commission directs Georgia Power to continue making the ABT available in the same manner for the next three years.

8.

With respect to Energy Efficiency, the Commission finds and concludes that the energy saving targets for the Company's residential and commercial energy efficiency programs be increased by 15 percent and the relative program budgets be increased by 10 percent. The Commission staff and the Company shall meet within 60 days of the Final Order to finalize the revised DSM portfolio and the DSM budgets for 2020 through 2022, which should include a projected 15 percent increase in savings.

9.

The record in this case identifies potential concerns with Georgia Power's current avoided cost calculation. The Company's obligation to determine the underlying avoided cost is imposed on the Company by the Public Utility Regulatory Policy Act (PURPA), a federal law. The Company proposed the RCB framework to identify additional cost savings resulting from the deployment of renewable generation resources in the 2016 IRP, and it was adopted by this Commission. PURPA's calculation of the Company's underlying avoided costs, and RCB's calculation of additional cost savings resulting from deployment of renewables, particularly distributed solar generation, seek different objectives and utilize different calculations. But together, PURPA and RCB are the building blocks used by the Company to set compensation rates for distributed solar generation.

The Commission is compelled by the testimony that highlighted the fact that, although the Company makes an annual filing of its avoided cost under PURPA, which are subject to the Commission's review, the methodology has not been the subject of a full review in twenty-five (25) years. The Commission finds and concludes that these concerns should be addressed shortly after the conclusion of Docket No. 42516, the 2019 Rate Case, through the Commission reopening a proceeding in Docket No. 4822 to ensure appropriate valuation of renewable and demand-side resources. PIA Staff is directed to initiate a review of the Company's methodology and computation of avoided cost under PURPA.

10.

The Commission finds and concludes that the remaining provisions of the agreement shall have full force and effect as stated in the Stipulation and concludes that all other recommendations and requests from the Non-signing parties are denied.

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ORDERING PARAGRAPHS

WHEREFORE, IT IS ORDERED, that the Commission adopts the Stipulation (Attachment A) as amended herein as a fair and reasonable resolution of the issues in Docket Nos. 42310 and 42311.

ORDERED FURTHER, that the amount of the utility scale renewable procurement shall increase to 2000 megawatts alternating current. The amount procured by the Customer Renewable Supply Procurement Program shall remain at 1000 megawatts with the additional 500 megawatts going to the retail customers. Each of the two proposed Requests for Proposals ("RFP") shall increase by 250 megawatts.

ORDERED FURTHER, that the amount of the distributed generation procurement shall increase to 210 megawatt alternating current, which includes 160 megawatts of DG Requests for Proposal and a 50 megawatt customer-sited DG program. The customer-sited program shall be greater than one kilowatt but not more than three megawatts. Procurement shall be done through an application process, and if oversubscribed, a lottery shall be conducted. The customer-sited projects shall be paid avoided costs as calculated by the Renewable Cost Benefit Framework.

ORDERED FURTHER, that the Company and Commission staff shall work together on a proposal to procure an additional 50 megawatts of new biomass generation to serve Georgia Power's customers. This generation shall utilize the competitive solicitation model that allows the Company to recover all of its program costs and grants the Company an additional sum. The Company and Commission staff shall come back to this Commission by no later than the end of second quarter 2020 with a proposed biomass procurement strategy for the Commission's consideration and approval.

ORDERED FURTHER, that the education initiative, Learning Power, budget shall be increased to $4 million annually for 2020 through 2022.

ORDERED FURTHER, that Georgia Power shall develop a pilot project utilizing used lithium ion batteries for a grid-connected charging system for electric vehicles. The goal for the pilot shall include keeping charging of clean electric vehicles affordable and insulating the grid from spikes in electricity demand. The cost of the pilot shall not exceed $250,000. Georgia Power shall work with the Commission staff in designing the project to ensure that the project has a public benefit.

ORDERED FURTHER, that the Company's Automated Benchmarking Tool ("ABT") shall be continued for the next three years.

ORDERED FURTHER, that the energy saving targets for the Company's residential and commercial energy efficiency programs shall be increased by 15 percent and the relative program budgets shall be increased by 10 percent. The Commission staff and the Company shall meet within 60 days of the issuance of this Order to finalize the revised DSM portfolio and the DSM budgets for 2020 through 2022, which must include a projected 15 percent increase in savings.

ORDERED FURTHER, that shortly after the conclusion of the 2019 Rate Case, Docket No. 42516, the PIA Staff shall initiate a review of the Company's methodology and computation of avoided cost in Docket No. 4822 pursuant to the Public Utility Regulatory Policy Act of 1978 to ensure appropriate valuation of renewable and demand-side resources.

ORDERED FURTHER, the Commission finds that remaining provisions of the agreement shall have full force and effect as stated in the Stipulation.

ORDERED FURTHER, that with the exception of the above findings of facts and conclusions of law, the Commission denies the remaining recommendations of all non-signing parties.

ORDERED FURTHER, all findings, conclusions, and decisions contained within the preceding sections of this Order are hereby adopted as findings of fact, conclusions of law, and decisions of regulatory policy of this Commission.

ORDERED FURTHER, that a motion for reconsideration, rehearing, oral argument, or any other motion shall not stay the effective date of this Order, unless otherwise ordered by the Commission.

ORDERED FURTHER, that jurisdiction over this matter is expressly retained for the purpose of entering such further Order(s) as this Commission may deem just and proper.

The above by action of the Commission in Administrative Session on the 16 day of July 2019.

Reece McAlister
Executive Secretary

7-29-19
Date

Lauren "Bubba" McDonald

Lauren "Bubba" McDonald
Chairman

Date 7/29/19

Georgia Public Service Commission

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June 6, 2019

Mr. Reece McAlister
Executive Secretary
Georgia Public Service Commission
244 Washington Street, S.W.
Atlanta, GA 30334

RE: Docket No. 42310 & Docket No. 42311 / Georgia Power Company's 2019 Integrated Resource Plan and Georgia Power Company's 2019 Demand Side Management

Dear Mr. McAlister:

Enclosed for filing please find a Stipulation executed on behalf of the Georgia Public Service Commission Public Interest Advocacy Staff and Georgia Power Company.

We have furnished an electronic and/or a copy by mail of this filing to all parties in this docket.

Sincerely,

Preston Thomas
Attorney

STATE OF GEORGIA

BEFORE THE GEORGIA PUBLIC SERVICE COMMISSION

In Re:

Georgia Power Company's 2019 Integrated Resource Plan and Application for Certification of Capacity From Plant Scherer Unit 3 and Plant Goat Rock Units 9-12 and Application for Decertification of Plant Hammond Units 1-4, Plant McIntosh Unit 1, Plant Langdale Units 5-6, Plant Riverview Units 1-2, and Plant Estatoah Unit 1	)	**Docket No. 42310**
In the Matter of: Georgia Power Company's Application for the Certification, Decertification, and Amended Demand Side Plan	)	**Docket No. 42311**

Stipulation

The Georgia Public Service Commission (the "Commission") Public Interest Advocacy Staff ("PIA Staff"), Georgia Power Company ("Georgia Power" or the "Company") and the undersigned intervenors (collectively the "Stipulating Parties") agree to the following stipulation as a resolution of the above-styled proceedings to consider the Company's 2019 Integrated Resource Plan (the "2019 IRP") and Application for the Certification, Decertification, and Amended Demand Side Management Plan (the "2019 DSM Plan"). The Stipulation is intended to resolve all of the issues in these Dockets. The Stipulating Parties agree as follows:

Supply Side Plan

1. The 2019 IRP is approved as amended by this Stipulation.

2. Plant Hammond Units 1-4, Plant McIntosh Unit 1, Plant Estatoah Unit 1, Plant Langdale Units 5-6, and Plant Riverview Units 1-2 shall be decertified and retired as provided for in the 2019 IRP.

3. The Company shall procure 1,500 MW alternating current ("AC") of new utility scale renewable resources, defined as projects greater than 3 MW AC. 500 MW of these new resources shall be dedicated to all retail customers. The Customer Renewable Supply Procurement Program ("CRSP") is approved and shall be increased such that it will procure energy from 1,000 MW (600 MW of utility scale renewable resources for subscription by existing CRSP eligible customers, and 400 MW for subscription by CRSP eligible customers adding new load). The Utility scale procurement shall take place through two separate Requests For Proposals ("RFP"). The first RFP is expected to be issued in 2020 and will seek 250 MW of renewables with in-service dates of 2022 and 2023 for all retail customers, 300 MW for subscription by existing CRSP eligible customers, and up to 400 MW for subscription by CRSP eligible customers adding new load. The second RFP is expected to be issued in 2021 and will seek 250 MW of renewables with in-service dates of 2023 and 2024 for all retail customers, 300 MW for subscription by existing CRSP eligible customers and 0 to 400 MW for subscription by CRSP eligible customers adding new load (0 MW to 400 MW represents the remainder of any resources not procured for subscription by CRSP eligible customers adding new load in the first RFP). Any capacity for new load that remains unsubscribed at the end of the second RFP would be offered to any existing CRSP eligible customers whose Notice of Intent ("NOI") capacity request had not been fully met. Any remaining amounts procured through the RFPs for CRSP but unsubscribed by CRSP participants will be used to serve all retail customers.

   All revenues collected through CRSP program, with the exception of the additional sum as described in Paragraph 7, and all appropriate costs, that are not being recovered elsewhere by the Company, incurred for CRSP procurement shall be included in the fuel clause and recovered through Fuel Cost Recovery mechanism ("FCR"). The CRSP costs and revenues to be included in FCR includes, but are not limited to, the costs to implement and administer the CRSP, the bid fees collected, the NOI Fees collected, and the cost of purchase power agreements ("PPA") executed through the CRSP program including any payments for PPAs made by participants. All revenues collected, and all appropriate costs, not being recovered elsewhere by the Company, incurred for the 500 MW of utility scale procurements for all customers shall be included in the fuel clause and recovered through FCR.

4. Within 60 days of the Final Order the PIA Staff and the Company shall begin to meet to develop the specific guidelines and NOI requirements for the CRSP Program. The proposed guidelines will be submitted to the Commission for

approval.

5. The Company shall issue an RFP to procure energy from up to 150 MW AC of distributed generation solar resources ("DG") greater than 1kW but not more than 3 MW AC. The projects must be at or below the Company's projected avoided costs. Contract terms will be up to 30 years. DG projects must interconnect to Georgia Power's distribution system. Bid fees will be set to recover the total cost of procurement for the solicitation. All revenues collected, and all appropriate costs not being recovered elsewhere by the Company incurred for DG procurements shall be included in the fuel clause and recovered through FCR.

6. The Renewable Cost Benefit Framework ("RCB") shall be utilized in the evaluation of bids received through the utility scale and DG RFPs. The PIA Staff has raised specific issues regarding the RCB components of Deferred Generation Capacity, Generation Remix, and Support Capacity and recommended that solar plus storage be considered its own technology using the RCB Framework. The Company and PIA Staff will work collaboratively to resolve the concerns raised by PIA Staff in this case. The Company and PIA Staff will meet within four months of issuance of Final Order in this case and make a good faith effort to resolve the issues. If the issues have not been resolved within this time, the Company and PIA Staff will work to resolve the issues before the next IRP. PIA Staff and the Company also understand that resolution of these issues does not limit the positions that either Party can take regarding the RCB in a future proceeding where modifications to the RCB may be considered. Until such time as these issues are resolved, the RCB used in evaluations will be based on the RCB components and methodologies as filed in the IRP using updated B2019 assumptions (or for later solicitations the applicable vintage assumptions) and calculations of deferred capacity value for the RCB will be based on the B2018 CWFT using the summer TRM of 16.25% as shown in Table B.1 of the January 2019 Reserve Margin Study.

7. The Additional Sum for utility scale resources procured pursuant to Paragraph 3 above and the DG resources in Paragraph 5 shall be set at 8.5% of the projected net benefits. This amount shall be levelized and recovered annually for the term of the PPA.

8. The use of seasonal planning by the Company to provide greater visibility into both summer and winter capacity needs is approved. In the event winter system conditions result in the need for transmission system assessments, the Company would incorporate applicable winter assessment results into future filings of

Technical Appendix Volume 3.

9. The Company and PIA Staff recognize that the use of a winter target reserve margin ("TRM") is necessary to effectuate seasonal planning as approved by this Stipulation. In the absence of a Commission approved winter TRM, the Company will use the System winter TRM for seasonal planning until such time as a winter TRM is agreed to between Staff and the Company and approved by the Commission. There is no requirement for the Commission to act upon the winter TRM until such time as one is approved. The Company may propose resource additions, if needed, to meet winter TRM, and the Commission can determine at that time what the appropriate winter TRM is and whether such additional capacity is needed. Stipulating Parties further agree that the Company may propose the adoption of a specific winter TRM in a future IRP proceeding or IRP update. The Company and PIA Staff will meet within six months of issuance of Final Order in this case to discuss these issues and will work to address the issues before the next IRP.

10. The Stipulating Parties agree that the Scherer Unit 3 Capacity offer should be rejected by the Commission. The offer by the Company, and the rejection by the Commission fulfills the Company's requirements under Docket No. 26550 to offer this capacity to the retail jurisdiction. The Company may, at its own discretion, offer such capacity in the wholesale market or to the retail jurisdiction in a future capacity solicitation or through other permissible vehicles.

11. The Company shall initiate a 2022-2023 and a 2026-2028 capacity-based RFP. The RFPs will be structured to address the capacity needs being sought and will require a level of capacity firmness and dispatchability that will be developed in conjunction with Commission Staff and the IE during the RFP development process. Specific RFP guidelines including resource eligibility requirements, updated IRP assumptions, and evaluation methodology and criteria will be approved by the Commission in accordance with the Commission's proscribed RFP process and may accommodate bids from renewable resources paired with storage. The Company agrees to include language in such RFPs that permit the Company to reject all bids at its discretion.

12. The parties acknowledge that should the retirement of Plant Bowen Units 1 and 2 be necessary there will be transmission issues that need to be addressed in the 2019 base rate case. However, the parties have not agreed on the best solutions to those issue. The Company will explore both traditional transmission solutions and alternatives to traditional transmission solutions (non-wire solutions) and

compare the costs of each approach.

13. The Company agrees to limit capital expenditures specific to Plant Bowen Units 1 and 2 through July 31, 2022. The capital expenditures approved in this paragraph are intended to allow for safe and reliable operations of the units. The Company agrees to annual limits on capital expenditures of $19 Million per year, or $57 Million for the three-year period ending July 31, 2022. The Company agrees to provide a justification to Staff for expenditures that may be needed to maintain safe and reliable operation of Bowen 1 and 2 that exceed the limits provided for in this Paragraph. Within 60 days of the final order in this case, Staff and the Company will meet to develop reporting requirements.

14. The certification of the upgrade to the Goat Rock Hydro-electric facility Units 9-12 is not approved at this time. The Stipulating Parties agree to modifications to the Company's plans to modernize its hydro-electric fleet so that such efforts focus upon five modernization projects. The projects are Terrora, Tugalo, Bartlett's Ferry, Nacoochee, and Oliver. The Company and PIA Staff agree to work together to determine the appropriate information sharing process to allow the Commission to monitor the Company's modernization efforts.

15. The Company is granted authority in this IRP to develop, own and operate energy storage demonstration projects totaling up to 80 MW. The Company will procure the batteries for its ownership through a competitive RFP process. The company will competitively solicit Engineering Procurement and Construction services and shall include the option of turnkey proposals as well. The Company will be required to file a plan with the Commission before undertaking construction and procurement of each project being proposed. In such filing the Company will provide the objectives of the project, location of the project, transmission evaluation of the project and detailed operating and testing plans. Commission Staff shall have 60 days to review the plans prior to Commission approval.

16. The Company's Environmental Compliance Strategy ("ECS") is approved. This includes specific approval of the Company's plans to address coal combustion residuals ("CCR") at the Company's ash ponds and landfills. Stipulating Parties acknowledge that projected CCR compliance cost have been reviewed in this case, but agree that it is not necessary for the Commission to approve a specific budget for CCR compliance in this IRP proceeding. The Parties agree that the Company will seek recovery of such costs in its 2019 base rate case. The PIA Staff reserves the right to challenge the Company's request in the 2019 base rate case, including, but not limited to, the period over which they

are recovered and the method by which they are recovered. To ensure the Commission is updated on CCR compliance efforts the Company will provide semi-annual reports to the Commission. The Company and Commission Staff will collaborate upon the schedule and content of such reports. The Company will also file the ECS annually with the Commission no later than March 31st of each year.

17. The detailed cost information that supports the measures taken to comply with the existing government imposed environmental mandates necessary for the Company to implement its environmental compliance plan as presented in Technical Appendix Volume 1 of the 2019 IRP, "Environmental Compliance Cost Recovery (ECCR) table" is acknowledged subject to the limits outlined in Paragraph 13 regarding Plant Bowen Units 1 and 2. Recovery of actual environmental compliance plan costs will be determined by the Commission in a rate case.

18. The remaining net book values of Plant Hammond Units 1-4, Plant McIntosh Unit 1, Plant Estatoah Unit 1, Plant Langdale Units 5-6, and Plant Riverview Unit 1-2 shall be reclassified as a regulatory asset and the Company shall continue to provide for amortization expense at the same rate as determined in the Company's 2013 base rate case. Timing of recovery of the remaining balance as of December 31, 2019 will be deferred for consideration in the Company's 2019 base rate case. The Stipulating Parties reserve the right to make any arguments, including policy and legal arguments, on the recovery mechanism and appropriate period in which the costs should be recovered if applicable. Parties may argue their respective positions on that issue in the 2019 base rate case.

Any unusable M&S inventory balance remaining at the date of the unit retirement shall be reclassified as a regulatory asset and the timing of recovery deferred for consideration in the Company's 2019 base rate case. The Stipulating Parties reserve the right to make any arguments, including policy and legal arguments, on the recovery mechanism and appropriate period in which the costs should be recovered if applicable. Parties may argue their respective positions on that issue in the 2019 base rate case.

19. Any over or under recovered cost of removal balances for each Retirement Unit shall be deferred for consideration until the Company's 2019 base rate case. The Stipulating Parties reserve the right to make any arguments, including policy and legal arguments, on the appropriate period in which the costs should be recovered. Parties may argue their respective positions on that issue in the 2019 base rate

case.

20. In Docket No. 36989 the Commission approved the donation of Kraft land to the Georgia Port Authority including approval of the accounting treatment for the donation proposed by Georgia Power. PIA Staff has raised a desire to propose alternative ratemaking treatment for the income tax benefits related to the Plant Kraft land donation. The Company believes the issue of the appropriate accounting treatment for the Kraft land donation is resolved per the Commission's Order in Docket No. 36989. To the extent PIA Staff disagrees, the Parties agree that any disagreement may be considered in the 2019 base rate case.

21. In the Commission's Final Order in Docket 40161 and 40162 the Commission authorized the Company to spend up to $99 million between now and the end of the second quarter of 2019 to investigate the option of pursuing new nuclear generation as a potential base load option at a site in Stewart County, Georgia. That Order further found that if the project was terminated, costs incurred toward that effort would be deferred for recovery to a regulatory asset and the timing of that recovery would be addressed in a future base rate case in which the Commission will determine the appropriate period to amortize the recovery of such costs. The Order also held that for ratemaking purposes, the Stewart County property shall continue to be categorized as Plant Held for Future Use. Nothing in this Stipulation is intended to limit the rights of PIA Staff or the Company to pursue their respective positions on cost recovery of Stewart County Site investigation cost.

22. When filing the 2022 IRP or when filing any updates to the IRP prior to the 2022 IRP filing, the Company agrees to provide the Commission Staff working copies of, or access to data used to develop charts, tables, and graphics contained in the filing; models (for example, transmission models, load forecast models, financial models and economic models), and results of relevant analyses performed in the development of that IRP. The models and analyses should be configured to replicate inputs used to derive results incorporated in its base case scenario, and this information shall be provided within 10 days after the IRP or update to the IRP is filed.

23. The Company will compute weather normalized peak demands for the winter and summer seasons of each historical year going forward starting in 2019.

24. The Company will investigate methodologies for allocating long-term annual energy sales for each class to monthly amounts to account for anticipated trends

in seasonal energy sales.

25. The Company agrees to file with the 2022 IRP a forecast scenario of Georgia Power's Peak and Energy forecast using data for the most recent 20 year normal weather.

26. In conjunction with the ongoing level of review and analysis required by this agreement, Georgia Power will agree to pay for any reasonably necessary specialized assistance to the Staff in an amount not to exceed $500,000 annually. This amount paid by Georgia Power under this paragraph shall be deemed as a necessary cost of providing service and the Company shall be entitled to recover the full amount of any costs charged to the utility.

27. Neither Staff nor the Company has recommended the Emory micro grid project. However, if the Commission decides that it is appropriate to move forward with the project, both the Staff and Company recommend that it be done so only on the condition that, if the project costs exceed the benefits to other ratepayers, Emory agrees to pay the difference.

Demand Side Plan

1. The Demand Side Plan is approved as amended by this Stipulation.

2. The Company and Staff shall collaborate to investigate methodologies to model DSM as an additional scenario in its supply side system planning tools as a part of its IRP development and resource optimization process where DSM will be modeled alongside traditional supply-side options. The company will produce a white paper and discuss its findings with the Staff nine months prior to the filing of the 2022 IRP.

3. Georgia Power and PIA Staff agree that calculations of the kWh and kW savings from the Company's certified DSM programs in 2023 be adjusted to actual savings once the Company has completed the impact and process evaluations for each certified DSM program and the Company and Staff reach agreement on evaluation impacts during 2021.

4. The Company and PIA Staff agree that the percentage increases in the current certified program budgets for non-incentive program costs per first-year kWh saved for the 2020 to 2022 period when compared to 2017 and 2018 actual spending on non-incentive costs per first-year kWh saved will be capped at no

more than a 50 percent increase. The 2020 to 2022 budgets for the Company's certified programs will be as presented in Staff Exhibits BSKA-8 and BCS-7. This agreement does not set a precedent for requested budget requests in future IRP cycles and only applies to 2020 through 2022 because implementation costs have the potential to change over time in future IRP cycles.

5. The Demand Side Management Working Group ("DSMWG") will continue in its present form and be involved in the development of future demand side management programs in the same manner as the DSMWG has operated in past IRP cycles.

6. For the Income-Qualified ("Crowd Funding") Program, the Company will maintain the current EASP participant cap of $3,750 per household, the Company will expand its potential crowd funding donation sources, and for the initial term of the Program the Company will not earn an Additional Sum on the savings realized by donations from individuals, non-profits, grants, companies, and partnerships. After the initial review of the Program, the Company may request an additional sum in the 2022 IRP for the Program.

7. The Company and PIA Staff agree to work together over the next nine-months to investigate the reduction of administrative costs for a potential Income Qualified Tariff Based Financing Pilot for 500 income qualified customers. The Company and Staff will also work together to set a policy for the collection of uncollectibles from a potential Income Qualified Pilot through the Residential DSM Tariff. The Company will file a more complete pilot plan with the Commission by April 1, 2020.

8. The Commercial Custom Program will include a per building cap of $75,000 in its final program plan.

9. Once a program implementer is selected and program plans are drafted, the program plans for all approved energy efficiency and demand response programs will be provided to Staff for review prior to the implementation of the programs. The Company should provide Staff up to 15 working days for review of the draft Final Program Plans. In order to deliver programs for customers on schedule, the Company will work with Staff to discuss and address potential concerns with final program plans without delaying program implementation schedules.

10. The current Commission policy that requires the Company to provide detailed evaluation plans for each of the approved DSM programs within 90 days of the selection of Program Implementers for each of the certified programs will

continue. However, the Staff will work with the Company to extend the 90 days on an as needed basis as it has in past IRP cycles.

11. The Education Initiative Learning Power budget will continue at $3 million annually for 2020 through 2022.

12. The Residential and Commercial Energy Efficiency Consumer Awareness annual budgets will continue at $4.5 million and $1.1 million, respectively.

13. The Company's pilot budget will be set at $3million annually and split between the Residential and Commercial classes. The Company will seek Staff's input before the start of any pilot. This pilot budget includes $400,000 in pilot evaluation costs.

14. The HopeWorks low income weatherization program budget will increase to $400,000 per year.

15. The Company will earn an Additional Sum for DSM programs according to the mechanism approved in the Commission's August 2, 2016 Final Order in Docket 40161 & 40162.

16. The Company agrees that all references to Non-Participant Spillover ("NPSO") will be removed from its program plans and will not be considered in future calculations of Additional Sum.

Agreed to this 6th day of June, 2019.

Preston Thomas

On Behalf of the Georgia Public Service Commission
Public Interest Advocacy Staff

Brandon F. Marzo

On Behalf of Georgia Power Company

I/A

BEFORE THE GEORGIA PUBLIC SERVICE COMMISSION

In the Matter of	)	
	)	**Docket No. 42310**
Georgia Power Company's	)	
2019 Integrated Resource Plan	)	
	)	
Georgia Power Company's	)	**Docket No. 42311**
2019 Demand Side Management Plan	)	

CERTIFICATE OF SERVICE

I hereby certify that the foregoing **Stipulation** in the above-referenced docket was filed with the Commission's Executive Secretary, an electronic copy of same was served upon all parties and persons listed below via electronic mail, or unless otherwise indicated, as follows:

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So certified, this 6th day of May 2019.

Preston Thomas
Attorney

EXHIBIT RW-5

ROCKY MOUNTAIN INSTITUTE

THE GROWING MARKET FOR CLEAN ENERGY PORTFOLIOS

ECONOMIC OPPORTUNITIES FOR A SHIFT FROM NEW GAS-FIRED GENERATION TO CLEAN ENERGY ACROSS THE UNITED STATES ELECTRICITY INDUSTRY

AUTHORS & ACKNOWLEDGMENTS

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Images courtesy of iStock unless otherwise noted.

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- Xin Zhang, Rocky Mountain Institute

ABOUT US

About Rocky Mountain Institute

Rocky Mountain Institute (RMI)—an independent nonprofit founded in 1982—transforms global energy use to create a clean, prosperous, and secure low-carbon future. It engages businesses, communities, institutions, and entrepreneurs to accelerate the adoption of market-based solutions that cost-effectively shift from fossil fuels to efficiency and renewables. RMI has offices in Basalt and Boulder, Colorado; New York City; the San Francisco Bay Area; Washington, D.C.; and Beijing.

Funding from the Rudy and Alice Ramsey Foundation supported this work

TABLE OF CONTENTS

EXECUTIVE SUMMARY

EXECUTIVE SUMMARY

Clean energy is now cost-competitive with new gas-fired generation

For more than a decade, gas-fired power plants have dominated new generation investments for the US grid, and the trend is set to continue. Public announcements include approximately $70 billion of planned gas-fired generation investment through the mid-2020s.

However, due to dramatic price declines of wind, solar, and storage (WSS) technologies, clean energy portfolios (CEPs)—optimized combinations of WSS and demand-side management—are now similar in cost to new gas-fired power plants. Further, recent CEP projects prove that these clean technologies can reliably meet grid needs. As a result, new gas investments have slowed.

This study compares the economics of CEPs against every proposed gas plant in the United States

In 2018, RMI released ***The Economics of Clean Energy Portfolios***, which introduced a methodology for comparing CEP costs against new gas-fired generation and showcased four case studies across the United States. The present study expands upon the original work. We systematically optimize least-cost combinations of region-specific WSS, efficiency, and demand flexibility to provide grid services equivalent to every proposed combined-cycle and combustion turbine gas project in the United States. Our approach requires each portfolio to provide the same (or more) monthly energy as the proposed gas plant, match or exceed the gas plant's expected availability during the peak 50 demand hours (net of renewable generation), and provide the same level of grid flexibility.

Our approach forces CEPs to match the grid services of gas generation. The model therefore forces CEPs to compete only on gas generation's own metrics, and omits other clean technology benefits, such as the network value of distributed technologies, the reduced risk of smaller projects, and carbon emissions reductions. Our modeling approach treats each proposed power plant independently, and assesses the economics of a CEP alternative based on how gas plants would be used when built with currently-planned growth in renewables. As such, our results are applicable to the economics and risks of near-term gas power plant investments, rather than the long-term role of gas generation in a future with a very high share (i.e., >50 percent) of renewable energy.

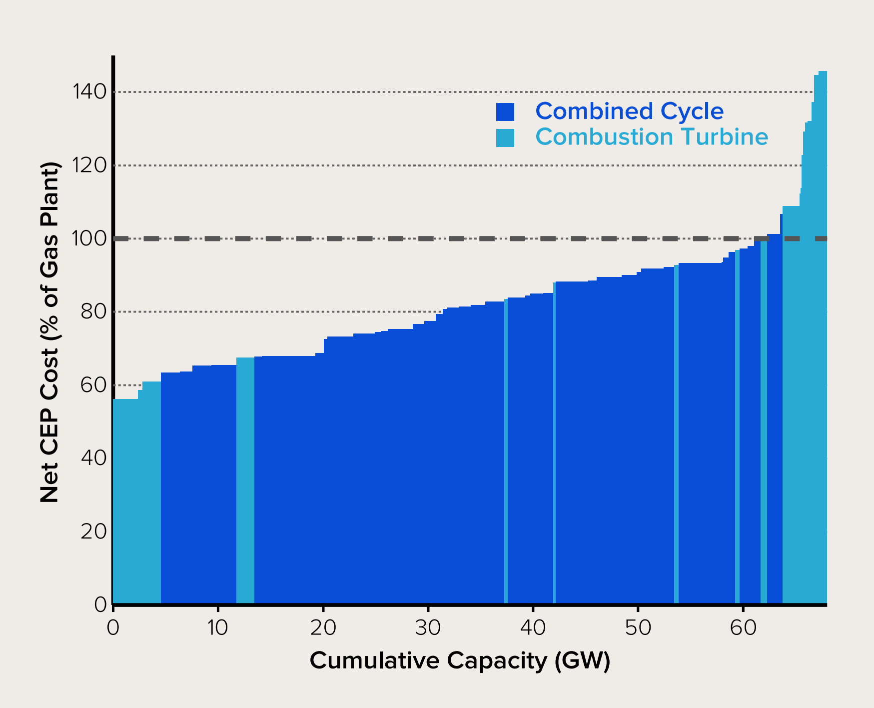
The analysis presents compelling evidence that 2019 represents a tipping point, with the economics now favoring clean energy over nearly all new US gas-fired generation. We present seven key findings:

1. CEPs are lower cost than 90 percent of the proposed 68 gigawatts (GW) of gas-fired power plant capacity

We find that CEPs are lower cost than 90 percent of proposed gas-fired generation at the proposed plant's in-service date (Figure ES 1). Investment in CEPs instead of new gas capacity would save customers over $29 billion and reduce CO_2 emissions by 100 million tons (MT)/year—equivalent to ~5 percent of current annual emissions from the power sector.[1]

FIGURE ES 1

NET CEP COST AS PERCENTAGE OF EQUIVALENT GAS PLANT COSTS AT PLANNED GAS BUILD IN SERVICE YEAR[2]



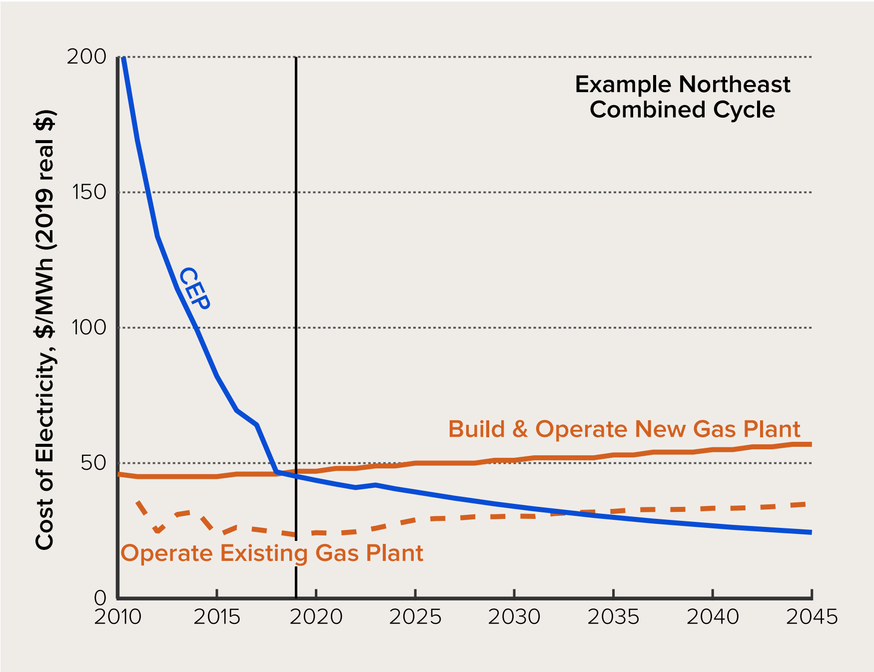
[1] Each case is analyzed independently, but we present aggregate results in this and subsequent findings by summing case study results across all 88 gas plants. This is reasonable because the 88 plants would 1) make up only ~7 percent of installed US generation capacity, limiting the impact of interactions between CEPs, and 2) we restrict the selection of CEP resources to ensure they are distinct from resources chosen in other CEPs.

[2] Net cost is shown here as total net present costs of the CEP compared to the gas plant, net of value from energy provided by the CEP and not provided by the gas plant; see Methodology section for details.

2. 2019 represents a tipping point for CEP economics

FIGURE ES 2

HISTORICAL AND PROJECTED EVOLUTION OF CEP COSTS



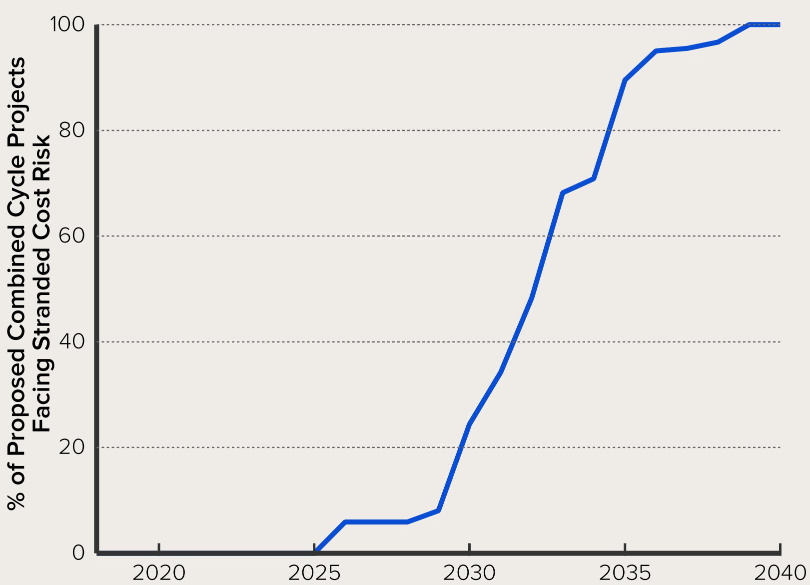
Note: The “kink” in the in the CEP cost curve in 2018 reflects the difference between historical cost decline rates for renewables and storage, and the much more moderate future cost decline rates predicted by technology analysts.

We find that the economics of new generation technologies in the United States are at a tipping point. Figure ES 2 compares the historical and projected costs of a representative CEP and the new combined-cycle plant it could replace for the years 2010 through 2045. The CEP's cost has declined by approximately 80 percent in the past decade, and, as of 2019, is lower than the costs of building and operating a new gas plant. Further, this typical CEP is likely to outcompete just the go-forward operating costs of a combined-cycle gas generator by the early 2030s. A number of factors, including continued fast clean technology cost declines or carbon pricing, would accelerate this timeline.

3. CEPs are likely to undercut the operating costs of over 90 percent of proposed new combined-cycle capacity by 2035, creating stranded asset risk for investors

FIGURE ES 3

PERCENT OF PROPOSED COMBINED-CYCLE GAS TURBINES (CCGTS) FACING STRANDED COST RISK IN EACH YEAR 2020–2040



Just as falling natural gas prices have limited the economic life of legacy coal assets and led to a wave of coal plant retirements, falling clean energy costs are likely to compromise the economic position of gas generation. For each proposed combined-cycle plant, we estimate the year in which the plant's operating costs will be higher than the costs of a new-build CEP that provides the same services (Figure ES 3). We find that nearly all combined cycles will be economically precarious well before they are fully paid for.[3] In 2035, it will be more expensive to operate 90 percent of proposed combined-cycle generation than to build new CEPs. We note that this analysis likely understates the economic case for future clean energy economics because it assumes a dramatic slowing of clean energy cost declines (Figure ES 2) and ignores the impact of potential local or national climate policies.

These economic trends imply significant risk for gas project investors. If gas generators are cost-effectively replaced by CEPs at a cost savings to customers, investors will be unable to meet the revenue targets needed to pay off the remaining gas plant book value and may not be able to cover outstanding debt or provide return on equity to investors. If planned projects are built, investors will likely face tens of billions of dollars' worth of stranded assets in the 2030s, as running these gas plants quickly becomes more expensive than building new CEPs.

[3] Conservatively assuming a 20-year planned economic life

4. The case for CEPs is strong across a range of modeling inputs

We analyzed the sensitivity of CEP economics against variations in all key model inputs, and found that in all cases, CEPs are robust against changes in component technology prices and gas prices. Our sensitivity analysis highlights a key value of piecemeal, modular clean energy investments. Unlike lump-sum investments in new gas-fired power plants, if one component of the CEP is more or less expensive than expected, it is possible to reoptimize the portfolio composition. In comparison, the economics of gas assets rely on a single capital expenditure and a single fuel source.

We also find that if clean technologies continue their recent, fast cost declines instead of following much slower industry projections (the difference explains the "kink" in the Figure ES 2 CEP curve), the case for CEPs is further accelerated.

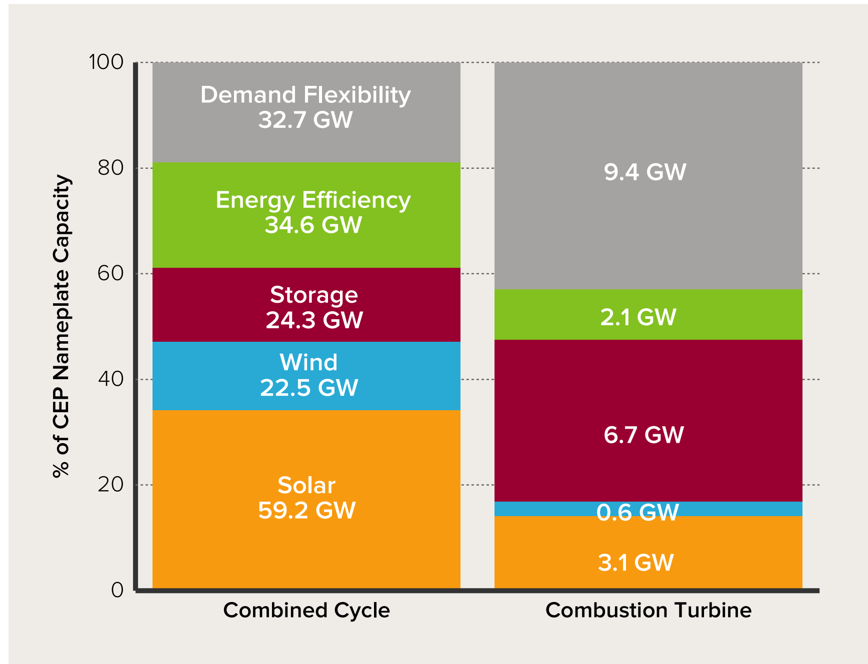
5. Ignoring the value of energy efficiency (EE) and demand flexibility shrinks the near-term market for CEPs to replace new gas by 70 percent and delays the economic opportunity by eight years

We consider portfolios of only WSS that omit EE and demand flexibility. Efficiency and demand flexibility are among the most cost-effective resources available to utility planners and investors, but usually require favorable state policies to achieve scale. If these cost-effective demand-side management resources are ignored, WSS is competitive with only 25 percent of proposed new gas plant capacity, compared with 90 percent for CEPs that include demand-side management. Using industry-standard projections for cost declines, we find it takes an additional eight years, on average, for WSS to reach cost parity with proposed gas plants.

6. CEP composition varies widely by region; all five clean technologies play important roles

FIGURE ES 4

AGGREGATE COMPOSITION OF CEPS ACROSS THE UNITED STATES



Note: More capacity, in megawatts (MW), of CEP resources is usually required to replace a given amount of gas capacity because the capacity factor (CF) of renewables is lower, though the levelized cost per MW is usually also lower.

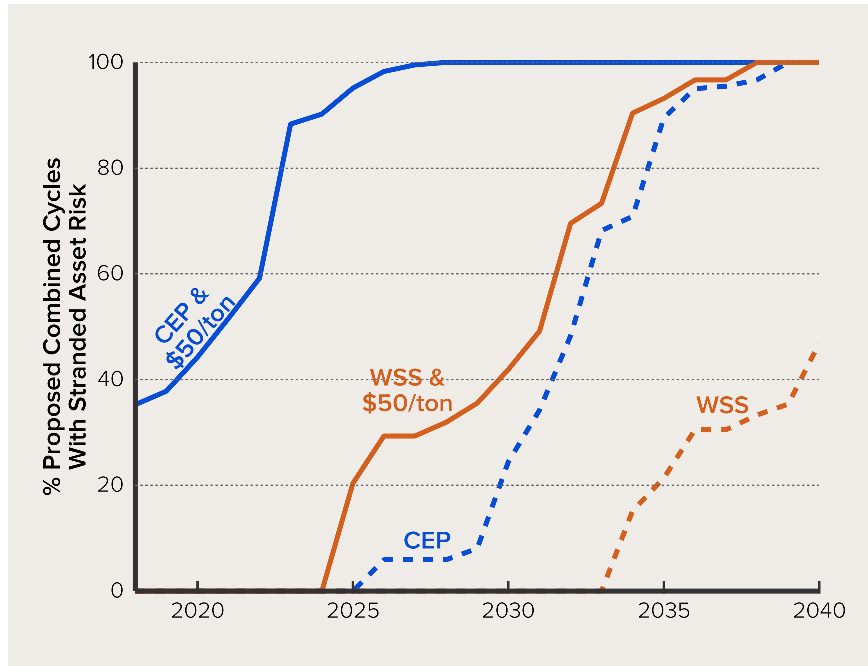
Figure ES 4 shows the aggregated resources that compose the CEPs equivalent to the proposed 56 GW of combined-cycle plants and 12 GW of combustion turbine plants. In total, CEPs designed to replace combined-cycle gas projects leverage low-cost wind and solar resources as well as EE. CEPs designed to replace lower-capacity factor, combustion turbine gas projects tend to favor storage and demand flexibility to provide peak-hour capacity.

Regional differences in least-cost CEP composition reflect both regional resource quality as well as the existing and predicted adoption of renewables. For example, Western region CEPs contain little new solar because significant existing solar capacity in California makes additional solar resources comparatively less valuable. In contrast, Texas CEPs prioritize solar relative to wind because of the large amount of existing and predicted wind capacity in Texas.

7. Carbon pricing bolsters the case for CEPs and accelerates stranded asset risk

FIGURE ES 5

TIMELINE OF WHEN GAS PLANT OPERATING COSTS EXCEED NEW-BUILD CEP INVESTMENT COSTS, WITH SENSITIVITIES FOR CO_2 PRICING AND EE AND DEMAND FLEXIBILITY



Our central analysis case assumptions do not include any explicit or implicit price on carbon emissions; even without carbon pricing, CEPs outcompete 90 percent of proposed gas-fired generation capacity. As a sensitivity, we assessed the impacts of imposing a $50/ton price on direct CO_2

emissions—on par with emissions prices used for planning in leading US jurisdictions. We do not account for upstream methane leakage. Figure ES 5 shows the implications; even a modest price on carbon pulls forward the timing of stranded asset risk for new-build gas-fired power plants by 5–10 years. For all-resource CEPs (blue lines), a $50/ton carbon price accelerates the economic risk for gas by 10 years so that 90 percent of plants are uneconomic in the early 2020s and all combined cycles are uneconomic in 2030. Even without EE and demand flexibility (orange lines), ~50 percent of proposed gas plants would be outcompeted by WSS in the early 2030s.

Implications and recommendations

The currently strong and quickly growing economic case for CEPs has significant implications for how investments in the electricity system are planned, incentivized, and regulated. The changing economics present an immense near-term opportunity—if the industry can quickly prioritize new, least-cost resources. On the other hand, there are significant risks if the industry is slow to evolve and continues to prioritize gas plant investments.

Informed by our findings, we suggest the following practices:

For vertically integrated utilities: Adopt emerging best practices with all-source, technology-neutral procurement

In leading vertically integrated utility service territories, where utilities invest in generation and regulators allow cost recovery through customer rates, utilities and their regulators are pioneering all-source, competitive bidding procurement processes where the economic advantages of CEPs emerge naturally. These procurement processes include the following proven steps:

1. **Define necessary grid services, not resource characteristics.** Start the planning and procurement process by specifying the services required, rather than characteristics of legacy generators that have historically provided them. Defining the need, not the solution, is crucial to ensuring the least-cost outcome.
2. **Create a level playing field for all resources.** Utility modeling tools must appropriately capture the capabilities of new, clean energy technologies, including storage, efficiency, and demand flexibility.
3. **Use competitive bidding to discover true resource prices and keep customer costs low.** Competitive bidding processes and real market input are essential to define the pricing assumptions used in planning and procurement.

For state utility regulators: Account for the significant risk that uneconomic gas generation will increase customer rates

Our analysis shows clean energy is lower cost than new gas-fired generation today and that its cost advantage will only increase with time. Before approving or rate-basing new gas generation, we suggest that regulators consider carefully whether gas generation is truly the lowest-cost way to meet the required grid services. Further, regulators should consider the risks of near-term gas investments, given the likelihood of continued clean energy cost declines and the potential for future carbon pricing. If new gas does appear marginally economic today, regulators may wish to mitigate risks to rate payers by 1) delaying approval of new gas investments, if possible; 2) requiring accelerated amortization schedules that reflect the limited economic life of new gas-fired power plants; and/or 3) changing risk allocation to protect customers.

For utilities and regulators: Embrace the value of demand-side resources in optimizing power supply portfolios

Historically, resource planning tools have not treated efficiency and demand response as resources on equal footing with centralized generation. Further, most cost-recovery regulation and utility business models do not incentivize utilities to reduce energy use. New incentives and mandates for demand-side resource investment, including performance incentive mechanisms and other forms of performance-based regulation, can provide utilities a profit motive for prioritizing and deploying these least-cost resources. These regulations can also encourage utilities to value other distributed energy resources (DERs), such as behind-the-meter solar and storage, in resource planning processes.

For wholesale market stakeholders: Restructure rules to encourage technology-neutral market competition to meet system needs

Approximately 60 percent of proposed gas-fired capacity is slated for construction in territories with restructured power markets, including the Northeast and Texas, where power plant investors respond to market signals for new capacity and the most cost-effective generation is deployed to meet demand. Unfortunately, the rules in these markets were designed to encourage competition primarily between fossil, nuclear, and hydro generation. With the dramatic declines in clean energy costs and demonstrated ability of these resources to meet grid needs, it is time to update market rules to promote technology-neutral competition for grid services, including demand side efficiency and flexibility. For example, the Federal Energy Regulatory Commission's (FERC's) new storage participation rules are an opportunity to test whether existing participation models match actual grid needs, or whether new models are needed to capture the full value of storage.

For merchant gas investors: Carefully consider the risk that new gas generation will be underused or stranded

We find that CEPs are lower cost than new generation today, and that clean energy is very likely to undercut the go-forward cost of electricity from deployed gas in the coming 10–15 years. Therefore, even if other estimates suggest new gas generation will be profitable given today's clean technology prices, building new gas today is a bet against any of the following three events:

- **Carbon pricing:** Even a modest carbon price (<$50/ton) accelerates the year in which new gas projects become uneconomic by 5–10 years.
- **Continued cost declines of clean energy:** Slightly faster learning rates for wind, solar, and batteries, splitting the difference between recent history and analyst forecasts, would reduce the expected economic lifetime of new gas plants by five years.
- **Market rules allowing full resource participation:** Current wholesale market rules favor legacy grid resources. The lag between market rule changes delays the transition to new technologies. However, participation rules for storage, demand flexibility, and EE are being tested and improved. As these rules are implemented, CEPs will become even more competitive in organized markets

Any one of these events would accelerate the economic case for CEPs and further degrade the profitability of new gas, and associated investor returns. Were two or three of these events to occur, the economics would tilt overwhelmingly in favor of CEPs, with dire consequences for investors in legacy assets.

1 INTRODUCTION

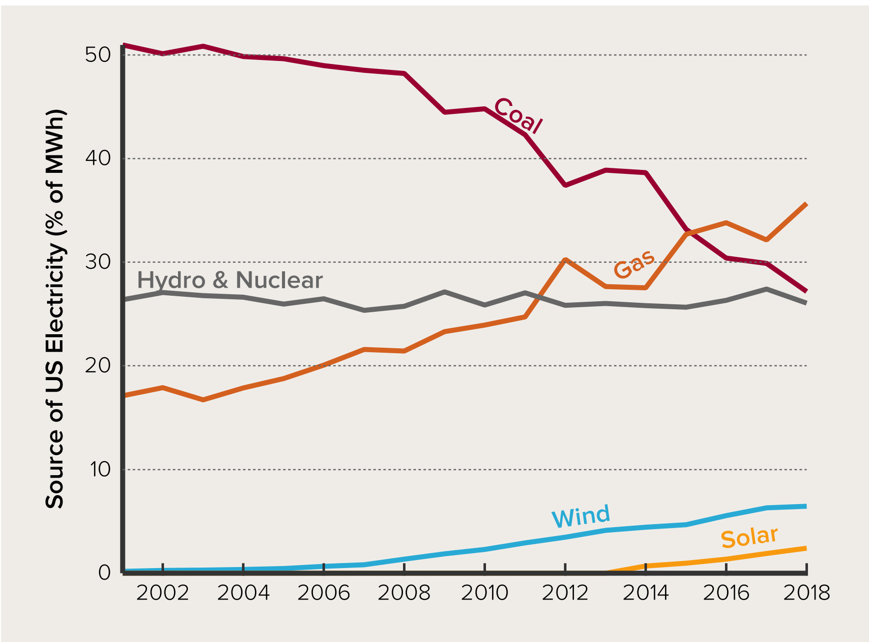
INTRODUCTION

The accelerating pace of clean energy progress

Since 2005, the United States has shifted its sources of electricity generation dramatically, away from coal and toward natural gas. Natural gas is now **the largest single fuel source for generation** (Figure 1) and falling natural gas prices have contributed to keeping average **electricity rates stable** across the United States. While direct emissions from natural gas are less carbon-intensive than the coal it has replaced, increased gas generation is contributing significantly to **rising power sector CO_2 emissions**.

FIGURE 1

SOURCE OF US ELECTRICITY



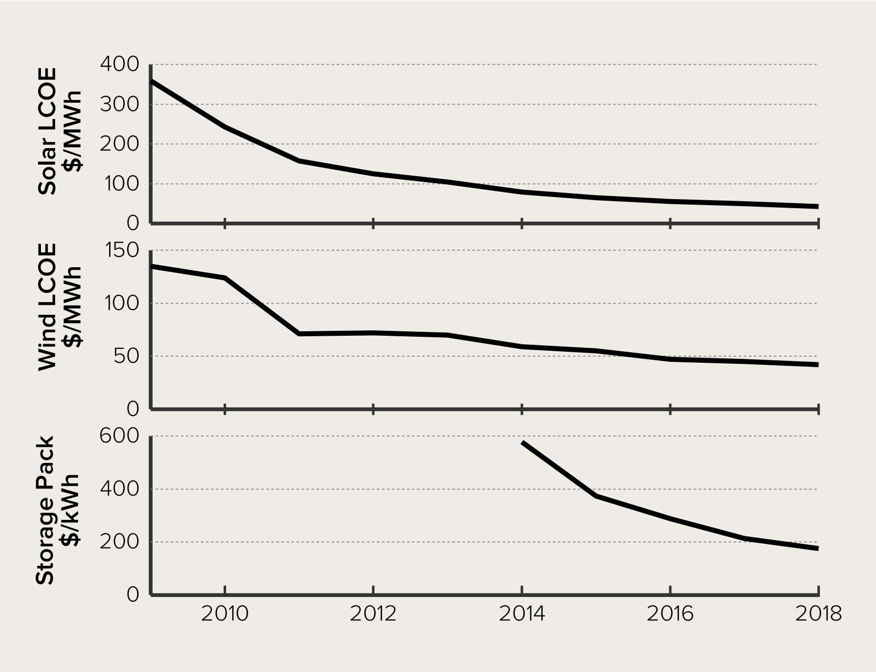
However, the growing market share of natural gas is only part of the story. Solar, wind, and battery storage prices have dropped precipitously (Figure 2), with prices for new renewables and storage projects significantly undercutting the levelized costs of new gas generation, and even approaching the typical operating costs of existing gas plants. For example, in June 2019, the **Los Angeles Board of Water and Power Commissioners approved** a 25-year contract for solar electricity supplemented with battery storage at less than $33 per megawatt-hour (MWh), significantly lower than **the benchmark price for new gas-fired generation of $41–74/MWh**. Solar and wind now contribute a meaningful and increasing portion to the country's electricity mix (Figure 1).

Now that solar, wind, efficiency, and demand response have proven track records, wholesale electricity markets and utilities are beginning to embrace how these resources can provide the reliability services that have previously been reserved for gas- or coal-fired generators. With **continued cost declines**, growing consumer and corporate demand, and a proven at-scale track record, solar and wind adoption is likely to accelerate.

However, despite the economics, planners are continuing to emphasize new gas generation projects; as described below, we identify 68 GW of new gas capacity proposed for construction across the United States. This continuing "rush to gas" is an economic risk to investors and utility customers, and represents significant committed CO_2 emissions if proposed projects are built.

FIGURE 2

UNSUBSIDIZED COSTS OF SOLAR, WIND, AND BATTERY STORAGE.



In RMI's 2018 paper, we described how CEPs[4] can provide grid services equivalent to fossil generators. Specifically, we showed that CEPs can provide monthly energy, peak-hour capacity, and flexibility that is equivalent to new gas-fired power plants. Our 2018 paper described the risks of building new gas-fired generation when clean energy portfolios are already cost-competitive and there is an implied stranded asset risk to investors (i.e., assets with undepreciated costs exceeding their expected future value).

This report expands RMI's 2018 analysis of four CEP case studies by analyzing the economics of a CEP alternative to every proposed gas power plant in the United States, using updated data and an improved methodology.

[4] Also referred to as "virtual power plants."

I/A

2 MARKET SNAPSHOT

MARKET SNAPSHOT

Gas-fired generation investment is falling as economics increasingly favor clean energy

Overall, the US market for new gas-fired generation is cooling. Final investment decisions to build new natural gas-fired power plants in the United States have **declined each year** since 2014. Investors in companies that made bets on the gas generation market have paid the price; General Electric's 2015 acquisition of gas-power business Alstom **led to a significant write-down** as the market for new gas generation projects declined, and the firm's competitors have taken notice and **made moves to exit** the declining gas power market.

The US power industry is instead increasingly investing in new clean energy technologies. Across the country, utilities have accelerated their transition to clean energy, and either minimized or avoided entirely any planned investment in new gas generation:

- In Michigan, **Consumers Energy filed a Clean Energy Plan** that voluntarily exceeds Michigan's 15 percent renewable portfolio standard (RPS), closes most remaining coal plants by 2030 and all by 2040, dramatically increases investments into efficiency and demand flexibility, plans for 5 GW of solar, and sets a target for 25 percent renewable electricity generation in 2030, all without investment in new gas-fired generation.
- In Colorado, **Xcel Energy will voluntarily retire two coal plants** ahead of schedule and replace them with WSS, without construction of new gas-fired power plants. Company-wide, Xcel has publicly stated its intention to reduce carbon emissions by 80 percent by 2030 (from 2005 levels) and generate 100 percent carbon-free electricity in 2050.
- In Minnesota, Xcel is replacing its final two coal plants primarily with a **combination of solar, existing gas, and ~800 MW of efficiency programs**. This choice was due, in part, to Xcel's resource modeling that now includes efficiency programs alongside supply-side resources.
- In Indiana, NIPSCO's 2018 integrated resource plan (IRP) process included technology-neutral open procurement, and led to a **proposal to replace all of the utility's coal generation with clean technologies** while avoiding new gas generation. The **utility** found that "the most viable path for customers involves accelerating the retirement of a majority of NIPSCO's remaining coal-fired generation in the next five years and all coal within the next 10 years. Replacement options point toward lower-cost renewable energy resources such as wind, solar, and battery storage technology."
- **Arizona Public Service** (APS) has committed to building 850 MW of storage to work alongside existing and new solar generation in order to meet their peak capacity needs. APS will install the first 200 MW in 2020 and 2021.
- **Portland General Electric** in its 2019 Integrated Resource Plan selected a preferred portfolio calling for efficiency, renewables, demand flexibility, and battery storage to meet growing capacity needs as existing coal retires, without requiring investment in new gas-fired generation.

State-level regulators have been increasingly reluctant to burden consumers with the risks of rate-based natural gas investments:

- In Indiana, the Indiana Utility Regulatory Commission (IURC) rejected a utility proposal to construct an 850 MW gas plant. The IURC **stated**, "The proposed large scale single resource investment for a utility of Vectren South's size does not present an outcome that reasonably minimizes the potential risk that customers could, sometime in the future, be saddled with an uneconomic investment or serve to foster utility and customer flexibility in an environment of rapid technological innovation."
- In Rhode Island, the Energy Facility Siting Board **rejected a developer's application** to build a 900 MW combined-cycle gas plant in Burrillville, RI, because it was not necessary to meet the state's needs, and clean energy resources, including offshore wind, would instead be sufficient.
- In Arizona, the Arizona Corporation Commission **voted to extend a moratorium** on construction of new gas-fired generating facilities, in recognition of an uncertain technology and clean energy policy landscape that could lead to stranded asset risk for such investments.

Even when new gas plants are proposed or approved, utilities find that downsizing the gas plant and treating it as a supplement to lower-cost clean energy resources is the most economic path forward:

- In the West, **PacifiCorp has announced** that the most economical way to replace coal generation in Montana, Wyoming, and Colorado is to replace it with wind, solar, storage, and small gas peaking plants.
- In California, Glendale Water & Power has **proposed** to reduce the size of its planned repowering of an existing gas-fired generator by 60 percent, replacing many of the services currently provided by the existing gas plant with a portfolio of solar, efficiency, and demand response to meet the utility's reliability needs.

- In North Carolina, Duke Energy has **effectively canceled a previously planned gas-fired power plant**, in part because the utility was able to procure significant battery storage, EE, and demand flexibility resources to obviate the need for the gas plant through the end of its planning horizon.

Technical and financial analysts have come to the same conclusions as leading US utilities regarding the market outlook for new gas-fired power plants in the United States:

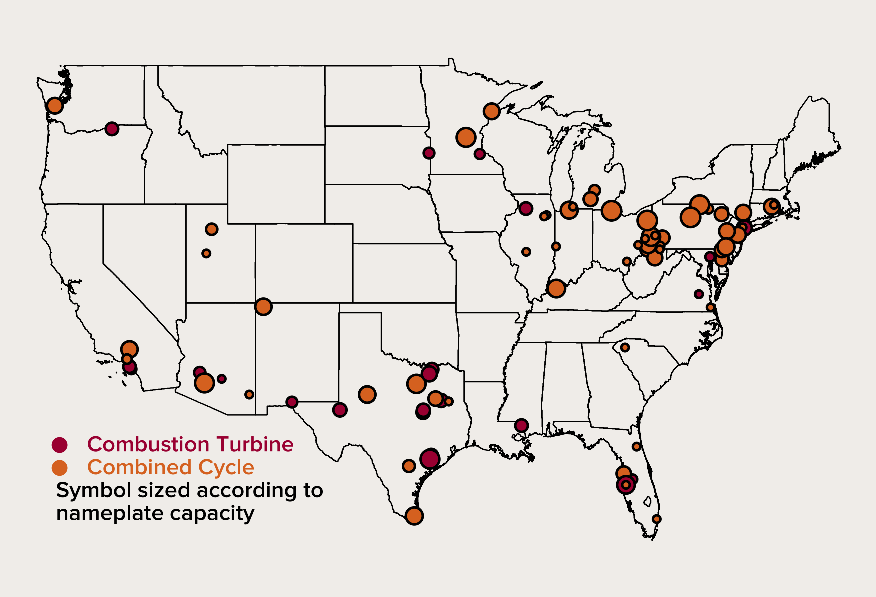
- A **recent report** from Carnegie Mellon and Fluence assessed the ability of solar and storage systems to compete with "mid-merit" combined cycle generators, finding that solar and storage systems were similar in cost—and less expensive when ancillary service revenue was credited to the solar and storage systems.
- A **study** from the National Renewable Energy Laboratory illustrates how solar and storage together can replace peaking gas capacity across the United States, with the potential for storage to offset more than 50 GW of peaking capacity nationwide as solar generation continues its rapid pace of adoption.

However, even as utilities and regulators across the country increasingly prioritize clean energy investment after critical assessment of the economics and risks of investment in new gas-fired generation, there remains a large, but shrinking, quantity of planned projects. We identified 88 proposed gas-fired generation projects, 25 combustion turbines and 63 combined-cycle plants, with a cumulative nameplate capacity of 68 GW that have been announced to begin operation by 2025 but not yet begun construction (as of early 2019). In addition to the named, sited projects reflected in these numbers, utility IRPs include a significant quantity of new gas capacity, often proposed for construction post-2025.

Together, the announced and IRP projects represent at least ~$90 billion in investment that would ultimately be borne by US electricity customers.[5] If built and run as planned, the identified plants would emit over 100 million tons of CO_2 per year, equivalent to 5 percent of present-day US power sector emissions. With the aim of informing stakeholders, regulators, utilities, and customers of alternatives to continued gas investments, this report comprehensively considers the economic case for clean energy portfolios as an alternative to investment in each of these plants.

FIGURE 3

ANNOUNCED GAS-FIRED GENERATION PROJECTS



[5] Assuming **average construction costs** of ~$1/W

3 METHODOLOGY

METHODOLOGY

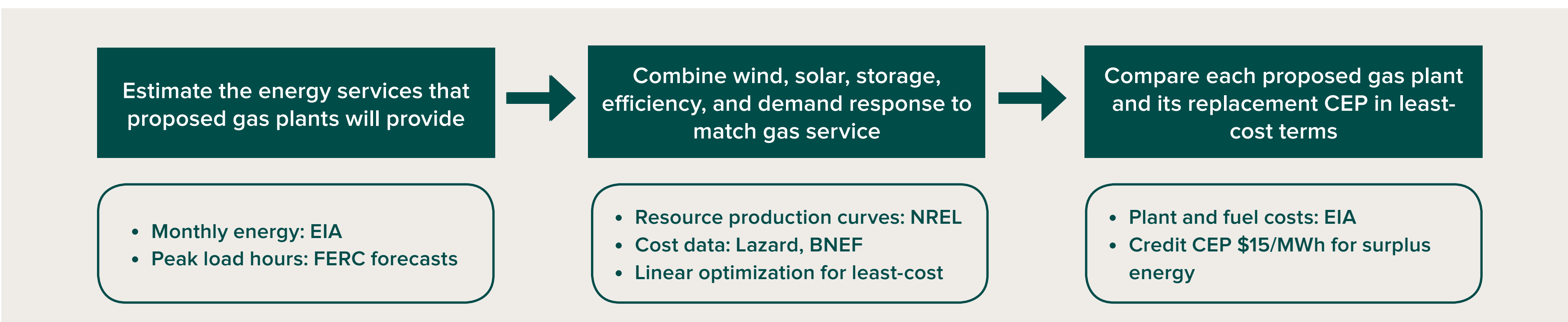
The Clean Energy Portfolio modeling approach

The model uses a three-step approach (Figure 4) to compare the economics of gas and clean energy. First, the model estimates the services of the proposed gas plant; then, it calculates the optimal combination of wind, solar, storage, efficiency, and demand flexibility to match these services; and, finally, we compare the total net costs of each option. We compare costs in two ways:

- **Total new-build costs for CEP and gas plant**: We compare the net present cost of building and operating a proposed gas plant and the CEP designed to replace the proposed gas plant. This is a comparison of a new gas plant with a new CEP, including capital, operating and maintenance, and variable operating costs (including fuel purchases, in the case of gas plants). For each proposed gas plant, we compare these costs for each year from the present day until 2045, to capture changing fuel and CEP technology costs.
- **Total new-build cost of CEP vs. cost of running existing gas plant**: We compare the cost of building and operating a new CEP with the go-forward cost of operating a gas plant in a future year. This is a comparison of an existing gas plant with a new CEP, including capital, operating and maintenance, and variable operating costs for the CEP, but only fuel purchases and other variable costs for the gas plant. For each proposed gas plant, we compare these costs for each year from the present day until 2045, to capture changing fuel and CEP technology costs. When new-build costs for a CEP fall below the go-forward costs of a gas plant, we refer to a stranded asset risk for the gas plant, as it would no longer be economic to run at expected CFs.

FIGURE 4

HIGH-LEVEL SUMMARY OF MODEL APPROACH



Below and in the Appendix, we describe our approach in greater detail. In the description, we provide example data for a representative (i.e., near the median in cost-effectiveness) combined-cycle project located in the Northeast, in order to illustrate the data used and optimization approach.

Clean energy portfolios must match the monthly energy and peak demand services of the gas plant

Our CEP model calculates the composition of least-cost portfolios of clean energy resources that can provide the same grid services as a proposed natural gas-fired power plant. The model requires that the CEP meet three key service requirements:

- **Monthly energy**: The CEP must produce at least as much energy each month as the gas plant. We estimate the gas plant's monthly CF by assuming operators will run the plant similarly to other comparable plants in the proposed region.
- **Peak-hour capacity**: The total power output (in megawatts) of the CEP must match or exceed the gas plant's seasonally adjusted nameplate capacity during the region's top 50 hours of peak net load in a year. These hours can be, but are not necessarily, sequential. To calculate peak net load, we start with the predicted total regional hourly load and subtract projected wind and solar (distinct from the CEP) installed to meet the state's RPS, if one exists.
- **Flexibility**: The total power output (in megawatts) of the CEP must match or exceed the gas plant's seasonally adjusted nameplate capacity during the hour when the region experiences its greatest one-hour increase in net load. Further, the model requires that the CEP not exacerbate ramping issues (i.e., the "duck curve"), by requiring that during the largest four-hour ramp-down of CEP solar generation, CEP total power output must be able to remain constant or increase (e.g., by charging storage during peak solar photovoltaic (PV) output and discharging as solar PV power output drops).

In Figure 5 and Figure 6, we show the required monthly energy and peak demand (black lines), and how each CEP technology contributes to meeting them (discussed below), for the example Northeast combined cycle.

FIGURE 5

MONTHLY ENERGY REQUIREMENT OF THE EXAMPLE NORTHEAST COMBINED CYCLE

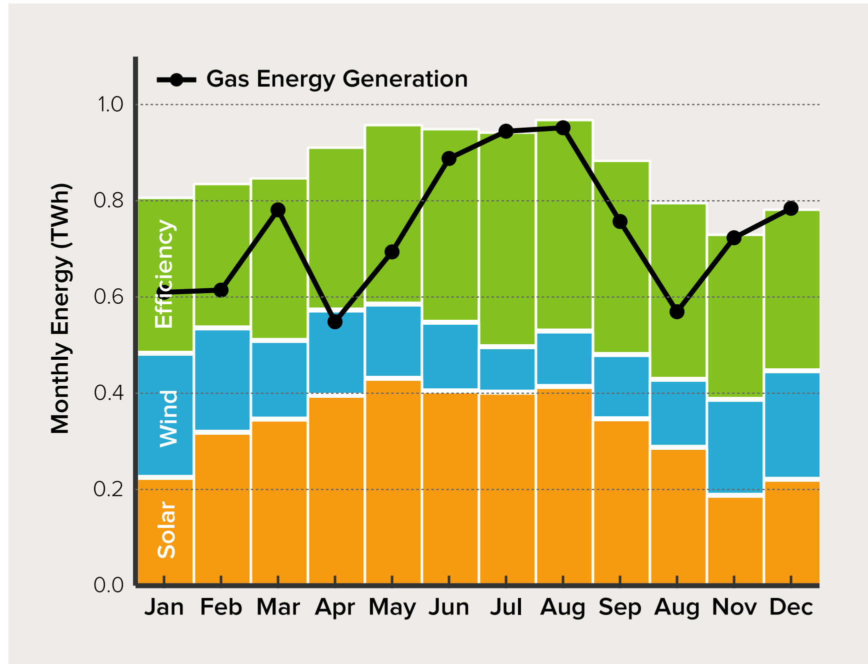
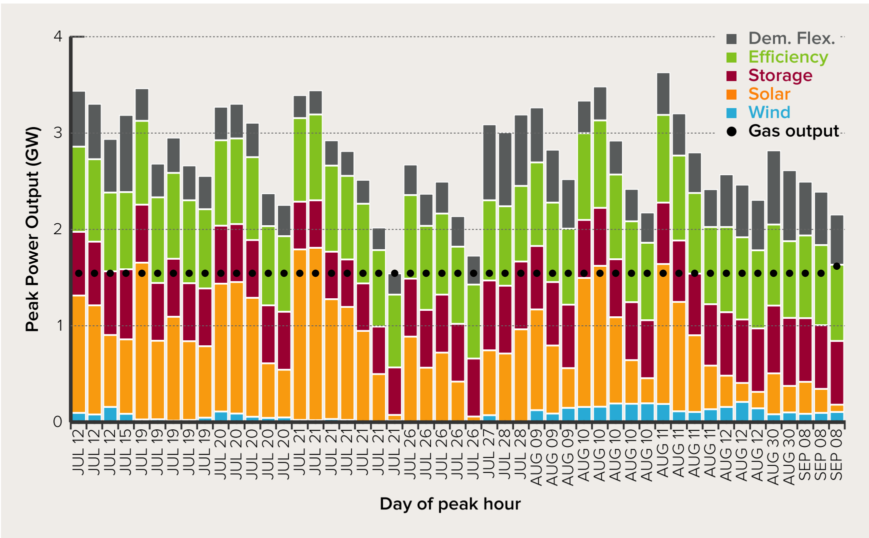


FIGURE 6

PEAK DEMAND REQUIREMENT OF THE EXAMPLE NORTHEAST COMBINED CYCLE



The CEP model calculates the least-cost combination of clean technologies to match the gas plant services

We use linear programming-based optimization to compute the least-cost combination of clean energy technologies that meet the required services described above. Our optimization methodology remains largely unchanged from our 2018 study's approach; see the Appendix of that report for detailed methodology and mathematical formulations. As in the 2018 study, we include five technologies in CEPs:

- **Energy efficiency**: We model the use of programs (either utility- or other administrator-enabled) to reduce the use of electricity while maintaining or improving the quality of end-use services. We estimate hourly demand reductions associated with these programs using historic regional, end-use load data, and model the associated program administrator costs based on regional data.
- **Demand flexibility**: We model the use of programs (either utility- or other administrator-enabled) to shift the timing of the use of electricity while maintaining the quality of end-use services. We estimate hourly demand reductions associated with these programs using historic regional, end-use load data, and model the associated program administrator costs based on regional data.
- **Utility-scale wind**: We model the ability of wind projects to contribute energy to the power grid, using modeled regional hourly production profiles matched to load profiles, and costs based on analyst forecasts.
- **Utility-scale solar**: We model the ability of solar projects to contribute energy to the power grid, using modeled regional hourly production profiles matched to load profiles, and costs based on analyst forecasts.
- **Battery energy storage**: We model the capability of batteries to reduce peak hour demand and provide flexibility to meet both system- and plant-level ramping needs, based on both power capacity and duration. We use analyst forecasts of expected pricing for battery projects of one- to eight-hour durations.

Figure 5 shows how solar, wind, and efficiency contribute to meet the monthly energy of the example Northeast gas plant. The most challenging months for energy generation are July, November, and December; the model adds solar, wind, and efficiency to just match the gas output in these months. In the other months, the CEP generates more energy than the gas plant, sometimes significantly more. As described below, we assume the value of this excess energy is $15/MWh, and net that value against the total cost of the CEP.

As shown in Figure 6, all five technologies contribute to meeting peak demand. The most challenging day is July 21, which includes 7 of the peak

50 hours. On the last of these hours, there is almost no contribution from wind or solar and peak demand is met with efficiency, storage, and demand flexibility. We find that it is common for the most challenging hour to be on a day with multiple hours among the top 50. To match the gas plant's power output on these days, the CEP model typically selects storage projects with increased power output capacity (to meet demand when solar and wind do not contribute) and increased duration (to meet demand across multiple hours on the same day). In our example plant, the storage is composed of approximately two-thirds six-hour storage, with a mix of one-hour, two-hour, and four-hour making up the remainder.

The efficiency and demand flexibility components of the example plant are a mix from different sectors and end uses, whose hourly production profiles we estimate from historical end-use survey data. The optimal CEP for each gas plant often includes significant quantities of specific end-use efficiency measures (e.g., commercial lighting) due to lower relative costs. We do note, that if these end uses are unavailable for continued efficiency program expansion (for example, because it had already been depleted by previous programs), it is generally possible to add the next most cost-effective efficiency option with a de minimis impact on total cost.

Cost comparison

We compare the costs of a proposed gas plant and an equivalent CEP using a metric of "net cost," in units of $/MWh for combined-cycle generation and dollars per kilowatt-year for combustion turbine projects. For combined-cycle plants, this $/MWh metric is similar to a standard levelized cost of energy (LCOE). For CEPs designed to replace combined-cycle plants, we calculate net cost by assessing the net present cost of all CEP resources, subtracting the value for the excess energy produced by the CEP over what the gas plant would produce, and dividing the result by the gas plant's expected energy production. We net out the value of

"excess" energy produced by the CEP because, to meet the most constraining month for energy production and the most constraining days of peak demand, a CEP always generates more overall total energy and more average peak capacity than an equivalent gas plant. We assign a value of $15/MWh for this excess energy, which is much lower than typical wholesale market energy prices of **$30–50/MWh**, as a conservative estimate of the value of renewable energy during times when a gas-fired power plant would not be economically dispatched. As discussed below, the analysis is not overly sensitive to the choice of $15/MWh.

We use a different cost metric for combustion turbine (CT) projects, as these projects are often expected to run less than combined-cycle assets, and primarily provide peak capacity, rather than bulk energy. We define a cost metric for CTs as the annualized net present cost of all capital, operational, and fuel expenses of the gas plant assuming a 20-year lifetime, divided by the maximum power output of the generator. For a CEP in each case, we define the net cost metric as the annualized net present cost of all capital and operational expenses of the CEP, netting out the value of energy sales in excess of gas plant production (as described above for combined-cycle plants), divided by the gas plant's maximum generating capacity (which the CEP is optimized to be able to provide during peak demand).

As described above, we compare the net cost of a CEP to both the cost of new gas plants and, for combined-cycle plants, to the operating costs of existing gas plants. The metric for the go-forward cost of an existing gas plant is the same as the metric for combined-cycle plants, except we exclude capital expenses. We compare CEPs to the go-forward operating cost of proposed gas plants in order to assess if and when CEPs would be able to cost-effectively replace gas plants, if they are built as proposed.

This metric allows for an estimate of the year in which proposed gas projects would become uneconomic to run, and face risks of becoming stranded assets for their investors.

Key methodology updates from RMI's 2018 study

We made the following improvements to the 2018 report:

1. We use hourly load profiles from wider regions to calculate when the CEP needs to meet peak demand, to better match renewable production data and minimize outlier effects for smaller balancing areas.
2. We adjust the maximum gas plant power output for the region and season using Energy Information Administration historical data.
3. We include multiple options for storage duration (one-hour, two-hour, four-hour, six-hour, and eight-hour) in order to provide the most flexibility to the model in optimizing a CEP.
4. We limit EE to account for no more than 50 percent of the required annual energy output and limit demand flexibility to average no more than 50 percent of the CEP peak hour capacity.
5. We calculate battery degradation rates (and the associated operating costs to replace degraded cells) by assuming storage used in CEPs to replace combined-cycle plants cycles 25 times each year in addition to the cycles necessary to meet the peak hour service requirements; for combustion turbines we assume an additional 10 cycles each year.
6. We consider CEPs both with and without EE and demand flexibility.

Data sources and key assumptions

We use data from a variety of vetted and established sources, detailed below, to parameterize the CEP model:

1. Planning area peak and growth forecasts: FERC **714**
2. Expected gas plant dispatch and monthly energy generation: Energy Information Administration (EIA) Forms **860** and **923**
3. Fuel costs: EIA **Annual Energy Outlook 2019**
4. Clean energy resource costs: **Lazard Levelized Cost of Energy v11**, Levelized Cost of Storage v4, Bloomberg New Energy Finance (BNEF) New Energy Outlook 2018: Charts. August 3, 2018, Lawrence Berkley National Lab (LBNL) **Program Administrator Cost of Saved Energy for Utility Customer-Funded Energy Efficiency Programs**, EIA Form **861**
5. US State RPSs: Center for Climate Energy Solutions **U.S. State Electricity Portfolio Standards**
6. Renewable Potential: NREL
7. Demand Flexibility Potential: FERC **A National Assessment of Demand Response Potential**
8. EE Potential: Electric Power Research Institute (EPRI) **State Level Electric Energy Efficiency Potential Estimates**
9. End Use Penetration: EIA Residential Energy Consumption Survey (**RECS**) and Commercial Buildings Energy Consumption Survey (**CBECS**)
10. Planning area customer data: EIA Form **861**
11. Proposed gas projects: S&P Market Intelligence
12. Regional hourly load shapes: RMI's ***Reinventing Fire***

We summarize the key analysis assumptions in Table 1.

TABLE 1

KEY ASSUMPTIONS USED IN CEP MODEL

ISSUE	ASSUMPTION
Storage duration	Model optimizes a combination of one-, two-, four-, six-, and eight-hour battery storage
Contribution of energy efficiency (EE)	Energy reduction from EE cannot account for >50% of the monthly energy requirement, on an annual basis. We also limit total available EE to the lesser of twice the fraction of the gas plant's capacity to the planning area's peak demand or 25% of the planning area's assessed EE availability.
Contribution of demand flexibility	Power reduction from demand flexibility cannot account for meeting >50% the required power output during peak demand hours. We also limit demand flexibility to the lesser of twice the fraction of the gas plant's capacity to the planning area's peak demand or 25% of the planning area's assessed demand flexibility availability.
Gas plant monthly CF	We use historical dispatch data from similar plants in the proposed plant's region and calculate the average monthly CF. For combined-cycle gas turbine projects (CCGTs), we disregard plants with CF<0.35, assuming that they are not representative of a new-build plant's likely operating characteristics.
Hours of peak demand	CEPs are required to match maximum gas power output during the top 50 hours of net peak demand. These hours are determined by extrapolating hourly demand profiles from 2010 regional load in Reinventing Fire and adjusting them to account for renewables deployment according to state-specific renewable energy targets.
Value of excess CEP Energy	We assign a value of $15/MWh for any energy produced by a CEP in excess of the expected production of the gas plant.
Imported wind	We allow the import of high CF wind for inclusion in CEPs, which is relevant particularly in regions without high-quality local wind resources. This resource carries transmission costs that are five times those of local wind.
Investment Tax Credit (ITC)	We assume that solar installations will benefit from a 26% ITC (the 2020 rate), even for plants built after 2020 on the assumption that they will take advantage of the "safe harbor" rule. We do not apply the ITC to storage.

TABLE 1

KEY ASSUMPTIONS USED IN CEP MODEL

ISSUE	ASSUMPTION
Production Tax Credit	Not included.
Battery charging	In all cases, the CEP generates the energy needed to charge the battery storage. We assume a round-trip charge/discharge efficiency of 90%.
Battery operating expenses (OpEx)	Storage operating expenses are dominated by the need to replace lost capacity that accumulates with each cycle. We assume 0.03% of energy storage capacity is lost each time the battery is cycled.
Valuation of ancillary services	We do not value any ancillary services that could be provided by the CEP or the gas plant.
Social cost of carbon	Our model does not consider any social impacts of carbon or other pollution in its optimization of resources. However, we consider and present sensitivity cases where gas plant costs are affected by carbon pricing.
Discount rate and time	We assume a 20-year life for the CEP. For resources with useful lives that are longer (e.g., solar PV) or shorter (e.g., some efficiency measures) than 20 years, we adjust their capital expenditures (CapEx) costs by taking the present value of 20 years of that resource's annualized CapEx. We use a real discount rate of 6%.
Accounting for deployment of future wind and solar	When estimating future demand shapes, we adjust the shape by accounting for solar and wind resources that allow each state to meet their RPS, if one exists. If an RPS does not exist, or if a state has exceeded its RPS, we assume that future renewable generation accounts for the same proportion as it does currently. We do not account for renewable generation implied but not specified by state-level, economy-wide greenhouse gas emissions targets such as those in CO and NJ. We do not account for renewable generation implied by CEPs designed in this study.

I/A

Rationale for the assumptions used and limitations of the model

Our study presents a conservative treatment of the potential value of CEPs relative to gas plants:

- **Clean energy portfolio costs**: We do not assume renewables and storage will continue their historical pace of rapid cost reductions, and instead use middle-of-the-road forecast assumptions for continuing cost declines, which historically have **been systematically biased upward** relative to observed cost declines. The average LCOEs assumed in this study for solar and wind are $34/MWh and $38/MWh, respectively, which are far above currently announced benchmark prices and well above more-aggressive future predictions of continuing cost declines. In addition, we do not consider the advantages of combining solar and/or wind with storage into **hybrid systems** that reduce cost with shared interconnection, nor do we apply the ITC to storage systems.
- **Ancillary and incremental value of clean energy portfolios**: We do not credit storage with any ancillary service values, even as other analysts have **quantified the incremental revenue** that could be captured by storage relative to gas power plants. We also do not credit CEPs with any incremental value associated with reducing demands on the transmission and distribution systems, as such revenue is location-specific and difficult to quantify.
- **Constrained optimization of CEPs**: We assess the economics of CEPs solely on their ability to perform the same services as gas plants. This approach implicitly starts with the assumption that a gas plant would closely match the grid's actual needs. By forcing CEPs to replicate gas plant services, we eliminate even lower-cost CEPs that would match actual grid needs, such as those identified in a true resource planning study.
- **Externalities**: Our base results do not assume any cost for carbon or other emissions.

We intend for our analysis to reveal the economics of *marginal* additions to regional generation capacity, assuming currently-planned levels of renewable generation growth and typical load and weather years. This analysis does not comprehensively assess gas plants' role in a dramatically different grid, such as one with a very high share (i.e., >50 percent) of renewable generation. For investors, policymakers, and system operators considering resources for a reliable, very low-carbon grid (typically in years after 2035), we recommend holistic **models that account for the different needs of a system with high wind and solar penetrations.**

In our analysis, each CEP is constructed independently, but we present aggregate results by summing all 88 gas plants in our sample. This is reasonable because 1) our sample would compose only ~7 percent of installed US generation capacity, and 2) our conservative resource selection assumptions ensure the resources selected within candidate CEPs are distinct from those in other CEPs.

Finally, this approach does not quantify the local impacts of clean energy and gas infrastructure development such as air pollution that adversely affect human health or the economic benefits of job creation. These and other local considerations are essential to any holistic and integrated resource planning process. We focus the economics of clean energy portfolios using the financial metrics traditionally used for fossil generation in order to inform near-term investment decisions and identify financial risks.

4 FINDINGS

FINDINGS

1. CEPs are lower cost than 90 percent of proposed gas-fired power plant capacity, presenting an opportunity to save customers $29 billion and prevent 100 million tons of annual CO_2 emissions

We find that CEPs have a clear economic advantage over proposed gas-fired plants:

- CEPs outcompete 61 GW, or 90 percent, of the 68 GW of proposed gas-fired plants in our sample.
- Cumulative customer savings from winning CEPs would total $29 billion over 20 years on a net present value basis.
- By building winning CEPs, we would reduce CO_2 emissions by 100 million tons per year—approximately 5 percent of current US power sector emissions. Were CO_2 emissions valued at $50/ton, reduced emissions would save $5 billion per year.

In Figure 7, we show the costs of CEPs relative to the gas plants they are designed to replace. For combined cycle replacements (top panel), we also show the levelized cost of electricity for the CEP in $/MWh. For combustion turbine replacements (bottom panel), we also show the CEP capacity cost. CEPs more easily replace combined-cycle plants, outcompeting 96 percent of the proposed combined-cycle capacity, compared to 61 percent of proposed combustion turbine capacity.

FIGURE 7

ECONOMICS OF CEPS DESIGNED TO REPLACE COMBINED CYCLE AND COMBUSTION TURBINE GAS POWER PLANTS

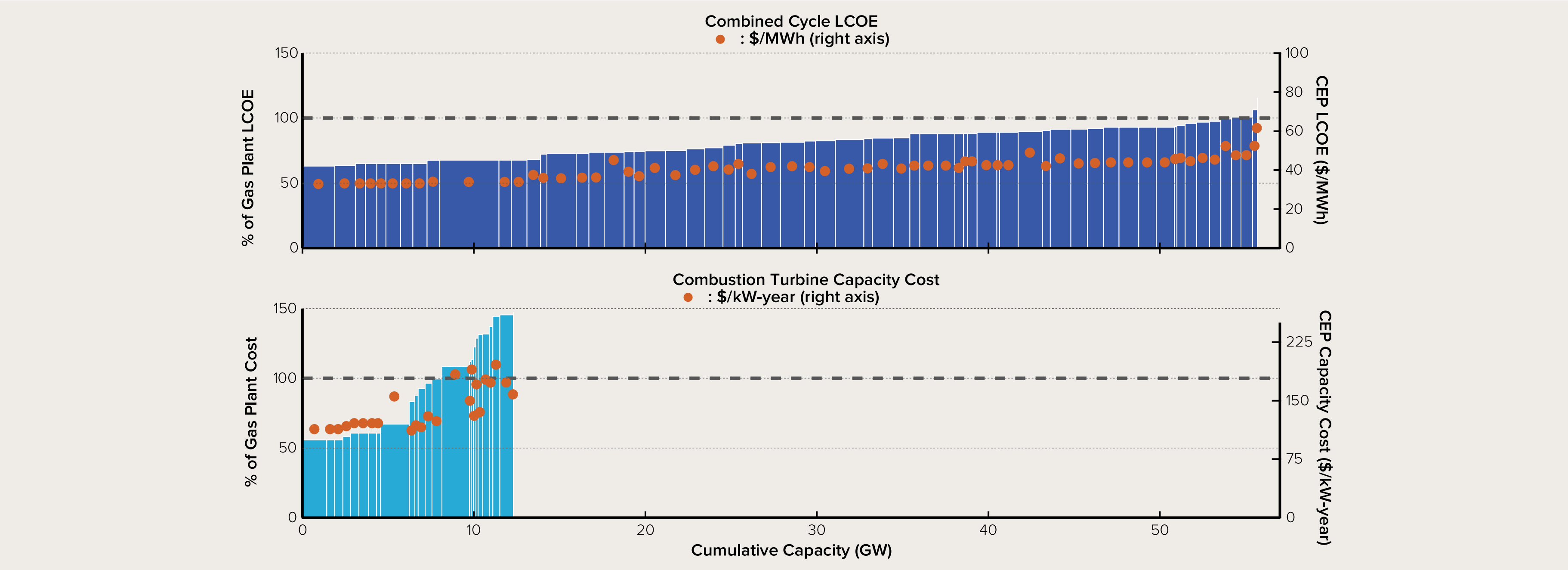
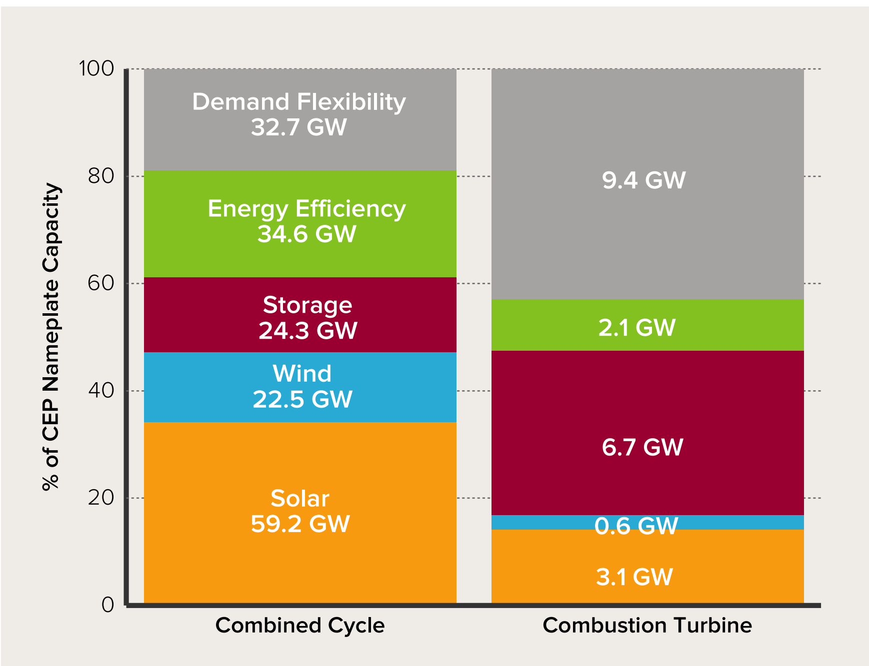


Figure 8 shows the cumulative contribution of the individual CEP technologies; all technologies play significant roles. Storage and demand flexibility play larger roles in CEPs designed to replace combustion turbines, where capacity during peak demand hours is most important. Efficiency and solar play large roles in CEPs designed to replace combined-cycle plants, where cost per MWh is more important.

FIGURE 8

TOTAL RESOURCE COMPOSITION OF ALL 88 CEPS



2. 2019 represents a tipping point for CEP economics

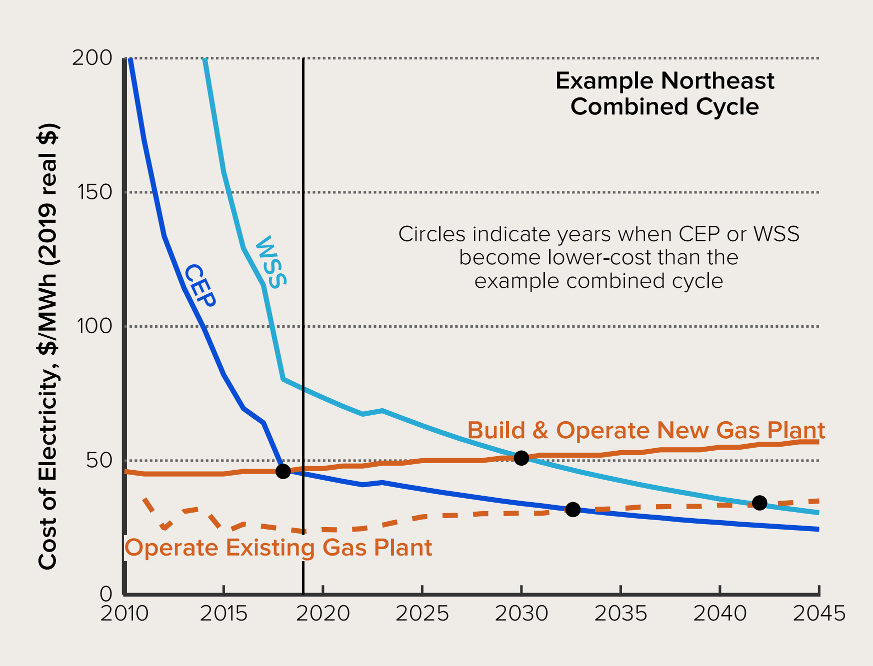
We summarize the historical evolution and trajectory of CEP economics using a representative Northeastern combined cycle (the same plant referred to in the Methodology section) in Figure 9.

Figure 9 illustrates the present tipping point in relative costs between CEPs and combined-cycle gas plants:

- **CEP costs have fallen 80% since 2010**: The falling costs of WSS has driven down the cost of a CEP equivalent to a typical CCGT by 80% since 2010.
- **CEPs win today against new gas**: It is now more cost-effective to build a new CEP in place of the vast majority of proposed new combined-cycle plants.
- **Further price declines will rapidly improve CEP economics**: Technological advances and market maturation for wind, solar, and batteries are expected to continue to drive the down costs of clean energy portfolios. By the early 2030s, we expect new-build CEPs to compete head-to-head with just the operating costs of modern, high-efficiency gas plants. If proposed gas plants are built, they risk becoming stranded assets.
- **Omitting demand-side resources delays the opportunity by ~8–10 years**: If we exclude efficiency and demand flexibility from CEPs, the combination of WSS will outcompete new gas in 2030 and outcompete just the operating costs of an existing gas plant by the early 2040s.

FIGURE 9

HISTORICAL AND PROJECTED EVOLUTION OF CEP COSTS



3. Clean energy portfolios are likely to undercut the operating costs of over 90 percent of proposed new combined-cycle capacity by 2035, creating stranded asset risk for investors

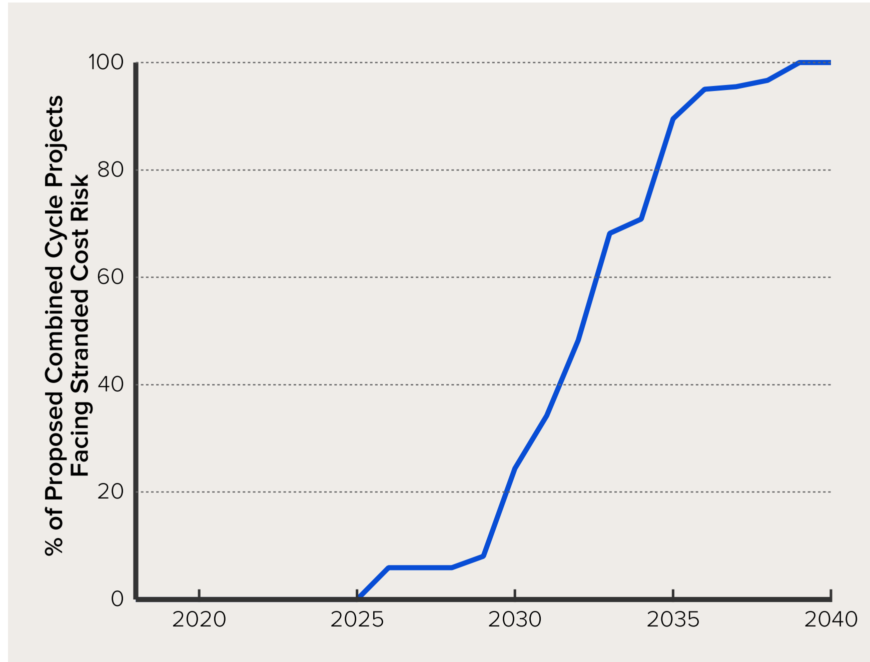
Just as the falling price of shale gas has allowed gas power plants to undercut coal plant operating costs, expected price declines in renewables and storage may soon strand existing or proposed gas plants. We find that over 90 percent of proposed combined-cycle gas plants, if they are built, will have higher operating costs than new CEPs in 2035.

Figure 10 summarizes the impacts of this economic trend for proposed combined-cycle projects. Within 15 years, nearly all currently proposed gas plant capacity will likely have operating costs higher than the cost of a new-build CEP, due to expected continued cost declines in WSS. The clear implication is that utilities or investors that move ahead with proposed plants face significant financial risk; consumer savings and/or market competition will dictate that the plants be shut down while book life remains. In short, combined-cycle investors face significant **stranded asset risk**.

We find that combustion turbines, expected to run at low CF, are less likely to have their operating costs undercut by the new-build costs of CEPs in future years. The cost structure of CT projects is dominated by capital costs (given the lower expected CF), leaving little total savings available in the case of retirement.

FIGURE 10

PERCENT OF PROPOSED CCGTS FACING STRANDED ASSET RISK IN EACH YEAR 2020–2040



4. The case for clean energy portfolios is strong across a range of modeling inputs

FIGURE 11

SENSITIVITY OF CEP ECONOMICS TO 25% CHANGE IN COST COMPONENTS—COMBINED-CYCLE PLANTS

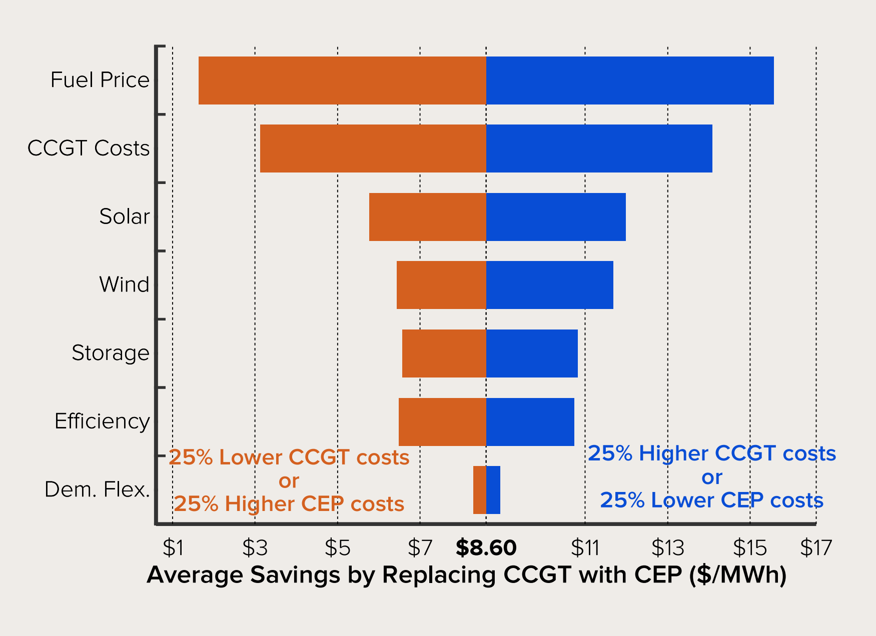


Figure 11 summarizes the sensitivity of our analysis to changes in individual cost inputs by showing the change in CEP savings when each of 7 costs is changed by ±25 percent. We find:

- Natural gas prices and combined cycle costs (CapEx and OpEx combined) have the most impact on savings, consistent with the fact that fuel accounts for just over half the net present cost of combined cycles, with capital and operating and maintenance costs making up the remainder.
- Changes to individual CEP technology costs have less overall negative impact because substitution between clean energy resources can mitigate the total cost increase. For example, if solar is assumed to be more expensive, the model may substitute wind because it is now comparatively more cost-competitive.
- The analysis is sensitive to WSS prices that have been dropping precipitously for a decade.

In Figure 12, we highlight the impact of clean energy technology cost declines using the example Northeast combined cycle plant. Figure 12 differs from Figure 9 only in that we assume 50 percent higher learning rates for wind, solar and storage than those predicted by BNEF. We consider the impact of a higher learning rate because 1) the higher learning rates are closer to recent, rapid cost declines of solar and storage (though still slower), 2) these technologies have only begun to scale and progress along their learning curves, and 3) historical cost projections have been uniformly too pessimistic. The figure shows:

- With faster cost declines, CEPs would outcompete existing gas in 2028 (dark blue line).
- With faster cost declines, WSS would outcompete a new gas plant in 2026 and outcompete the operating costs of this gas plant in 2034 (light blue line).

- Even with the 50 percent higher learning rate for WSS, the CEP cost declines are still dramatically lower than the historical rate (i.e., there is still a kink between historical and projected CEP costs).

FIGURE 12

HISTORICAL AND PROJECTED CEP COSTS, WITH FASTER CLEAN TECHNOLOGY LEARNING RATES.

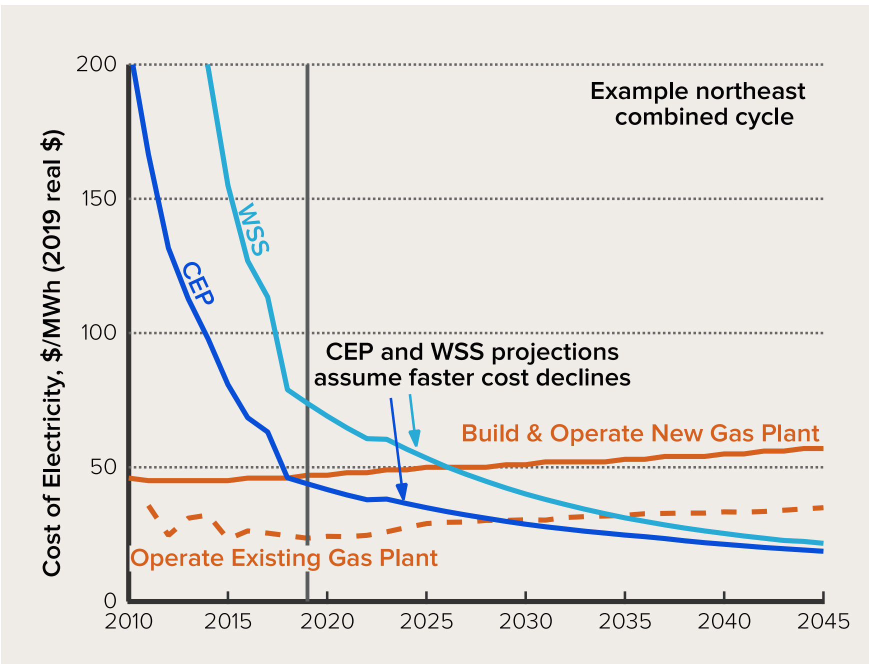


FIGURE 13

SENSITIVITY OF CEP ECONOMICS TO 25% CHANGE IN COST COMPONENTS—COMBUSTION TURBINE PLANTS

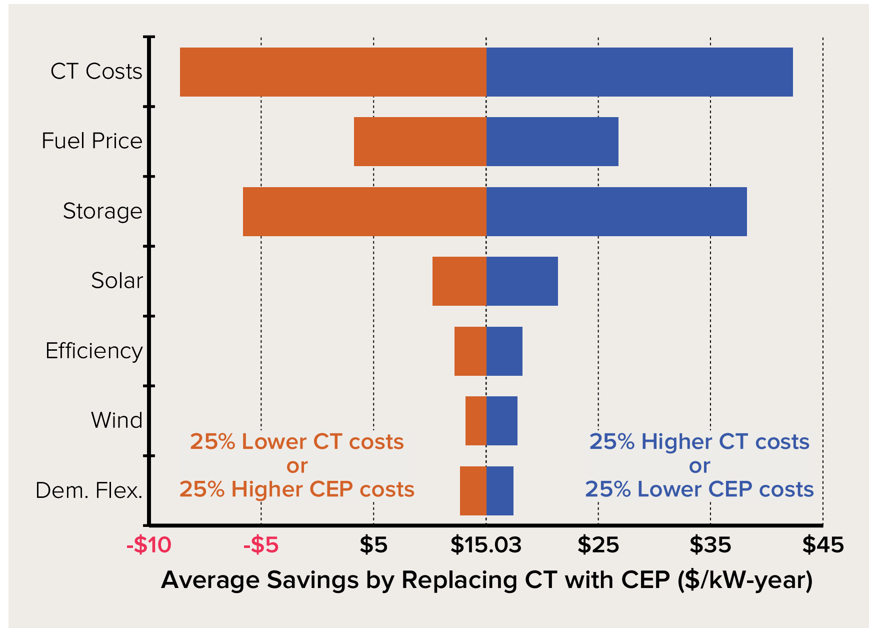


Figure 13 summarizes the sensitivity of combustion turbine results to changes in individual costs assumptions. There are two primary differences from combined cycles:

- Plant costs are much more important than fuel costs, consistent with the expectation that such "peaking" plants run at much lower CFs, and thus fixed costs are a much higher percentage of total costs.
- Total CEP cost is extremely sensitive to storage prices. Storage is often the only CEP technology that can meet some peak demand hours, and meeting peak capacity needs dominates peaker plant requirements and cost structures.

We note that CEP economics are not dramatically impacted by our choice to value “surplus” CEP energy (energy generated when the gas plant would not run) at $15/MWh. At this value for excess energy (compared with the marginal cost to operate a new gas plant at ~$25/MWh), the excess energy only represents 7 percent of the CEP’s value for combined cycle systems, on average. For combustion turbines, excess energy represents only 3 percent of the system value, on average.

In addition to assessing the impact of individual cost drivers, we also estimate the impact of applying the ITC to storage technologies, a practice commonly used today by developers of solar-plus-storage projects but omitted from our analysis. We note that in our comparisons of future CEP costs, we do assume that the ITC is retired in 2023; the ITC retirement explains the 2023 CEP and WSS cost increases visible in Figures 9 and 12. We summarize the impact of applying the ITC to storage in Table 2. Because of the increased importance of storage for combustion turbines and when efficiency and demand flexibility are excluded, these cases benefit more from the extension of the ITC to storage.

TABLE 2

BENEFIT OF APPLYING THE ITC TO STORAGE ON CEPS AND WSS.

	COMBINED CYCLES		COMBUSTION TURBINES	
	% PLANTS WHERE CEPS ARE LOWER COST	TOTAL SAVINGS	% PLANTS WHERE CEPS ARE LOWER COST	TOTAL SAVINGS
CEP. ITC not applied to storage	94%	$25.2B	56%	$3.5B
CEP. ITC applied to storage	98%	$30.3B	72%	$4.5B
WSS. ITC not applied to storage	16%	$2.3B	40%	$1.1B
WSS. ITC applied to storage	27%	$3.8B	52%	$2.1B

5. Ignoring the value of EE and demand flexibility shrinks the near-term market for CEPs to replace new gas by 70 percent, and delays the economic opportunity by eight years.

In our base case analysis, we allow the CEP model to select targeted demand-side management programs (i.e., **EE** and **demand flexibility**) that can provide energy, capacity, and flexibility to the grid. Efficiency and demand response are among the most cost-effective resources available to utility planners and investors, and can provide grid services comparable to generation and storage technologies, but usually require favorable state policies to scale effectively. As a sensitivity analysis, we also consider portfolios of only WSS that omit EE and demand flexibility.

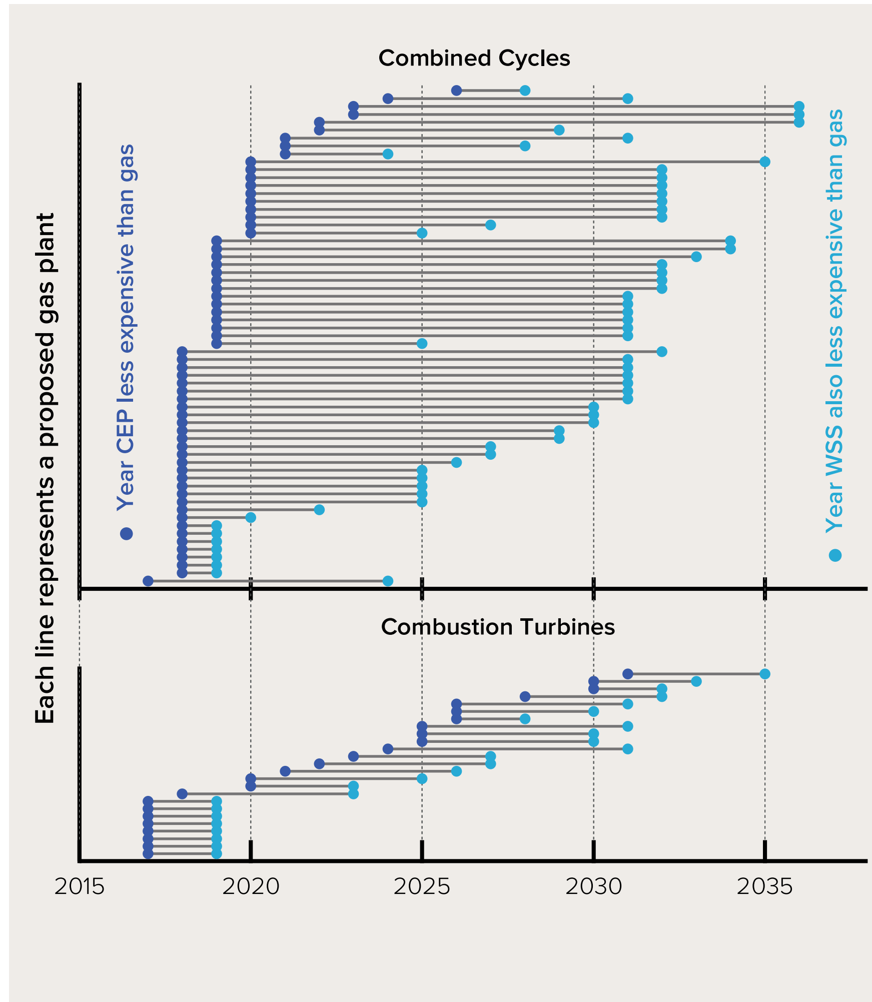
Figure 14 shows the results of this analysis, by summarizing for each proposed gas plant (one per row) the timeline for when either a new-build CEP or new-build WSS undercut the costs of the proposed plant:

- **Near-term market shrinks by 70 percent**. Figure 14 shows that most CEPs begin to undercut the costs of new gas-fired generation in or before the early 2020s (dark blue dots). However, excluding EE and demand flexibility (light blue dots) means that by the expected in-service date of most proposed gas plants, WSS is still more expensive.
- **Ignoring demand-side resources delays opportunity to cost-effectively avoid new gas by eight years, on average**. Lines representing each proposed gas plant in Figure 14 show the delay between when CEPs outcompete a proposed gas project, and when WSS alone does the same. On average, ignoring EE and demand flexibility pushes out the date of cost parity by eight years.

Delaying the market for clean energy by ignoring efficiency and demand flexibility both reduces customer value and increases carbon emissions. Available customer savings from WSS projects alone declines by 88 percent, to $3.5 billion, compared to the value available from CEPs that include demand-side management of $29 billion. Annual CO_2 emissions from proposed gas plants more cost-effective at their in-service date than WSS total 77 million tons, nearly all of which could be avoided by allowing demand-side resources to compete with gas as part of CEPs.

FIGURE 14

TIMELINE FOR EACH PROPOSED GAS PLANT SHOWING ECONOMIC OPTIONS FOR NEW GENERATION



6. Least-cost CEP composition varies, reflecting regional price, load, and renewable generation profiles

Figure 15 shows the regional variation in CEP composition for combined-cycle and combustion turbine gas plants. We show the state-by-state regional definitions in Figure 16. All five clean technologies play important roles in portfolios designed to replace both combustion turbines and combined cycles. The requirements to replace combined-cycle projects weight monthly energy production more heavily than peak capacity; therefore, their CEP replacements rely more heavily on wind, solar, and efficiency. In contrast, the requirements to replace combustion turbine projects heavily favor availability during peak demand; therefore, CEPs designed to replace CTs rely more heavily on storage and demand flexibility.

FIGURE 15

REGIONAL VARIATION IN AVERAGE LEAST-COST CEP COMPOSITION

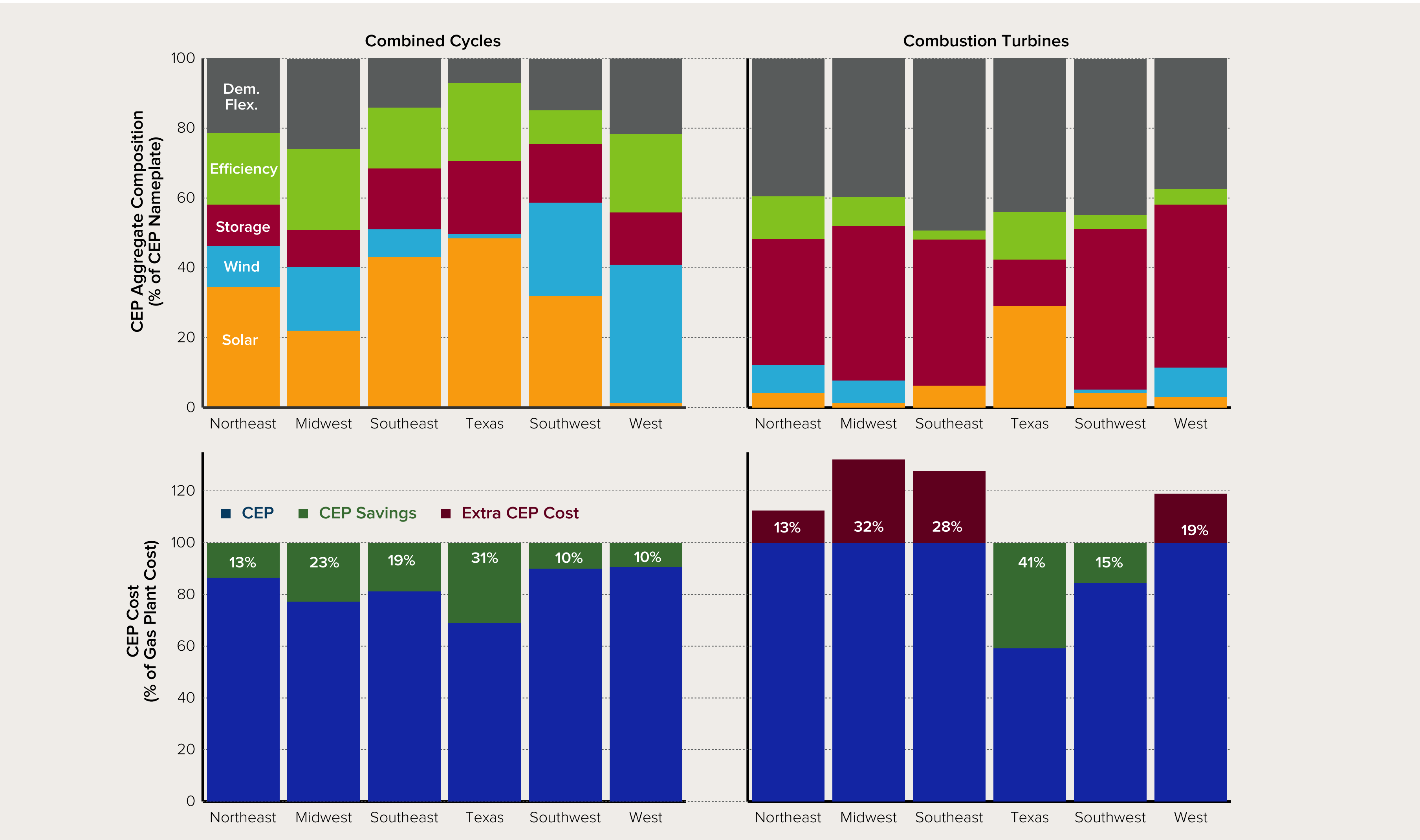
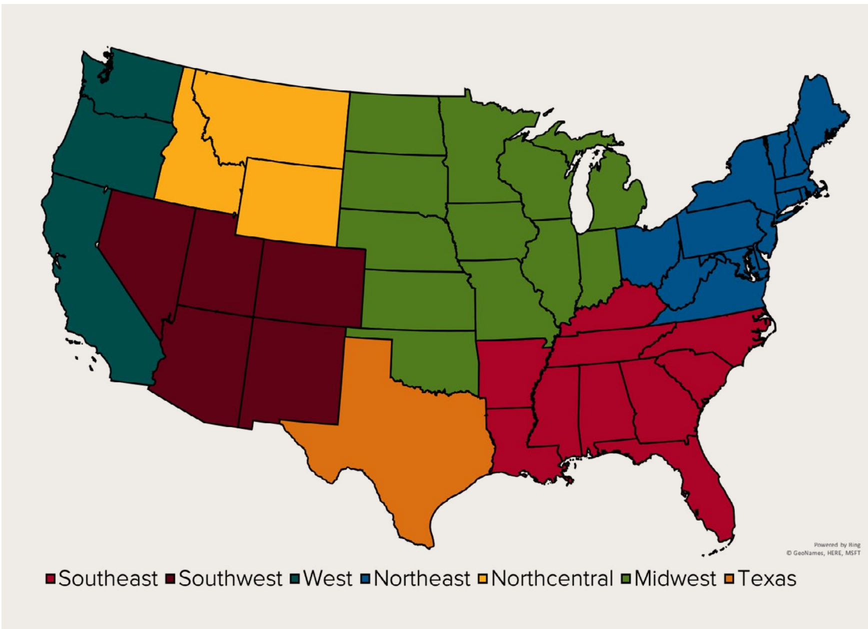


FIGURE 16

REGIONS USED IN CEP ANALYSIS



Below, we summarize key regional differences (note that some states have no new planned gas):

- **Northeast** (CT, DE, MD, NJ, NY, OH, PA, RI, VA, WV): Northeast CEPs include a balanced technology mix. Combined cycle replacements include a relatively higher share of solar, due to a relatively smaller onshore wind resource; this analysis does not model the contribution of offshore wind projects as part of CEPs.
- **Midwest** (IL, IN, MI, MN, SD, WI): Midwestern CEPs include balanced mixes of the five clean technologies.
- **Southeast** (FL, KY, LA, SC): Southeastern CEPs designed to replace combined-cycle projects include a great deal of solar due to its availability and low cost. Southeastern CEPs designed to replace combustion turbines are dominated by demand response and storage.
- **Texas**: Solar dominates CEP composition for both combined-cycle and combustion turbine projects, due to load profiles in the state that are well-aligned with solar production profiles and the large amount of existing and planned wind.
- **Southwest** (AZ, NM, UT): Renewables dominate CEP composition of combined cycle replacements, reflecting the region's excellent renewable resources.
- **West** (CA, OR, WA): Solar is largely absent from CEPs in this region, due to the large amount of existing California solar capacity; instead, CEPs preferentially include wind that balances solar generation.

7. Pricing carbon amplifies the economic case for clean energy portfolios and accelerates stranded asset risk for gas plants

Our main analysis case does not include any implicit or explicit CO_2 pricing. Figure 17 shows the predicted, cumulative regional emissions from proposed combined cycle and combustion turbine plants included in this study. To quantify the impact of emissions pricing, we analyze CEP economics with carbon prices ranging from $0 to $100 per ton of CO_2 emitted. CO_2 pricing primarily impacts combined-cycle gas plants, as these plants run with much higher CFs.

In Figure 18, we show the combined-cycle gas capacity that is economically displaced by just WSS as a function of carbon price. We highlight portfolios of just WSS because, with efficiency and demand flexibility, CEPs are lower

FIGURE 17

EXPECTED ANNUAL CO_2 EMISSIONS OF PROPOSED GAS PLANTS

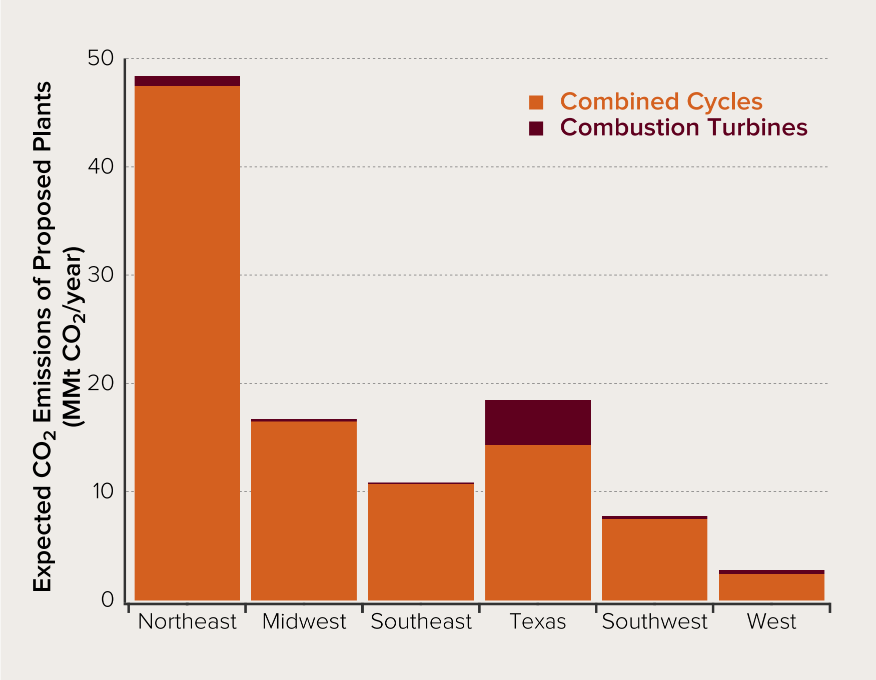
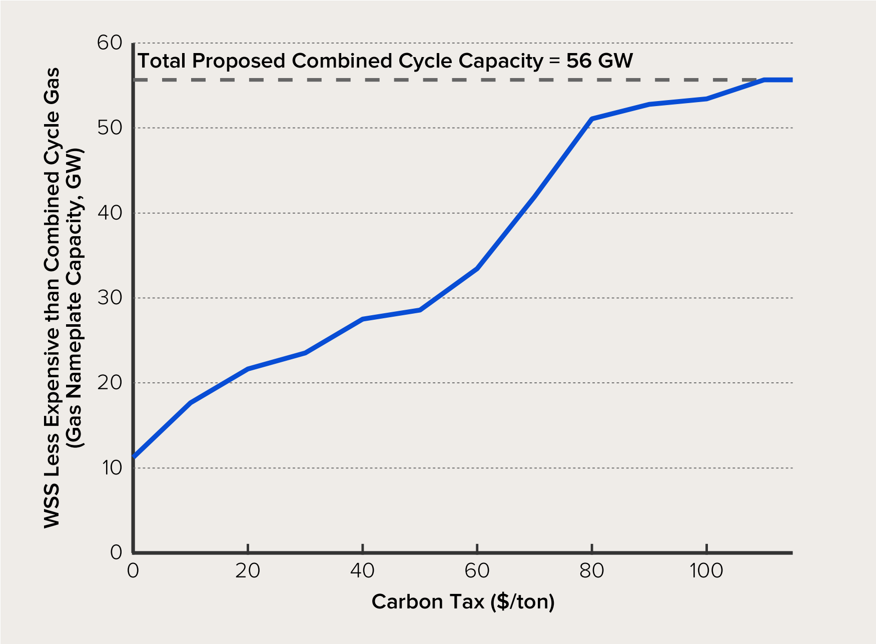


FIGURE 18

IMPACT OF CARBON PRICING ON ECONOMICS OF WSS RELATIVE TO COMBINED-CYCLE PROJECTS



net cost than combined-cycle plants even without any carbon price. We find that the economic capacity of WSS grows smoothly until the price reaches $100/ton, when WSS is less costly than all proposed combined cycles.

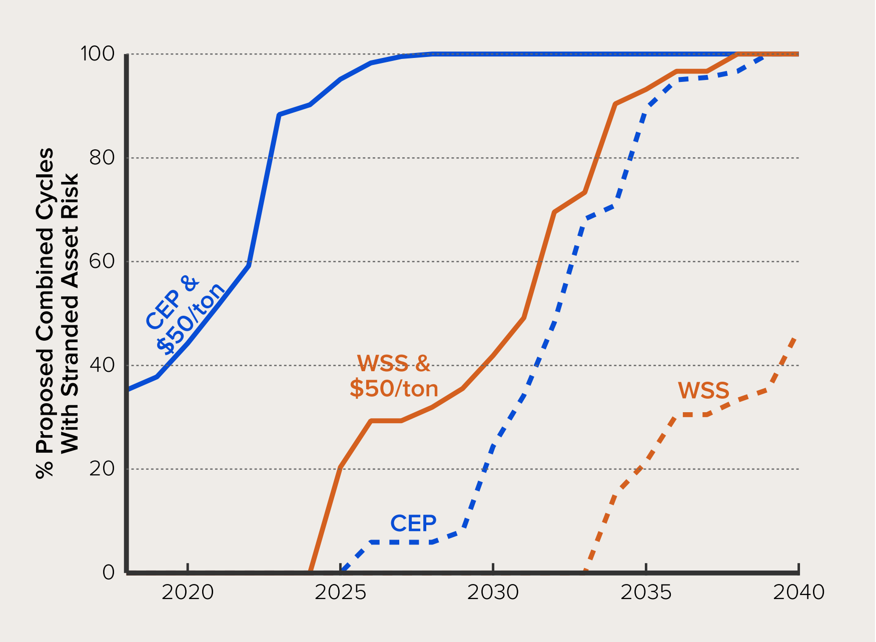
For plants that are built (or already in service), a carbon price accelerates the timeline for when the gas plant's operating costs become higher than the new-build CEP cost. Figure 19 summarizes the impact of a $50/ton price on carbon dioxide—similar to prices already included in **utility planning processes** or **policy requirements in leading states**—on the crossover point for both CEP and for portfolios of WSS:

- With a $50/ton carbon price, new CEPs start to outcompete existing combined-cycle gas plants in 2019, and would render nearly all combined-cycle plants uneconomic by 2025 (solid blue line).
- With a $50/ton carbon price, WSS alone start undercutting gas plant operating costs in the early 2020s (solid orange line), and would outcompete nearly all proposed gas capacity by 2035, much faster than WSS competing against gas without any carbon price (dashed orange line).

In short, a $50/ton carbon price accelerates the year in which a gas power plant becomes uneconomic to run relative to a new-build CEP by ~10 years; higher carbon prices would have a greater effect.

FIGURE 19

TIMELINE OF WHEN CCGT OPERATING COSTS EXCEED NEW-BUILD CEP INVESTMENT COSTS, WITH SENSITIVITIES FOR CO_2 PRICING AND EXCLUSION OF DEMAND-SIDE RESOURCES



5 IMPLICATIONS & RECOMMENDATIONS

IMPLICATIONS & RECOMMENDATIONS

The currently strong and quickly growing economic case for clean energy portfolios has significant implications for how investments in the electricity system are planned, incentivized, and regulated.

On one hand, lower clean energy costs are an obvious and enormous opportunity. If the economic value of clean energy portfolios can be fully captured, customers would save $29 billion through 2040 and the electricity sector would reduce CO_2 emissions by 100 MT/year.

On the other hand, if the electricity sector fails to embrace the transition to clean energy, there are enormous risks for investors, customers, and the climate. Our results suggest that 90 percent of proposed combined-cycle plants could be uneconomic by 2035, less than 10–15 years after construction. Under current regulatory structures, captive utility customers will ultimately bear most of this risk and be left paying for fixed costs after the assets have been replaced by lower-cost clean technologies.

Planners and regulators can help the industry capture the opportunity at hand and mitigate the risks of this ongoing energy transition.

For vertically integrated utilities: Adopt emerging best practices around all-source, technology-neutral generation procurement

In leading vertically integrated utility service territories, where utilities invest in generation and regulators allow cost recovery through customer rates, utilities and their regulators are pioneering all-source, technology-neutral procurement. Technology-neutral procurement allows the economic advantages of clean energy portfolios to emerge naturally. Numerous states including Hawaii, Colorado, Indiana, and California have found that clean energy resources meet system needs at lower costs than both legacy fossil and new gas-fired generation. These procurement processes share the following commonalities:

1. **Define necessary grid services, not resource characteristics.** Legacy procurement and resource planning processes tend to define characteristics of specific generating technologies and request vendors bid accordingly. By definition, such a process limits new technologies from bidding, even if they can provide the needed grid services. Instead, we suggest starting the planning and procurement process by specifying the services required (i.e., by specifying the problem instead of the solution).
2. **Allow all resources to compete on a level playing field.** Legacy planning processes frequently omit certain resources, most notably EE, in consideration of candidate technologies to meet grid service needs. Additionally, legacy modeling software that is used to evaluate a technologies' ability to provide grid services often fails to account for advances in wind, solar, and battery storage capabilities. These legacy software tools were originally developed to model cost tradeoffs between coal, gas, nuclear, and hydro, and in many cases are structurally unable to properly represent the ability of battery storage and renewable energy to meet system reliability requirements. Now, processes and modeling tools deployed by leading utilities increasingly show a path forward for properly assessing and modeling these resources in the resource planning and selection process.
3. **Use competitive bidding to discover resource prices.** Legacy utility planning and procurement processes tend to use administratively determined assumptions relying on outdated data to generate cost inputs for portfolio optimization software. With costs for renewable energy and storage technologies falling so rapidly, this approach risks grossly misrepresenting the costs of these technologies; leading utilities are now using competitive bids and other market input to determine pricing assumptions used in planning and procurement, and relying on the same competitive bidding process to ensure that costs for final selection passed on to customers are as low as possible.

For state utility regulators: Account for the significant risk that uneconomic gas generation will increase customer rates

Our analysis shows that most proposed gas plants are both uneconomic today and, if built anyway, likely to be outcompeted before the end of their useful lives by clean energy. However, we acknowledge that some regional constraints (not considered in our model) can favor new gas-fired capacity. We hope this study will motivate regulators to carefully assess grid service needs, encourage competitive processes, and test renewable and storage costs assumptions as they assess proposals to build new gas-fired generation.

In addition to considering today's economics of proposed gas plants, regulators should also consider the long-term viability of gas investments, given likely continued clean energy cost declines and the potential for future carbon emission pricing. For example, we find that a carbon price of $50/ton reduces the expected useful life of a new-build gas plant by 10 years (Figure 19). Further, cost declines of renewables and storage closer to recent rates would lower useful lifetime for a gas plant by approximately five years (Figure 12). Power purchase agreement prices disclosed at the time of this report's release indicate Lazard and BNEF cost assumptions for current and future clean energy resources may already be **out-of-date**. Before saddling customers with these and other risks, regulators should consider mitigating actions such as delaying approval of new gas investment decisions until price trends become more clear, accelerated amortization schedules, or changing risk allocation to ensure customers are protected.

For utilities and regulators: Embrace the value of demand-side, distributed resources in optimizing power supply portfolios

Our modeling shows that EE and demand flexibility continue to be the least-cost route to meeting energy, capacity, and flexibility needs, and including them as candidate resources in CEPs unlocks $25 billion in net customer savings. Utilities should include these resources as options in selecting least-cost power supply portfolios, following the example of leading **utility proposals** and **regulatory requirements** in the past several years.

However, common regulatory frameworks and utility business models make it difficult for utilities to profit from energy conservation or reduced peak demand. **Performance incentive mechanisms and other performance-based regulation** can allow utilities to capture the value of demand-side resources.

There is also demonstrable value available from distributed generation and storage, not systematically modeled as part of this study due to limitations in scope of analysis and available data, which should be considered in evaluating all resources for inclusion in CEPs. For example, distributed solar-plus-storage systems, where allowed to compete in **all-source procurements** or **wholesale energy markets**, can bid in at lower net costs to the utility or market due to the customer-facing value they provide. Utilities and regulators can extend the same planning, procurement, and cost-recovery processes that help scale efficiency and demand flexibility to other DERs, and allow them to play a greater role in cost-effectively avoiding new gas investment.

For wholesale market stakeholders: Reconsider wholesale market participation rules to better align with system needs and the capabilities of emerging clean energy resources

Approximately 60 percent of proposed gas-fired capacity is slated for construction within restructured power markets, including much of the Northeast United States and Texas, where merchant investors respond to market signals for new capacity. However, most recent examples from the United States of clean energy portfolios avoiding construction of new gas plants are from vertically integrated, regulated service territories, where leading utilities have pioneered new approaches to planning and resource procurement that can accurately compare clean energy portfolios against legacy and incumbent asset types. There is an opportunity to use the present tipping point in clean energy resource costs and capabilities to test the extent to which wholesale energy markets, designed for an era in which fossil, nuclear, and hydro generators competed only against each other, are well-suited to enabling open and fair competition within a growing class of electricity resources. For example, the **current process of defining participation rules for storage** within organized electricity markets presents a clear opportunity to test whether current participation models are well-matched to grid needs, or whether new models can allow markets to capture more value from emerging resources.

For merchant gas investors: Carefully consider the risks of merchant projects in the face of falling clean energy prices and other future uncertainties

Investors in merchant gas-fired power plants are already beginning to realize the financial risks of investment in long-lived assets in markets that offer only short-run cost recovery assurance, but significant capacity (60 percent of the capacity included in this study) remains in the planning queue in such markets. However, our results illustrate the fact that continued prioritization of investment in new gas projects in these regions represents a bet against any of the following three outcomes occurring:

- **Carbon pricing:** Our results indicate that including even a modest carbon price accelerates the stranded asset timeline for new gas projects by 5 to 10 years.
- **Continued cost declines of clean energy:** Slightly faster learning rates for wind, solar, and batteries, splitting the difference between recent history and analyst forecasts, would accelerate stranded asset risk timelines for new gas plants by three to six years.
- **Market rules allowing full resource participation:** As explained above, current wholesale market rules tend to favor the last generation of resources, reflecting a lag time in rulemaking and change management at large and reliability-oriented institutions. As this lag is resolved, clean energy portfolios will become even more competitive in organized markets (e.g., as participation rules for storage, demand flexibility, and EE are tested and improved).

Any one of these events would accelerate the economic case for clean energy portfolios and further degrade the future profitability of new gas plants and associated investor returns. Were two or three of these events to occur, the economics would tilt overwhelmingly in favor of clean energy portfolios, with dire consequences for investors in legacy assets.

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6 TECHNICAL APPENDIX

TECHNICAL APPENDIX

Clean energy portfolio model data sources

- We use FERC **714** as the starting point for planning area load growth forecasts and peak load. We construct projections of gross load profiles in future years, as described below.
- We use EIA Form **860** (2017) to identify capacity, build year, and location of existing power plants. We also use EIA Form 860 to identify plants comparable to proposed plants in order to estimate future monthly energy generation and to calculate the planning areas' current renewable capacity.
- We also use EIA Form **923** (2017) to estimate existing power plants monthly energy generation.
- We use EIA Form **861** (2017) to obtain utility customer counts, energy sales by customer class, and demand response program costs. We use the former two data types in our bottom-up estimates of efficiency and demand flexibility resource potential. The latter data type is the basis for our estimates of the cost of demand flexibility resources.
- We use EIA **AEO 2019** for natural gas price projections.
- We use **Lazard Levelized Cost of Energy v11** for CapEx and OpEx for gas-fired power plants, CapEx and OpEx for wind, and OpEx for Solar.
- We use **Lazard Levelized Cost of Storage v4** for storage OpEx, including what Lazard refers to as "augmentation costs," which are the equipment and/or operational costs required to maintain the system at the assumed performance level for 20 years.
- We use BNEF New Energy Outlook 2018: Charts. August 3, 2018 for solar and battery energy storage CapEx as well as CapEx learning rates for solar, wind, and battery energy storage.
- We use LBNL **Program Administrator Cost of Saved Energy for Utility Customer-Funded Energy Efficiency Programs** for EE program costs.
- We use Center for Climate Energy Solutions **U.S. State Electricity Portfolio Standards** for each state's renewable portfolio target percentage and year. This data is used to estimate projected renewable capacity in future years to construct projected net load profiles.
- We use NREL's **Estimating Renewable Energy Economic Potential in the United States** for state-level estimates of total installable capacity for solar, onshore wind, and offshore wind.
- We use FERC's **A National Assessment of Demand Response Potential** for sector-level potentials for demand flexibility by state that constrain CEP use of demand flexibility.
- We use EPRI **State Level Electric Energy Efficiency Potential Estimates** for sector-level potentials for EE by state that constrain CEP use of EE.
- We use EIA **RECS** and **CBECS** for the penetration of the various electricity end uses by region. This data is used in our bottom-up estimates of EE and demand flexibility potential.
- We use S&P Market Intelligence to identify planned gas-fired power plants in the continental US, excluding Alaska. The plants in this analysis are from the Power Plants database as of June 3, 2019. The list is further screened to only include plants whose status is Announced, Early Development, or Advanced Development; whose capacity is greater than 100 MW; and which are not combined heat and power units.
- We use RMI's ***Reinventing Fire*** for hourly load, end use, and renewable profiles by region. The hourly load is used to calculate gross and net load profiles for each proposed plant and the renewable profiles are used to predict hour-by-hour renewable generation output. We also use *Reinventing Fire* scenario data to assess the cost of incremental transmission needs associated with wind and solar projects.
- We use **Public Service Company of Colorado 120 day Report**, in addition to *Reinventing Fire* data, for transmission costs that we add to renewable costs.

Scenarios

In the analysis, we used our model to construct least-cost clean energy portfolios using various combinations of assumptions that we call "scenarios":

- **The *CEP* scenario** includes all clean energy resources: EE, demand flexibility, utility-scale wind, utility-scale solar, and battery energy storage. We detail this scenario in Table 1: Key assumptions used in CEP model.
- **The WSS scenario** is identical to the Main scenario except that it excludes EE and demand flexibility from portfolios.
- The **faster cost declines scenario** is identical to the Main scenario except that the learning rates for WSS CapEx are increased to 150 percent of those in the Main scenario.

Methodology

This analysis compares the net present value (NPV) of cost for a proposed gas plant with a portfolio of DERs and utility-scale renewables. The CEP alternative is constructed to provide at least as much energy, capacity, and flexibility as the gas plant.

The analysis includes five steps:

1. Service requirement calculation
2. Resource potential assessment
3. Resource cost assessment
4. Portfolio optimizer
5. Gas plant cost assessment.

1. Service requirements model

The service requirements model begins by forecasting hourly system net load for the gas plant plant's in-service year by applying our projection of the planning area's peak load to a normalized 2010 regional load profile and subtracting projected renewable generation. We derive projected renewable generation from current renewable capacity and the capacity additions necessary to meet the state's RPS.

We use the top 50 hours of system net load in the capacity constraints, and the hour of highest system net load increase for the flexibility constraints. We calculate hourly system net load in the plant's in-service year by projecting gross hourly system load and then subtracting the system's projected hourly renewable production. We project gross hourly system load by first projecting gross system peak in the plant's in-service year based on the planning area's 2017 peak as reported in FERC 714 and the planning area's growth rate calculated from FERC 714's demand forecasts. We then apply that projected peak value to the plant region's normalized hourly load profile from *Reinventing Fire*. To determine projected hourly renewable production, we begin with the planning area's current annual renewable production, as reported in EIA Forms 923 and 860, and add the amount of renewable generation that would be required for the planning area to be on track to meet the state's RPS (we assume that the current ratio of wind to solar energy is maintained into the future). We then convert these values for projected energy from wind and solar into projected wind and solar capacity using regional CFs. The resulting capacities are then applied to regional renewable hourly profiles from *Reinventing Fire* to get projected hourly renewable production.

We base monthly energy requirements on average monthly CFs for the newest half of plants of the same type in the gas plant's planning area. To determine the CFs of combined-cycle plants, we use an additional screen that removes plants with annual CFs below 35 percent. The data for these monthly CF calculations comes from EIA's Forms 923 and 860.

We define an additional set of flexibility requirements by determining the largest four-hour decline in solar production during the year and require that that decline is fully offset by increases in wind, efficiency, demand flexibility, and storage. In this constraint, storage can contribute two times at its installed capacity to account for its ability to charge at the beginning of the decline and discharge at the end.

2. Resource potential assessment

The resource assessment performs bottom-up estimates of EE and demand flexibility potential by end use along with top-down potential estimates by customer sector. Top-down sector estimates for EE potential are calculated from EPRI state-level economic potential for EE savings by sector, which are percentages that we scale by the gross load from the service requirement model to determine sector-level potential.

Top-down estimates of achievable demand flexibility participation by sector are based on FERC-estimated shares of peak load that could be reduced by DR and the gross load from the service requirement model. Both demand flexibility and EE top-down potential estimates serve as sector-level limits on EE and DR resources available to the clean portfolio linear programming model. Bottom-up estimates for EE and demand flexibility are used to limit potential resources for a given end use.

For EE, these estimates are based on RECS 2015 and CBECS 2012 shares of households and businesses with a given electrical end use for the applicable region and EIA data on the number of customers for a given planning area. Potential for these end uses is estimated by multiplying the number of devices by the assumed average peak reduction on a given end-use technology. Demand flexibility end-use potential is estimated in the same fashion, with estimates of the number of devices from RECS and CBECS along with average peak reduction from enabling demand flexibility. This provides the total amount of efficiency or demand flexibility potential for each end use in a given planning area. For any particular plant we analyze, we multiply those planning area potentials by the lesser of 25 percent or twice the ratio of the proposed plant's capacity and the planning area's peak.

In addition to the previously described top-down and bottom-up constraints placed on EE and demand flexibility, we also limit these resources at the plant level. The contribution of EE to a CEP's energy production is limited to 50 percent of the annual energy of the gas plant. The contribution of DR to meeting the CEP's capacity requirement is limited to 50 percent of the gas plant's capacity.

The resource potential assessment also determines the amount of solar, onshore wind, and offshore wind potential based on NREL's estimates of the state-level economic potential of each renewable resource.

3. Resource cost assessment

Renewable and energy storage CapEx and OpEx costs and annual CapEx declines are taken from Lazard LCOE v11, Lazard LCOS v4, and BNEF. We apply the 2020 value of the ITC to solar resource costs in all cases to reflect the use of the law's safe-harbor provisions.

CapEx for all resources are converted to present costs for the in-service year by decreasing capital costs where appropriate to reflect the impact of a learning rate, and then discounting back to the current year. For resources with lives that differ from the assumed life of a gas plant of 20 years, we adjust that resource's CapEx by annualizing it and then taking the present value of the first 20 cash flows. OpEx for the first 20 years of the resource's life is discounted back to the current year.

For utility-scale wind and utility-scale solar, an additional term is added to both CapEx and OpEx to account for the cost of new transmission to connect those resources to the system. Those adders are derived from PSCO's 120-day report and *Reinventing Fire* scenarios. For wind imported from other regions, those transmission adders are multiplied by five.

The OpEx for battery energy storage includes what Lazard refers to as "augmentation costs," which are the equipment and/or operational costs required to maintain the system at the assumed performance level for 20 years. We calculate those costs by assuming that supplying one MWh of energy through the battery reduces its storage capacity by 0.03 percent, which must then be replaced. We assume that the cost of this replacement falls over time as battery pack prices fall. To determine the number of MWh supplied by the battery, we assume that a battery is used 25 times per year (10 times for combustion turbine cases) in addition to the occasions necessary to meet the peak hour service requirements.

EE resource costs are based on estimated costs of running an effective EE program, and have a CapEx cost from incenting the deployment of EE measures but no OpEx costs. CapEx costs for particular EE end-use resources are based on the levelized-savings weighted-average costs from the LBNL PACSE study for the most similar measure category in the study. These levelized costs are converted to first-year costs with a capital recovery factor, and scaled by annual energy saved by a single MW of that particular end use which is region specific. We then adjust CapEx costs to account for the different lives of different EE measures as described above.

Demand flexibility cost estimates are also program based, and calculated for each sector from 75th-percentile annual DR program costs in EIA's Form 861. We assume 10 percent of that cost is for fixed annual O&M, and the remainder is CapEx that can be de-annualized into a first-year cost with a capital recovery factor. In addition to fixed O&M, demand flexibility OpEx includes variable O&M, which assumes it will be used 25 times per year (10 times for combustion turbine cases) in addition to the occasions necessary to meet the peak hour service requirements.

4. Portfolio optimizer

We use linear programming to select the portfolio of resources that can provide at least the same energy, capacity, and flexibility services as the gas plant for the lowest cost. To do this, we use resource cost estimates from the resource cost assessment, service requirements from the service requirement model, and available resources from the resource potential assessment. These three elements form our linear program's objective function, and its two groups of constraints: service constraints and resource constraints. The objective function states, mathematically, what we are trying to achieve: the lowest-cost portfolio. The constraints state all requirements (e.g., produce a certain amount of energy each month) and limitations (e.g. don't include more efficiency than we estimate is reasonable) the portfolio must satisfy. The full mathematical formulation of the optimization model is available in the appendix of our 2018 paper.

5. Gas plant cost assessment

The gas plant cost assessment includes CapEx, fixed O&M, variable O&M, fuel expenses, and carbon expenses (if any). Cost data used to determine gas plant CapEx, fixed O&M, and variable O&M are taken from Lazard LCOE v11 as are heat rates by plant type. Cost data used to determine gas fuel costs are from EIA's AEO 2019 reference case . These values are region-specific time series of annual fuel price projections from 2018 through 2050. Cost data used to determine carbon expenses are set by a parameter. In our base case, we do not include a price on carbon dioxide. In a few sensitivity cases, we set a price of $50/ton of CO_2 emitted.

Gas plant CapEx is calculated by multiplying the per unit capacity cost of CapEx by the nameplate capacity of the gas plant. Annual gas plant fixed O&M is directly proportional to the plant's nameplate capacity. Annual gas plant variable O&M is a direct function of the plant's annual energy production, the calculation for which is explained above as the monthly energy requirement for the CEP. Annual gas plant fuel expenses are calculated as the product of the plant's yearly fuel need and the per unit fuel price for the given year. A plant's yearly fuel need is calculated as the product of the plant's annual energy production and its heat rate. A plant's lifetime fuel expenses are calculated assuming a constant annual fuel need and a variable per unit fuel price for each year, as specified by the fuel cost data. Finally, annual gas plant carbon expenses are a function of the plant's yearly fuel need, a value for carbon intensity per unit energy, and a carbon price per ton of emitted carbon dioxide. The carbon intensity used for all gas-fired power plants was 53.07 kg CO_2/MMBtu, as reported by EIA . Our analysis excludes the effect of upstream greenhouse gas emissions from the natural gas system including leaks.

To convert annual gas plant expenses (fixed O&M, variable O&M, fuel expenses, and carbon expenses) into lifetime expenses, we follow two standard accounting steps:

- Take the present value of all annual expenses for 20 years (the value used for plant lifetime) using a 6 percent real discount rate
- Discount the present value of all annual expenses to the current year

We also discount gas plant CapEx to the current year for consistency.

Calculating CEP excess energy

As a post-optimization step, the model assesses how much energy the portfolio produces beyond the service requirement, reduced by round-trip losses in the batteries, we call the resulting amount "excess energy." We value this excess energy at $15/MWh.

Cost comparison

We compare the costs of a proposed gas plant and an equivalent CEP using a metric of "net cost," in units of $/MWh for combined-cycle generation and $/kW-y for combustion turbine projects. We use a standard LCOE metric for combined-cycle plants. We calculate this LCOE as the present value of all lifetime capital, operational, and fuel expenses of the gas plant, divided by the present value of all lifetime energy produced by the gas plant, assuming a 20-year lifetime.

$$\text{CC Cost (\$/MWh)} = \frac{\text{NPV of CC total cost (\$)}}{\text{NPV of energy produced by CC (MWh)}}$$

For CEPs designed to replace combined-cycle plants, we define a cost metric by assessing the present value of the lifetime capital and operational expenses for all CEP resources, subtracting the value of the excess energy produced by the CEP over what the gas plant would produce, and dividing the present value of all lifetime energy produced by the gas plant, assuming a 20-year lifetime.

$$\text{CEP Net Cost (\$/MWh)} = \frac{\text{NPV of CEP total cost (\$)} - [\text{CEP excess energy (MWh)} \times \$15/\text{MWh}]}{\text{NPV of energy produced by CC (MWh)}}$$

We use a different cost metric for CT projects, as these projects are often expected to run less than combined-cycle assets, and primarily provide peak capacity, rather than bulk energy. We define a cost metric for CTs as the annualized net present cost of all capital, operational, and fuel expenses of the gas plant assuming a 20-year lifetime, divided by the gas plant's average operating capacity during the system's top 50 net load hours.

$$\text{CT Cost (\$/kW-y)} = \frac{\text{CT total cost, annualized (\$/y)}}{\text{Average peak power output of CT (kW)}}$$

For CEPs that replace combustion turbines, we define a cost metric as the annualized present value of all capital and operational expenses of the CEP, less the value of energy sales in excess of gas plant production (as described above for combined-cycle plants), divided by the gas plant's average operating capacity during the system's top 50 net load hours.

$$\text{CEP Net Cost (\$/kW-y)} = \frac{\text{CEP total cost, annualized (\$)} - [\text{CEP annual excess energy (MWh/y)} \times \$15/\text{MWh}]}{\text{Average peak power output of CT (kW)}}$$

As described above, we compare the net cost of a CEP to both the cost of new gas plants and, for combined-cycle plants, to the go-forward costs of existing gas plants. The metric for the go-forward cost of an existing gas plant is similar to the metric for combined-cycle plants, except we exclude capital expenses.

$$\text{CC operating cost (\$/MWh)} = \frac{\text{Annual fuel, variable, and fixed costs (\$/y)}}{\text{Annual energy produced by CC (MWh/y)}}$$

Stranded asset risk

Our analysis of stranded asset risk compares the net cost of CEPs to the operating cost of proposed gas plants in order to assess if and when CEPs would be able to cost-effectively replace gas plants if said plants are built as proposed. The stranded asset analysis reruns the optimization for each year from 2010 to 2045 and compares, in terms of $/MWh, the net cost of a new-build CEP to the go-forward cost of operating the proposed gas plant in that year. The year in which the cost of a new-build CEP is less than the go-forward cost of operating the proposed gas plant is the year in which the gas plant is rendered uneconomic. Gas plants that are outcompeted by an equivalent CEP before the end of their expected useful life are considered to be at risk of becoming stranded assets for their investors. Note that we only include cases for combined-cycle gas plants in our stranded asset analysis, to reflect the greater risk associated with these plants, typically designed and financed to run at high CFs, if they are outcompeted by clean energy technologies and thus run significantly fewer hours.

Carbon dioxide emissions

We calculate the expected annual carbon dioxide emissions in million tons of CO_2 per year as a function of the plant's annual energy production, heat rate, and CO_2 emissions factor.

$$\text{Annual } CO_2 \text{ emissions (MT } CO_2\text{/y)} = \text{Annual energy production (MWh/y)*}$$
$$\text{Heat rate (MMBtu/MWh)*}CO_2 \text{ emissions factor (MT } CO_2\text{/MMBtu)}$$

As referenced above, in this study we use a CO_2 emissions factor of 53.07 kg CO_2/MMBtu and do not include upstream greenhouse gas emissions from the natural gas system including leaks.

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Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States

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Nexant, Inc.

January 2015

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Disclaimer

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Abstract

This report updates the 2009 meta-analysis that provides estimates of the value of service reliability for electricity customers in the United States (U.S.). The meta-dataset now includes 34 different datasets from surveys fielded by 10 different utility companies between 1989 and 2012. Because these studies used nearly identical interruption cost estimation or willingness-to-pay/accept methods, it was possible to integrate their results into a single meta-dataset describing the value of electric service reliability observed in all of them. Once the datasets from the various studies were combined, a two-part regression model was used to estimate customer damage functions that can be generally applied to calculate customer interruption costs per event by season, time of day, day of week, and geographical regions within the U.S. for industrial, commercial, and residential customers. This report focuses on the backwards stepwise selection process that was used to develop the final revised model for all customer classes. Across customer classes, the revised customer interruption cost model has improved significantly because it incorporates more data and does not include the many extraneous variables that were in the original specification from the 2009 meta-analysis. The backwards stepwise selection process led to a more parsimonious model that only included key variables, while still achieving comparable out-of-sample predictive performance. In turn, users of interruption cost estimation tools such as the Interruption Cost Estimate (ICE) Calculator will have less customer characteristics information to provide and the associated inputs page will be far less cumbersome. The upcoming new version of the ICE Calculator is anticipated to be released in 2015.

Table of Contents

List of Figures and Tables

Acronyms and Abbreviations

AIC	Akaike's Information Criterion
C&I	Commercial and Industrial
GLM	Generalized Linear Model
ICE	Interruption Cost Estimate
MAE	Mean Absolute Error
OLS	Ordinary Least Squares
RMSE	Root Mean Square Error

Executive Summary

In 2009, Freeman, Sullivan & Co. (now Nexant) conducted a meta-analysis that provided estimates of the value of service reliability for electricity customers in the United States (U.S.). These estimates were obtained by analyzing the results from 28 customer value of service reliability studies conducted by 10 major U.S. electric utilities over the 16-year period from 1989 to 2005. Because these studies used nearly identical interruption cost estimation or willingness-to-pay/accept methods, it was possible to integrate their results into a single meta-dataset describing the value of electric service reliability observed in all of them. The meta-analysis and its associated econometric models were summarized in a report entitled “Estimated Value of Service Reliability for Electric Utility Customers in the United States,”[1] which was prepared for Lawrence Berkeley National Laboratory (LBNL) and the Office of Electricity Delivery and Energy Reliability of the U.S. Department of Energy (DOE). The econometric models were subsequently integrated into the Interruption Cost Estimate (ICE) Calculator (available at icecalculator.com), which is an online tool designed for electric reliability planners at utilities, government organizations or other entities that are interested in estimating interruption costs and/or the benefits associated with reliability improvements (also funded by LBNL and DOE).

Since the report was finalized in June 2009 and the ICE Calculator was released in July 2011, Nexant, LBNL, DOE, and ICE Calculator users have identified several ways to improve the interruption cost estimates and the ICE Calculator user experience. These improvements include:

- Incorporating more recent utility interruption cost studies;
- Enabling the ICE Calculator to provide estimates for power interruptions lasting longer than eight hours;
- Reducing the amount of detailed customer characteristics information that ICE Calculator users must provide;
- Subjecting the econometric model selection process to rigorous cross-validation techniques, using the most recent model validation methods;[2] and
- Providing a batch processing feature that allows the user to save results and modify inputs.

These improvements will be addressed through this updated report and the upcoming new version of the ICE Calculator, which is anticipated to be released in 2015. This report provides updated value of service reliability estimates and details the revised econometric model, which is based on a meta-analysis that includes two new interruption cost studies. The upcoming new version of the ICE Calculator will incorporate the revised econometric model and include a batch processing feature that will allow the user to save results and modify inputs.

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[1] Sullivan, M.J., M. Mercurio, and J. Schellenberg (2009). *Estimated Value of Service Reliability for Electric Utility Customers in the United States*. Lawrence Berkeley National Laboratory Report No. LBNL-2132E.

[2] For a discussion of these methods, see: Varian, Hal R. “Big Data: New Tricks for Econometrics.” *Journal of Economic Perspectives*. Volume 28, Number 2. Spring 2014. Pages 3–28. Available here: http://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.28.2.3

Updated Interruption Cost Estimates

For each customer class, Table ES-1 provides the three key metrics that are most useful for planning purposes. These metrics are:

- Cost per event (cost for an individual interruption for a typical customer[3]);
- Cost per average kW (cost per event normalized by average demand); and
- Cost per unserved kWh (cost per event normalized by the expected amount of unserved kWh for each interruption duration).

Cost per unserved kWh is relatively high for a momentary interruption because the expected amount of unserved kWh over a 5-minute period is relatively low.

In general, even though the econometric model has been considerably simplified, it produces similar estimates to those of the 2009 model. As in the 2009 study, medium and large C&I customers have the highest interruption costs, but when normalized by average kW, interruption costs are highest in the small C&I customer class. On both an absolute and normalized basis, residential customers experience the lowest costs as a result of a power interruption.

Table ES-1: Estimated Interruption Cost per Event, Average kW and Unserved kWh (U.S.2013$) by Duration and Customer Class

Interruption Cost	Interruption Duration					
	Momentary	30 Minutes	1 Hour	4 Hours	8 Hours	16 Hours
Medium and Large C&I (Over 50,000 Annual kWh)						
Cost per Event	$12,952	$15,241	$17,804	$39,458	$84,083	$165,482
Cost per Average kW	$15.9	$18.7	$21.8	$48.4	$103.2	$203.0
Cost per Unserved kWh	$190.7	$37.4	$21.8	$12.1	$12.9	$12.7
Small C&I (Under 50,000 Annual kWh)						
Cost per Event	$412	$520	$647	$1,880	$4,690	$9,055
Cost per Average kW	$187.9	$237.0	$295.0	$857.1	$2,138.1	$4,128.3
Cost per Unserved kWh	$2,254.6	$474.1	$295.0	$214.3	$267.3	$258.0
Residential						
Cost per Event	$3.9	$4.5	$5.1	$9.5	$17.2	$32.4
Cost per Average kW	$2.6	$2.9	$3.3	$6.2	$11.3	$21.2
Cost per Unserved kWh	$30.9	$5.9	$3.3	$1.6	$1.4	$1.3

Table ES-2 shows how customer interruption costs vary by season and time of day, based on the key drivers of interruption costs that were identified in the model selection process. For medium and large C&I customers, interruption costs only meaningfully vary by season (summer vs. non-summer). For medium and large C&I customers, the cost of a summer power interruption is

[3] The interruption costs in Table ES- 1 are for the average-sized customer in the meta-database. The average annual kWh usages for the respondents in the meta-database are 7,140,501 kWh for medium and large C&I customers, 19,214 kWh for small C&I customers and 13,351 kWh for residential customers.

around 21% to 43% higher than a non-summer one, depending on duration (the percent difference lowers as duration increases). For small C&I customers, the seasonal pattern is the opposite, with the cost of summer power interruptions lower by around 9% to 30%, depending on duration, season, and time of day. Small C&I interruption costs also vary by time of day, with the highest costs in the afternoon and morning. In the evening and nighttime, small C&I interruption costs are substantially lower, which makes sense given that small businesses typically operate during daytime hours. For residential customers, interruption costs are generally higher during the summer and in the morning and night (10 PM to 12 noon). The table also includes a weighted-average interruption cost estimate (equal to the cost per event estimates in Table ES-1), which is weighted by the proportion of hours of the year that each interruption scenario represents, depending on season and time of day. This weighted-average interruption cost estimate is most appropriate to use for planning purposes, unless the distribution of interruptions by season and time of day is known and accounted for in the analysis.

Table ES-2: Estimated Customer Interruption Costs (U.S.2013$) by Duration, Timing of Interruption and Customer Class

Timing of Interruption	% of Hours per Year	Interruption Duration					
		Momentary	30 Minutes	1 Hour	4 Hours	8 Hours	16 Hours
Medium and Large C&I							
Summer	33%	$16,172	$18,861	$21,850	$46,546	$96,252	$186,983
Non-summer	67%	$11,342	$13,431	$15,781	$35,915	$77,998	$154,731
Weighted Average		*$12,952*	*$15,241*	*$17,804*	*$39,458*	*$84,083*	*$165,482*
Small C&I							
Summer Morning	8%	$461	$569	$692	$1,798	$4,073	$7,409
Summer Afternoon	7%	$527	$645	$780	$1,954	$4,313	$7,737
Summer Evening/Night	18%	$272	$349	$440	$1,357	$3,518	$6,916
Non-summer Morning	17%	$549	$687	$848	$2,350	$5,592	$10,452
Non-summer Afternoon	14%	$640	$794	$972	$2,590	$5,980	$10,992
Non-summer Evening/Night	36%	$298	$388	$497	$1,656	$4,577	$9,367
Weighted Average		*$412*	*$520*	*$647*	*$1,880*	*$4,690*	*$9,055*
Residential							
Summer Morning/Night	19%	$6.8	$7.5	$8.4	$14.3	$24.0	$42.4
Summer Afternoon	7%	$4.3	$4.9	$5.5	$9.8	$17.1	$31.1
Summer Evening	7%	$3.5	$4.0	$4.6	$9.2	$17.5	$34.1
Non-summer Morning/Night	39%	$3.9	$4.5	$5.1	$9.8	$17.8	$33.5
Non-summer Afternoon	14%	$2.3	$2.7	$3.1	$6.2	$12.1	$23.7
Non-summer Evening	14%	$1.5	$1.8	$2.2	$5.0	$10.8	$23.6
Weighted Average		*$3.9*	*$4.5*	*$5.1*	*$9.5*	*$17.2*	*$32.4*

Study Limitations

As in the 2009 study, there are limitations to how the data from this meta-analysis should be used. It is important to fully understand these limitations, so they are further described in this section and in more detail in Section 6. These limitations are:

- Certain very important variables in the data are confounded among the studies we examined. In particular, region of the country and year of the study are correlated in such a way that it is impossible to separate the effects of these two variables on customer interruption costs;
- There is further correlation between regions and scenario characteristics. The sponsors of the interruption cost studies were generally interested in measuring interruption costs for conditions that were important for planning their specific systems. As a result, interruption conditions described in the surveys for a given region tended to focus on periods of time when interruptions were more problematic for that region;
- A further limitation of our research is that the surveys that formed the basis of the studies we examined were limited to certain parts of the country. No data were available from the northeast/mid-Atlantic region, and limited data were available for cities along the Great Lakes;
- Another caveat is that around half of the data from the meta-database is from surveys that are 15 or more years old. Although the intertemporal analysis in the 2009 study showed that interruption costs have not changed significantly over time, the outdated vintage of the data presents concerns that, in addition to the limitations above, underscore the need for a coordinated, nationwide effort that collects interruption cost estimates for many regions and utilities simultaneously, using a consistent survey design and data collection method; and
- Finally, although the revised model is able to estimate costs for interruptions lasting longer than eight hours, it is important to note that the estimates in this report are not appropriate for resiliency planning. This meta-study focuses on the direct costs that customers experience as a result of relatively short power interruptions of up to 24 hours at most. For resiliency considerations that involve planning for long duration power interruptions of 24 hours or more, the nature of costs change and the indirect, spillover effects to the greater economy must be considered.[4] These factors are not captured in this meta-analysis.

[4] For a detailed study and literature review on estimating the costs associated with long duration power interruptions lasting 24 hours to 7 weeks, see: Sullivan, Michael and Schellenberg, Josh. *Downtown San Francisco Long Duration Outage Cost Study*. March 27, 2013. Prepared for Pacific Gas & Electric Company.

1. Introduction

In 2009, Freeman, Sullivan & Co. (now Nexant) conducted a meta-analysis that provided estimates of the value of service reliability for electricity customers in the United States (U.S.). These estimates were obtained by analyzing the results from 28 customer value of service reliability studies conducted by 10 major U.S. electric utilities over the 16-year period from 1989 to 2005. Because these studies used nearly identical interruption cost estimation or willingness-to-pay/accept methods, it was possible to integrate their results into a single meta-dataset describing the value of electric service reliability observed in all of them. Once the datasets from the various studies were combined, a two-part regression model was used to estimate customer damage functions that can be generally applied to calculate customer interruption costs per event by season, time of day, day of week, and geographical regions within the U.S. for industrial, commercial, and residential customers. The meta-analysis and its associated econometric models were summarized in a report entitled "Estimated Value of Service Reliability for Electric Utility Customers in the United States,"[5] which was prepared for Lawrence Berkeley National Laboratory (LBNL) and the Office of Electricity Delivery and Energy Reliability of the U.S. Department of Energy (DOE). The econometric models were subsequently integrated into the Interruption Cost Estimate (ICE) Calculator (available at icecalculator.com), which is an online tool designed for electric reliability planners at utilities, government organizations or other entities that are interested in estimating interruption costs and/or the benefits associated with reliability improvements (also funded by LBNL and DOE).

Since the report was finalized in June 2009 and the ICE Calculator was released in July 2011, Nexant, LBNL, DOE, and ICE Calculator users have identified several ways to improve the interruption cost estimates and the ICE Calculator user experience. These improvements include:

- Incorporating more recent utility interruption cost studies;
- Enabling the ICE Calculator to provide estimates for power interruptions lasting longer than eight hours;
- Reducing the amount of detailed customer characteristics information that ICE Calculator users must provide;
- Subjecting the econometric model selection process to rigorous cross-validation techniques, using the most recent model validation methods;[6] and
- Providing a batch processing feature that allows the user to save results and modify inputs.

These improvements will be addressed through this updated report and the upcoming new version of the ICE Calculator, which is anticipated to be released in 2015. This report provides updated value of service reliability estimates and details the revised econometric model, which is based on a meta-analysis that includes two new interruption cost studies. The upcoming new

[5] Sullivan, M.J., M. Mercurio, and J. Schellenberg (2009). *Estimated Value of Service Reliability for Electric Utility Customers in the United States*. Lawrence Berkeley National Laboratory Report No. LBNL-2132E.

[6] For a discussion of these methods, see: Varian, Hal R. "Big Data: New Tricks for Econometrics." *Journal of Economic Perspectives*. Volume 28, Number 2. Spring 2014. Pages 3–28. Available here: http://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.28.2.3

version of the ICE Calculator will incorporate the revised econometric model and include a batch processing feature that will allow the user to save results and modify inputs.

1.1 Recent Interruption Cost Studies

Since conducting the meta-analysis in 2009, there have been two large interruption cost surveys in the U.S., one in the southeast and another in the west. The 2011 study in the southeast involved a systemwide interruption cost survey of over 3,300 residential and small/medium business customers and nearly 100 in-person interviews of large business customers. The 2012 study in the west involved a systemwide interruption cost survey of nearly 2,700 residential and small/medium business customers and 210 in-person interviews of large business customers. Although the basic survey methodology is similar to previous work, the 2012 interruption cost study in the west featured several noteworthy methodological improvements. In particular, a dynamic survey instrument design for that study produced interruption cost estimates from 5 minutes to 24 hours, for weekdays and weekends and across many different times of the day (morning, afternoon, evening and night). As such, incorporating the 2012 data and re-estimating the underlying econometric models will enable the ICE Calculator to estimate costs for interruptions lasting longer than 8 hours, which will address one of the improvements above.

Table 1-1 provides an updated inventory of interruption cost studies that are included in the meta-dataset. The number of observations for each study is provided along with the minimum and maximum duration of power interruption scenarios in each study. Altogether, the meta-dataset now includes 34 different datasets from surveys fielded by 10 different utility companies between 1989 and 2012, totaling over 105,000 observations.[7] Some of the utilities surveyed all three customer types – medium and large commercial and industrial (C&I), small C&I, and residential – while others did not. In some cases there was only one dataset for C&I customers, in which case they were sorted into medium and large C&I or small C&I according to electricity usage. The split between small C&I and medium/large C&I is at 50,000 annual kWh. In total, the meta-dataset includes 44,328 observations for medium and large C&I customers, 27,751 observations for small C&I customers and 34,212 observations for residential customers. Each observation corresponds to a response for a single power interruption scenario. The surveys usually included four to six power interruption scenarios.

Table 1-1: Updated Inventory of Interruption Cost Studies in the Meta-dataset

<table>
<tr><th rowspan="2">Utility Company</th><th rowspan="2">Survey Year</th><th colspan="3">Number of Observations</th><th rowspan="2">Min. Duration (Hours)</th><th rowspan="2">Max. Duration (hours)</th></tr>
<tr><th>Medium and Large C&I</th><th>Small C&I</th><th>Residential</th></tr>
<tr><td>Southeast-1</td><td>1997</td><td colspan="2">90</td><td></td><td>0</td><td>1</td></tr>
<tr><td rowspan="2">Southeast-2</td><td>1993</td><td>3,926</td><td>1,559</td><td>3,107</td><td>0</td><td>4</td></tr>
<tr><td>1997</td><td>3,055</td><td>2,787</td><td>3,608</td><td>0</td><td>12</td></tr>
<tr><td>Southeast-3</td><td>1990</td><td>2,095</td><td>765</td><td></td><td>0.5</td><td>4</td></tr>
</table>

[7] To the knowledge of the authors, this dataset includes nearly all large power interruption cost studies that have been conducted in the US. Some studies may not have been included for data confidentiality reasons.

Utility Company	Survey Year	Number of Observations			Min. Duration (Hours)	Max. Duration (hours)
		Medium and Large C&I	Small C&I	Residential		
	2011	7,941	2,480	3,969	1	8
Midwest-1	2002	3,171			0	8
Midwest-2	1996	1,956	206		0	4
West-1	2000	2,379	3,236	3,137	1	8
West-2	1989	2,025	5		0	4
	1993	1,790	825	2,005	0	4
	2005	3,052	3,223	4,257	0	8
	2012	5,342	4,632	4,106	0	24
Southwest	2000	3,991	2,247	3,598	0	4
Northwest-1	1989	2,210		2,126	0.25	8
Northwest-2	1999	7,091		4,299	0	12

= Recently incorporated data

Prior to adding the 2012 West-2 survey, the meta-dataset included power interruption scenarios with durations of up to 12 hours. However, the 2009 model for each customer class estimated interruption costs that reached a maximum at 8 hours, and then the estimated interruption costs would decrease, which indicated that the prior model clearly did not provide reliable predictions beyond 8 hours (i.e., it is unreasonable that a 9-hour power interruption would cost less than an 8-hour one). As discussed in Sections 3 through 5, for interruptions from 8 to 16 hours, the new model produces estimates that are more reasonable and show gradually increasing costs up to 16 hours. This improvement in model performance is attributed to the addition of the 24-hour interruption scenarios (2012 West-2) and to the much simpler model specification that resulted from the rigorous selection process.

Although the revised model is able to estimate costs for interruptions lasting longer than 8 hours, it is important to note that the estimates in this report are not appropriate for resiliency planning. This meta-study focuses on the direct costs that customers experience as a result of relatively short power interruptions of up to 24 hours at most. In fact, the final models and results that are presented in Sections 3 through 5 truncate the estimates at 16 hours, due to the relatively few number of observations beyond 12 hours (scenarios of more than 12 hours account for around 2% to 3% of observations for all customer classes). For resiliency considerations that involve planning for long duration power interruptions of 24 hours or more, the nature of costs change and the indirect, spillover effects to the greater economy must be considered.[8] These factors are not captured in this meta-analysis.

[8] For a detailed study and literature review on estimating the costs associated with long duration power interruptions lasting 24 hours to 7 weeks, see: Sullivan, Michael and Schellenberg, Josh. *Downtown San Francisco Long Duration Outage Cost Study*. March 27, 2013. Prepared for Pacific Gas & Electric Company.

As discussed in Section 6, another caveat is that this meta-analysis may not accurately reflect current interruption costs, given that around half of the data in the meta-database is from surveys that are 15 or more years old. To address this issue, the 2009 study included an intertemporal analysis, which suggested that interruption costs did not change significantly throughout the 1990s and early 2000s. However, during the past decade in particular, technology trends may have led to an increase in interruption costs. For example, home and business life has become increasingly reliant on data centers and “cloud” computing, which may have led to an increase in interruption costs for both producers and consumers of these services. Therefore, the outdated vintage of the data presents concerns that underscore the need for a coordinated, nationwide effort that collects interruption cost estimates for many regions and utilities simultaneously, using a consistent survey design and data collection method.

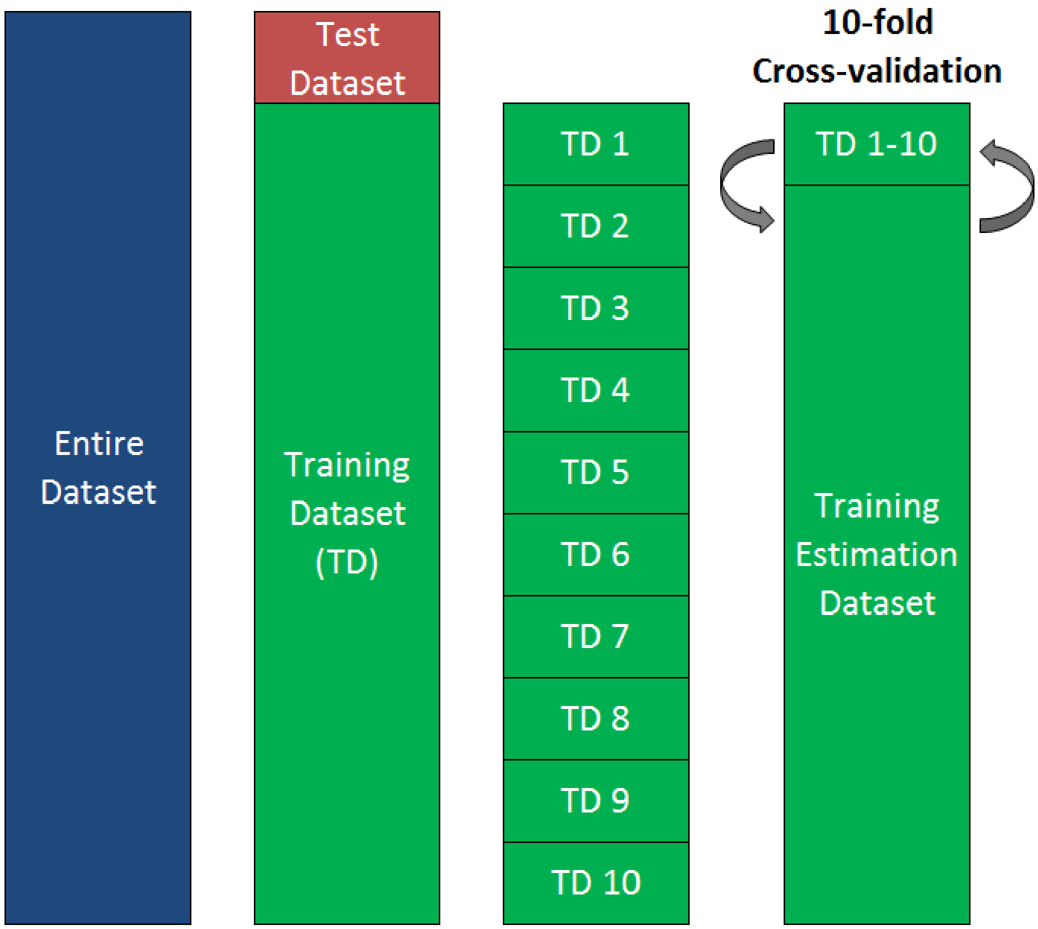
1.2 Re-estimating Econometric Models

Using the new meta-dataset, Nexant re-estimated the econometric models that relate interruption costs to duration, customer characteristics such as annual kWh, and other factors. Nexant then compared the results of the original model specification to those of several alternatives that included a reduced number of variables. This model selection process addressed another ICE Calculator improvement – reducing the amount of detailed customer characteristics information that ICE Calculator users must provide, which has been a significant barrier to the tool’s use. When the econometric models were originally estimated in 2009, statistical significance was the focus of the analysis and, due to the large number of observations in the meta-dataset, many of the customer characteristics variables were statistically significant in the model, even if the marginal effect of the variable was negligible and/or collinear with other variables. Basically, many of the variables in the original specification were statistically significant, but not practically significant. In re-estimating the models, Nexant focused on the practical significance of each variable by conducting sensitivity tests to determine which variables have a substantive impact on the interruption cost estimates. Nexant also employed more recent model selection methods that have been developed since 2009, which significantly improved the rigor with which variables were selected for the model. This process led to a more parsimonious model that only included key variables. In turn, ICE Calculator users will have less customer characteristics information to provide and the associated inputs page will be far less cumbersome.

1.3 Overview of Model Selection Process

Figure 1-1 provides an overview of the model selection process. The entire dataset of interruption cost estimates for each customer class is first randomly divided into a test dataset (10% of the entire dataset) and a training dataset (the remaining 90%). The training dataset is used to train the model, which refers to the process of selecting variables for the final specification. The test dataset is excluded from the model training process so that it can be used as a test of the final model performance on unseen data, which refers to data that is completely separate from the model training process. Next, the training dataset is randomly divided into 10 equally sized parts. Then, each candidate model specification is estimated on nine of 10 parts of the training dataset. The estimated coefficients for each candidate model specification are subsequently used to predict interruption costs on the tenth part of the training dataset. This process, which is referred to as 10-fold cross-validation, is repeated nine times while withholding one of the remaining nine parts of the training dataset each time. Relevant accuracy metrics for each model specification are computed for each of the 10 parts of the training dataset. Those accuracy metrics are ranked to determine the final model specification through a backwards stepwise selection process. Next, the final model specification is run on the entire training dataset and the estimated coefficients are used to predict interruption costs for the test dataset. Relevant accuracy metrics for the test dataset are also computed. If model performance on the test dataset is similar, the final specification is then estimated on the entire dataset and those estimated coefficients make up the final model. This process is conducted for each of the three customer classes separately.

Figure 1-1: Overview of Model Selection Process



1.4 Variable Definitions and Units

There are many variables that are common among customer classes, so all variable definitions and units are provided in this section. Table 1-2 provides the units and definitions of variables that are used in the models for all customer classes.

Table 1-2: Units and Definitions of Variables for All Customer Classes

Variable Name	Variable Definition	Units
annual MWh	Annual MWh of customer	MWh
duration	Duration of power interruption scenario	Minutes
time of day	Time of day of power interruption scenario	Categorical – Morning (6 AM to 12 PM); Afternoon (12 to 5 PM; Evening (5 to 10 PM); Night (10 PM to 6 AM)
weekday	Time of week of power interruption scenario	Binary – Weekday = 1; Weekend = 0
summer	Time of year of power interruption scenario	Binary – Summer = 1; Non-summer = 0
warning	Whether power interruption scenario had advance warning	Binary – Warning = 1; No warning = 0

Table 1-3 provides the units and definitions of variables that are used in the models for both the small and medium/large C&I customer classes. For both C&I customer classes, the model selection process begins with separate variables for all eight of the industry groups in the table, with Agriculture, Forestry & Fishing as the reference category by default. However, given that each industry group is tested separately for inclusion in the model, only one or two industry variables may remain in the final model, in which case the dropped industry variables are relegated to the reference category. Within the reference category, there may be multiple industries with presumably varying interruption costs, but if the model selection process has shown that there are not any meaningful differences within the industries in the reference category, those industry variables will be grouped together. The same logic applies for other categorical variables.

Table 1-3: Units and Definitions of Variables for C&I Customers

Variable Name	Variable Definition	Units
industry	Customer business type, based on NAICS or SIC code	Categorical – Agriculture, Forestry & Fishing; Mining; Construction; Manufacturing; Transportation, Communication & Utilities; Wholesale & Retail Trade; Finance, Insurance & Real Estate; Services; Public Administration; Unknown
backup equipment	Presence of backup equipment at facility	Categorical – None; Backup Gen or Power Conditioning; Backup Gen and Power Conditioning

Finally, Table 1-4 provides the units and definitions of variables that are only used in the residential customer models.

Table 1-4: Units and Definitions of Variables for Residential Customers

Variable Name	Variable Definition	Units
household income	Household income	$
medical equip.	Presence of medical equipment in home	Binary – Medical equipment = 1; No medical equipment = 0
backup generation	Presence of backup generation in home	Binary – Backup = 1; No backup = 0
outage in last 12 months	Interruption of longer than 5 minutes within past year	Binary – Yes = 1; No = 0
# residents X-Y	Number of residents in home within X-Y age range	Number of people
housing	Type of housing	Categorical – Detached; Attached; Apartment/Condo; Mobile; Manufactured; Unknown

1.5 Report Organization

The remainder of this report proceeds as follows. Section 2 summarizes the regression modeling methodology and selection process that applies to all three customer classes – medium and large C&I, small C&I and residential. This is followed by three sections that describe the final model selection and provide the final regression coefficients for each customer class. Finally, Section 6 describes some of the study's limitations.

2. Methodology

This section summarizes the study methodology, including the regression model structure and selection process.

2.1 Model Structure

A two-part regression model was used to estimate the customer interruption cost functions (also referred to as customer damage functions). This is the same class of model used in the previous meta-study. The two-part model assumes that the zero values in the distribution of interruption costs are correctly observed zero values, rather than censored values. In the first step, a probit model is used to predict the probability that a particular customer will report any positive value versus a value of zero for a particular interruption scenario. This model is based on a set of independent variables that describe the nature of the interruption as well as customer characteristics. The predicted probabilities from this first stage are retained. In the second step, using a generalized linear model (GLM), interruption costs for only those customers who report positive costs are related to the same set of independent variables used in the first stage. Predictions are made from this model for all observations, including those with a reported interruption cost of zero. Finally, the predicted probabilities from the first part are multiplied by the estimated interruption costs from the second part to generate the final interruption cost predictions.

The functional form for the second part of the two-part model must take into account that the interruption cost distribution is bounded at zero and extremely right skewed (i.e. it has a long tail in the upper end of the distribution). Ordinary least squares (OLS) is not an appropriate functional form given these conditions. A simple way to define the customer damage function given the above constraints is to estimate the mean interruption cost, which is linked to the predictor variables through a logarithmic link function using a GLM.

The parameter values in the two-part model cannot be directly interpreted in terms of their influence on interruption costs because the relationships are among the variables in their logarithms. However, the estimated model produces a predicted interruption cost, given the values of variables in the models. To analyze the magnitude of the impact of variables in the model on interruption cost, it is necessary to compare the predictions made by the function under varying assumptions. For example, it is possible to observe the effect of duration on interruption cost by holding the other variables constant at their sample means. In this way one can predict average customer interruption costs of varying durations holding other factors constant statistically.

For a more detailed discussion of the two-part model, its functional form and the reasons why it is most appropriate for this type of data, refer to the methodology section of the 2009 report.

2.2 Summary of Model Selection Process

Nexant aimed to estimate a more parsimonious model that only included key predictor variables. This facilitates interruption cost estimation by simplifying the ICE Calculator interface and reducing the burden that ICE Calculator users face in providing numerous, accurate customer characteristics information. This section first outlines the steps involved in the model selection process that Nexant undertook, followed by a more detailed exposition of the problem at hand, and a justification for the method.

To select a more parsimonious model, Nexant conducted the following steps for each of the three customer classes:

1. Randomly sample 10% of the data and hold it out as the test dataset (assign other 90% as the training dataset);
2. Split training dataset into 10 randomly assigned, equally sized parts;
3. Start with the original specification (the global model) and identify model variables that are candidates for removal (all variables except ineligible lower power terms);
4. Remove one of the eligible model variables to yield a new model;
5. Estimate model on nine of 10 parts of the training dataset and retain estimates;
6. Use retained estimates from step 5 to predict on the tenth part of the training dataset, computing relevant accuracy metrics;
7. Repeat steps 5 and 6, cycling over each of the remaining 9 parts of the training dataset;
8. Take the average and standard deviation of the accuracy metrics from the predictions for each of 10 parts of the training dataset;
9. Repeat steps 4 through 8, for each possible candidate variable for removal;
10. Use saved accuracy metrics to rank models;
11. Exclude from the global model the variable, which when dropped, produced estimates that outperformed the rest;
12. Repeat steps 2 through 11 until only a constant remains;
13. Inspect results and select model that is parsimonious, yet sufficiently accurate according to the out-of-sample accuracy metrics described above; and
14. Test final model against the original global model using the test dataset to estimate model's performance on unseen data (ensures that the model predicts well for data that was not included in the model training process).

As discussed in Section 1, this model selection process draws from the recent model selection methods that have been developed since 2009,[9] which significantly improves the rigor with which variables are selected for the model. The remainder of this section describes this process in more detail.

[9] For a discussion of these methods, see: Varian, Hal R. "Big Data: New Tricks for Econometrics." *Journal of Economic Perspectives*. Volume 28, Number 2. Spring 2014. Pages 3–28. Available here: http://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.28.2.3

2.3 Details of Model Selection Process

A model selection problem involves choosing a statistical model from a set of candidate models, given some data. In this case, the data were the pre-existing set of interruption cost surveys for each customer class. Nexant selected a candidate set of models that included the original model specification from the 2009 study, henceforth referred to as the global model, as well as all models that were nested in the global model, that is to say all models that occur when removing one of more predictor variables from the global model. This candidate set is appropriate for several reasons. First of all, nearly all of the variables that were available in the meta-dataset were already included in the global model. Secondly, all the variables in the global model are plausibly related to interruption costs, and are not simply spuriously correlated. For example, it is reasonable to conclude that a resident with medical equipment that requires a power supply would be willing to pay more to avoid a power interruption than a resident without such medical equipment. Similar conclusions can be made for the other predictor variables in the global model, across sectors, making all of them viable to include in candidate models. Furthermore, to introduce candidate models that feature predictors not already included in the global model, such as new characteristics or higher power terms, would make the task of selecting a more parsimonious model significantly more challenging. Adding new predictors to candidate models not only increases the complexity of those candidate models, but the number of candidate models increases exponentially, making selecting among them computationally challenging.[10] It therefore makes practical sense to limit the predictors used in candidate models to those used in the global model. Also in the interest of simplifying the selection process, Nexant restricted the specifications of the probit and GLM models to be identical. This was the same form that the original regression model took.

Nexant developed an iterative process to choose among the candidate set of models. This is a backwards stepwise selection method that parses down the global model one variable at a time. At each step of the process, a variable is removed from the prior model (the global model in the first step) and the resulting model is evaluated in out-of-sample tests using a variety of metrics. This is performed for all possible variables that can be excluded, and the model that performs best on average across the various metrics is retained, or rather its exclusion is retained, and becomes the prior model in the next step of the process. (Alternatively, one can consider the excluded variable as that which diminished the performance of the global model the least, relative to the other possible exclusions, although it was often the case that the performance improved.) The outcome at each step is carefully examined to determine whether an acceptably parsimonious model has been selected, and whether excluding a particular variable will severely diminish the model's predictive power, in which case that variable is retained in the final model.

The selection process uses rigorous out-of-sample testing to evaluate the performance of various models and ensure that the final model is not over-fitted.[11] Nexant divided the sample into a training dataset, used to fit models; a validation dataset, used to compare models; and a test

[10] It can be shown that a global model with n predictors has $2^n - 1$ possible nested models. Furthermore, when m new predictors are added to the global model, the number of possible nested models increases by $(2^m - 1)2^n$.

[11] Over-fitting occurs when a model describes random variation in the data. The problem manifests itself through good predictive performance on the fitted data, but poor predictive performance on unseen data that the model was not fitted to.

dataset, used as a final independent test to show how well the selected model will generalize to unseen data. The test dataset comprised 10% of the sample, and was "held out" throughout the model fitting and selection process. At each step of the selection process, the models were compared using 10-fold cross-validation. Ten-fold cross-validation divides the remaining sample data into ten equal size subsamples. Nine of those subsamples are used as the training dataset to fit the model, and the tenth is used to validate the performance of that fitted model and choose among models. This process is repeated ten times with each of the subsamples used once to validate the fitted model. This method reduces the likelihood of over-fitting the model by using unseen data in the validation step; models that generalize well to new data will be selected over those that do not. Furthermore, by "folding" the data and iterating over subsamples, each observation is used exactly once in the validation step, so all of the available data (other than the 10% in the test dataset) are used to select models.

Rather than rely on a single metric to select a model, Nexant computed several metrics, ranked models by each of these metrics, then averaged the ranks to give an overall rank across metrics. Root-mean-square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R-squared) are computed in out-of-sample tests. RMSE measures the average prediction error of a model. The differences between observed and predicted values are computed, squared, and then averaged before the square root is taken to correct the units. Because errors are squared before the average, RMSE penalizes larger errors more than smaller errors. MAE also measures the average prediction error of a model. The differences between observed and predicted values are computed, their absolute value is taken, and then the absolute errors are averaged. Errors of every magnitude are penalized equally. In the case of both RMSE and MAE, values range from zero to infinity, and smaller values are preferred. R-squared measures the fraction of variation of the dependent variable that is explained by a model. Its values range from 0 to 1, and a larger value is preferred. At each step, an information theoretic approach is also used to produce a fourth ranking of models that is incorporated into the average. This ranking uses Akaike's Information Criterion (AIC), which is an estimate of the expected, relative distance between the fitted model and the unknown true mechanism that generated the observed data. It is a measure of the information that is lost when a model is used to approximate the true mechanism. A thorough exposition of the relative advantages and disadvantages of these different metrics is beyond the scope of this report. That said, by averaging the ranks obtained from each metric and choosing an overall winner, Nexant does not prioritize minimizing one kind of error over another, but rather adopts a holistic approach.

3. Medium and Large C&I Results

This section summarizes the results of the model selection process and provides the model coefficients for medium and large C&I customers, which are C&I customers with annual usage of 50,000 kWh or above.

3.1 Final Model Selection

The global model for medium and large C&I customers is shown below:

$$Interruption\ Cost = f(\ln(annual\ MWH),duration,duration^2,duration \times \ln(annual\ MWh),duration^2 \times \ln(annual\ MWh),weekday,warning,summer,industry,time\ of\ day,backup\ equipment)$$

Interruption cost is expressed as a function of various explanatory variables. Note that the dependent variables differ between the probit and GLM models; hence the above equation expresses the two-part model in its most general form. Industry, time of day and backup equipment are all categorical variables, and their respective categories are shown in Table 3-1 below. As is typical in indicatory coding, the first category within each categorical variable is not included explicitly as a binary variable, but rather serves as a reference category.

Table 3-1: Breakdown of Categorical Variables Featured in Global Model – Medium and Large C&I

Variable	Categories
industry	Agriculture, Forestry & Fishing; Mining; Construction; Manufacturing; Transportation, Communication & Utilities; Wholesale & Retail Trade; Finance, Insurance & Real Estate; Services; Public Administration; Unknown
time of day	Night (10 PM to 6 AM); Morning (6 AM to 12 PM); Afternoon (12 to 5 PM); Evening (5 to 10 PM)
backup equipment	None; Backup Gen or Power Conditioning; Backup Gen and Power Conditioning

The global model was successfully parsed down to only key variables. In selecting among variables, categorical variables were not treated as a set (either all or none removed), but rather each binary variable was removed one at a time. This allowed for a particularly important category to remain, while others that might have had a smaller effect were no longer represented. Table 3-2 shows the results of each step in the process. Each iteration represents the exclusion of a variable from the global model, and the variable listed is the one that, when excluded, produces the model with the best performance across various metrics in out-of-sample tests. The model's value and rank (relative to the other possible exclusions) in the metrics is listed, along with its overall rank, which is an average of the individual ranks. Note that iteration zero represents the global model alone, so some metrics that are only meaningful when compared with other models, such as ranks and AICs, are not listed. The highlighted row shows the final exclusion that was made; the rows that follow show the variables that remain in the final model. Ultimately, interruption costs for medium and large C&I customers can be estimated relatively accurately with a few variables and interactions representing customer usage and interruption duration, along with binary variables for manufacturing customers and for power interruptions that occur during the summer. A few of the 15 excluded variables show a minor improvement in predictive accuracy, but considering how difficult it can be for ICE Calculator users to find information for some of those inputs, this minor improvement in predictive accuracy was not sufficient to justify keeping those variables in the final model.

Table 3-2: Excluded Variables and Relevant Metrics from Backwards Stepwise Selection Process – Medium and Large C&I

Iteration	Excluded Variable	RMSE		MAE		R2		AIC			Overall Rank
		Value (Thousands)	Rank	Value (Thousands)	Rank	Value	Rank	Probit Value (Thousands)	GLM Value (Thousands)	Rank	
0	-	116	-	29.6	-	0.143	-	-	-	-	-
1	*evening*	116	1	29.5	1	0.148	1	44.1	589	4.5	1 9
2	*weekday*	116	1	29.5	2	0.150	1	44.1	589	7.0	2 8
3	*morning*	116	1	29.5	2	0.151	1	44.3	589	9.5	3.4
4	*afternoon*	116	1	29.4	1	0.153	1	44.5	589	10.0	3 3
5	*wholesale & retail trade*	116	2	29.4	2	0.153	2	44.5	589	4.0	2 5
6	*backupgen and power conditioning*	116	1	29.4	3	0.155	1	44.6	589	8.5	3.4
7	*services*	116	1	29.4	1	0.155	1	44.7	589	8.5	2 9
8	*public administration*	116	3	29.5	2	0.155	3	44.7	589	2.5	2.6
9	*unknown*	116	1	29.5	3	0.155	1	44.7	590	3.0	2 0
10	*finance, insurance & real estate*	116	1	29.5	1	0.154	1	44.7	590	4.0	1 8
11	*transportation, communication & utilities*	116	1	29.5	2	0.154	1	44.7	591	4.5	2.1
12	*construction*	116	1	29.5	1	0.154	1	44.8	591	4.5	1 9
13	*mining*	116	1	29.5	1	0.153	1	44.8	591	2.5	1.4
14	*backupgen or power conditioning*	116	1	29.5	1	0.152	1	44.8	591	1.0	1 0
15	*warning*	116	1	29.6	1	0.148	1	44.9	592	2.5	1.4
16	*manufacturing*	117	1	29.9	2	0.137	1	45.0	595	2.5	1.6
17	*summer*	117	1	30.0	1	0.128	1	45.4	595	1.5	1.1
18	*duration^2 x ln(annual MWh)*	119	1	30.5	1	0.106	1	45.5	595	1.0	1 0
19	*duration x ln(annual MWh)*	120	1	30.7	1	0.096	1	45.5	595	1.0	1 0
20	*duration^2*	129	2	32.8	1	-0.054	2	46.2	598	1.0	1 5
21	*duration*	118	1	31.3	1	0.118	1	47.8	604	1.5	1.1
22	*ln(MWh annual)*	126	1	37.4	1	0.000	1	48.7	640	1.0	1 0

The final model for medium/large C&I customers is shown below:

$$\begin{aligned} &Interruption\ Cost \\ &\qquad = f(\ln(annual\ MWH)\,, duration, duration^2, duration \\ &\qquad \times \ln(annual\ MWh)\,, duration^2 \times \ln(annual\ MWh)\,, summer, industry) \end{aligned}$$

Manufacturing is the only remaining industry category in the model. Note that as categories are removed, they are relegated to the reference category, so for example the manufacturing binary variable should now be interpreted as the average impact on interruption cost associated with being in the manufacturing industry, relative to all other industries.

To confirm that the selection process did not produce an over-fitted model, and to estimate the predictive performance of the final model when evaluated on unseen data, Nexant evaluated the final model against the global model using the test dataset, which is the 10% of data that was held out from the backwards stepwise selection process. Both models were fitted to the remaining data, and then the test dataset was used to evaluate their predictive performance.

The results are shown in Table 3-3. The final model outperforms the global model in each accuracy metric.

Table 3-3: Test Dataset Predictive Performance Metrics for Final and Initial Models – Medium and Large C&I

Model	RMSE (Thousands)	MAE (Thousands)	R-squared
Final	111	29.6	0.118
Global	111	29.8	0.115

3.2 Model Coefficients

Nexant then estimated the final two-part regression model specification on the full dataset for medium and large C&I customers. Table 3-4 describes the final probit regression model that specifies the relationship between the presence of zero interruption costs and a set of independent variables that includes interruption characteristics, customer usage, and industry designation. Although the purpose of this preliminary limited dependent variable model is only to normalize the predictions from the interruption costs regression in the second part of the two-part model, there are a few interesting results to note (these remain consistent with the original specification):

- All of the coefficients are statistically significant at a less than 1% level;
- The longer the interruption, the more likely that the costs associated with it are positive (the presence of a negative coefficient on the square of duration indicates that this effect diminishes for longer durations);
- Summer interruptions are more likely to incur costs than non-summer interruptions; and
- Manufacturing industry customers are more likely to incur costs than non-manufacturing industry customers.

Table 3-4: Regression Output for Probit Estimation – Medium and Large C&I

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
duration	0.005	0.000	0.000
duration^2	-2.820E-06	0.000	0.000
summer	0.410	0.023	0.000
Customer Characteristics			
ln(annual MWh)	0.118	0.006	0.000
Interactions			
duration x ln(annual MWh)	-3.416E-04	0.000	0.000
duration^2 *x ln(annual MWh)*	1.640E-07	0.000	0.000
Industry			
manufacturing	0.200	0.025	0.000
Constant	-0.958	0.047	0.000

Table 3-5 describes the final GLM regression model, which relates the level of interruption costs to customer usage and interruption characteristics as well as industry designation. A few results of note:

- The longer the interruption, the higher the interruption cost;
- Larger customers (in terms of annual MWh usage) incur larger costs for similar interruptions (however, interruption costs increase at a decreasing rate as usage increases);
- Manufacturing industry customers incur larger costs for similar interruptions than equivalent non-manufacturing customers;
- The difference between summer and non-summer interruption costs is statistically insignificant (all other coefficients are statistically significant).

Table 3-5: Customer Regression Output for GLM Estimation – Medium and Large C&I

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
duration	0.006	0.001	0.000
duration^2	-3.260E-06	0.000	0.000
summer	0.113	0.060	0.058
Customer Characteristics			
ln(annual MWh)	0.495	0.016	0.000
Interactions			
duration x ln(annual MWh)	-1.882E-04	0.000	0.047
duration^2 x ln(annual MWh)	1.480E-07	0.000	0.028
Industry			
manufacturing	0.823	0.069	0.000
Constant	5.292	0.127	0.000

Finally, Table 3-6 shows the average values of the regression inputs for medium and large C&I customers, which are useful for modeling purposes and for assessing marginal effects. Other descriptive statistics are also provided.

Table 3-6: Descriptive Statistics for Regression Inputs – Medium and Large C&I

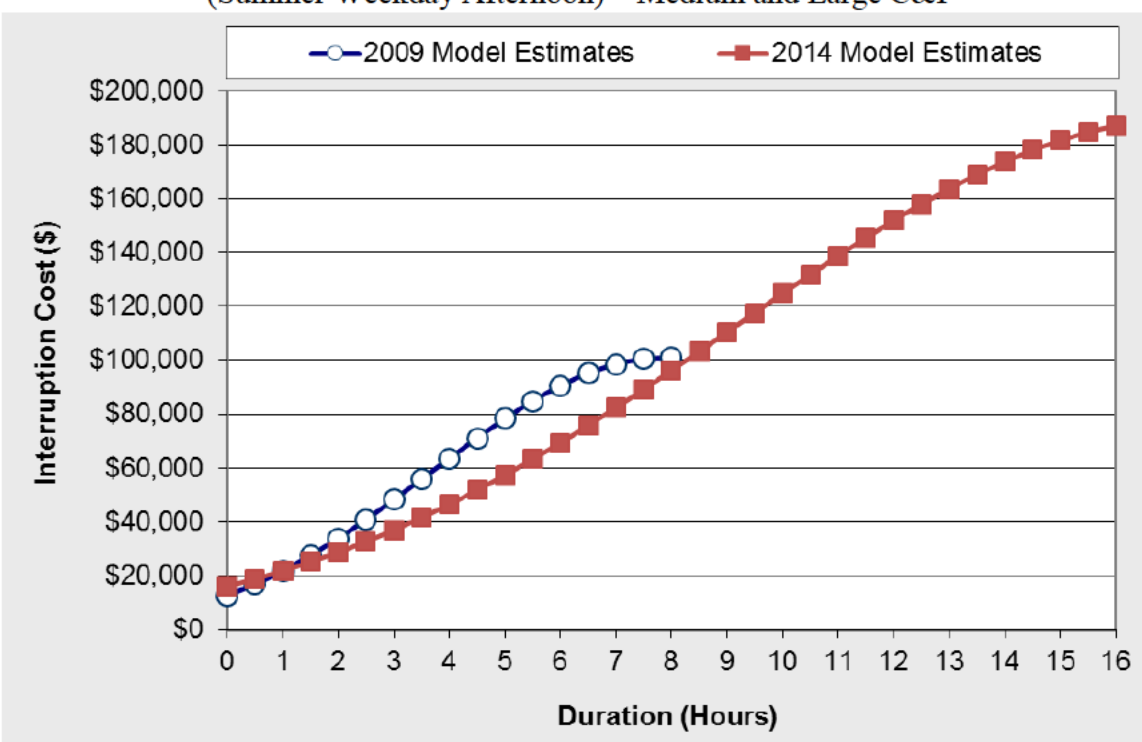
Variable	N	Average	Minimum	25th Percentile	Median	75th Percentile	Maximum
Interruption Characteristics							
duration	44,328	162	0	60	60	240	1,440
duration^2	44,328	82,724	0	3,600	3,600	57,600	2,073,600
summer	44,328	86.5%	0%	100%	100%	100%	100%
Customer Characteristics							
ln(annual MWh)	44,328	6.6	3.9	4.9	6.2	7.9	13.9

Variable	N	Average	Minimum	25th Percentile	Median	75th Percentile	Maximum
Interactions							
duration x ln(annual MWh)	44,328	1,060	0	255	437	1,327	17,064
duration^2 x ln(annual MWh)	44,328	530,872	0	14,881	26,250	317,870	24,600,000
Industry							
manufacturing	44,328	23.3%	0%	0%	0%	0%	100%

3.3 Comparison of 2009 and 2014 Model Estimates

Figure 3-1 provides a comparison of the 2009 model estimates and the 2014 model estimates by interruption duration, in 2013 dollars. The 2014 model estimates have been extended to 16 hours because the addition of data on 24-hour power interruption scenarios has allowed to model to more reliably predict costs up to 16 hours. The magnitude of the interruption cost estimates is similar between the two models, but there is a noticeable change in the functional form, which is attributable to the addition of the longer duration scenarios and to the significant change in the model specification. The functional form is more linear and no longer levels off at 8 hours, which seems more plausible.

Figure 3-1: Estimated Customer Interruption Costs (U.S.2013$) by Duration and Model (Summer Weekday Afternoon) – Medium and Large C&I



3.4 Interruption Cost Estimates and Key Drivers

Table 3-7 shows how medium and large C&I customer interruption costs vary by season. Considering that time of day and day of week were not important factors in the model for medium and large C&I customers, the only temporal variable to consider is season (summer or non-summer). The cost of a summer power interruption is around 21% to 43% higher than a non-summer one, depending on duration (the percent difference lowers as duration increases). Considering that the non-summer time period (October through May) accounts for two-thirds of the year, the weighted-average interruption cost estimate is closer to the non-summer estimate. This weighted-average interruption cost estimate is most appropriate to use for planning purposes, unless the distribution of interruptions by season is known.

Table 3-7: Estimated Customer Interruption Costs (U.S.2013$) by Duration and Timing of Interruption – Medium and Large C&I

Timing of Interruption	% of Hours per Year	Interruption Duration					
		Momentary	30 Minutes	1 Hour	4 Hours	8 Hours	16 Hours
Summer	33%	$16,172	$18,861	$21,850	$46,546	$96,252	$186,983
Non-summer	67%	$11,342	$13,431	$15,781	$35,915	$77,998	$154,731
Weighted Average		**$12,952**	**$15,241**	**$17,804**	**$39,458**	**$84,083**	**$165,482**

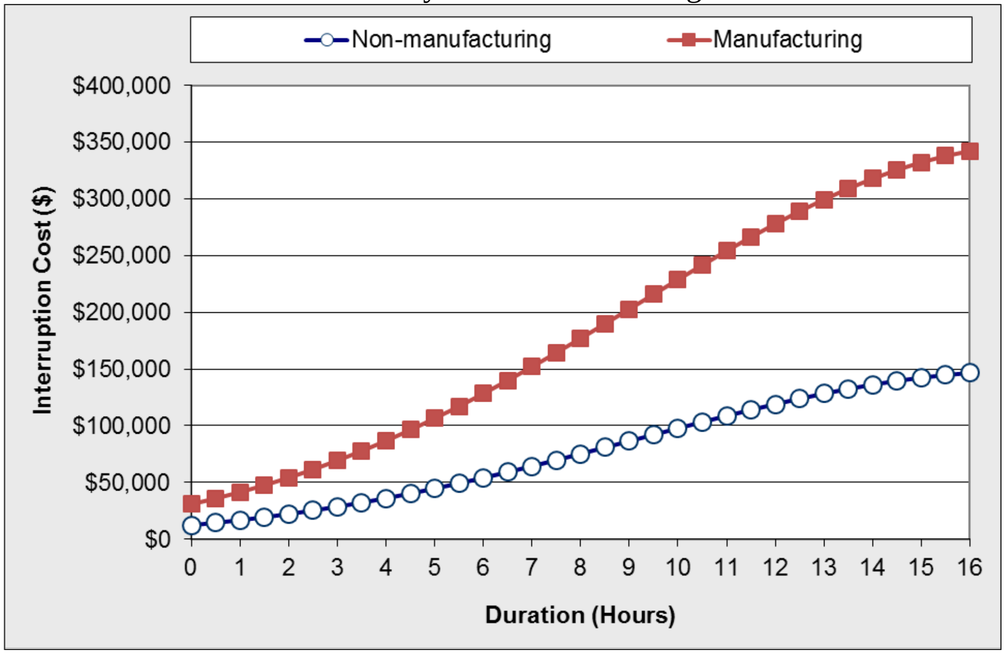
Based on the weighted-average interruption cost estimate, Table 3-8 provides cost per event (equal to the weighted-average interruption cost), cost per average kW and cost per unserved kWh for medium and large C&I customers. Cost per unserved kWh is relatively high for a momentary interruption because the expected amount of unserved kWh over a 5-minute period is relatively low.

Table 3-8: Cost per Event, Average kW and Unserved kWh – Medium and Large C&I

Interruption Cost	Interruption Duration					
	Momentary	30 Minutes	1 Hour	4 Hours	8 Hours	16 Hours
Cost per Event	$12,952	$15,241	$17,804	$39,458	$84,083	$165,482
Cost per Average kW	$15.9	$18.7	$21.8	$48.4	$103.2	$203.0
Cost per Unserved kWh	$190.7	$37.4	$21.8	$12.1	$12.9	$12.7

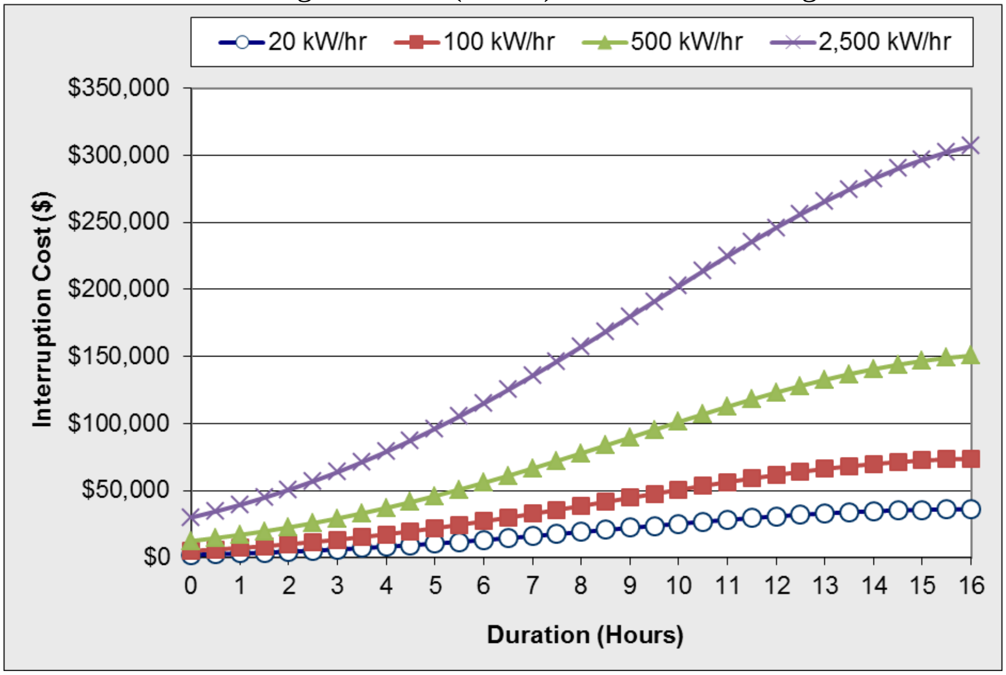
Figure 3-2 shows the medium and large C&I interruption costs in the summer for non-manufacturing and manufacturing customers. As in the 2009 model, interruption costs in the manufacturing sector are relatively high. At all durations, the estimated interruption cost for manufacturing customers is more than double the cost for non-manufacturing customers. This is a key driver to consider for planning purposes – whether the planning area of interest includes medium and large C&I customers with manufacturing facilities that may be particularly sensitive to power interruptions.

Figure 3-2: Estimated Summer Customer Interruption Costs (U.S.2013$) by Duration and Industry – Medium and Large C&I



Finally, Figure 3-3 shows the medium and large C&I interruption costs in the summer for various levels of average demand. As discussed above, medium and large C&I interruption costs increase at a decreasing rate as usage increases. This pattern is notable in the figure. Each increment in average demand represents a 5-fold increase in usage, but interruption costs only increase by a factor of 2.0 to 2.5 from one level of average demand to the next.

Figure 3-3: Estimated Summer Customer Interruption Costs (U.S.2013$) by Duration and Average Demand (kW/hr) – Medium and Large C&I



4. Small C&I Results

This section summarizes the results of the model selection process and provides the model coefficients for small C&I customers, which are C&I customers with annual usage of less than 50,000 kWh.

4.1 Final Model Selection

The global model for small C&I customers was identical to that for the medium and large C&I customers. Refer to Section 3.1 above for a discussion of the global model specification. The global model was successfully parsed down to only key variables. In selecting among variables, categorical variables were not treated as a set (either all or none removed), but rather each binary variable was removed one at a time. This allowed for a particularly important category to remain, while others that might have had a smaller effect were no longer represented. Table 4-1 shows the results of each step in the process. Each iteration represents the exclusion of a variable from the global model, and the variable listed is the one that, when excluded, produces the model with the best performance across various metrics in out-of-sample tests. The model's value and rank (relative to the other possible exclusions) in the metrics is listed, along with its overall rank, which is an average of the individual ranks. Note that iteration zero represents the global model alone, so some metrics that are only meaningful when compared with other models, such as ranks and AICs, are not listed. The highlighted row shows the final exclusion that was made; the rows that follow show the variables that remain in the final model. Ultimately, interruption costs for small C&I customers can be estimated relatively accurately with variables representing customer usage and interruption duration, along with some binary variables for customer characteristics and interruption timing. Considering how difficult it can be for ICE Calculator users to find information for some of the 12 excluded variables (especially for small C&I customers), this final model will be much easier to use.

Table 4-1: Excluded Variables and Relevant Metrics from Backwards Stepwise Selection Process – Small C&I

Iteration	Excluded Variable	RMSE		MAE		R2		AIC			Overall Rank
		Value (Thousands)	Rank	Value (Thousands)	Rank	Value	Rank	Probit Value (Thousands)	GLM Value (Thousands)	Rank	
0	-	6.17	-	1.95	-	0.044	-	-	-	-	-
1	*transportation, comunication & utilities*	6.16	1	1.94	2	0.048	1	30.6	245	8.0	3.0
2	*mining*	6.16	1	1.94	1	0.049	1	30.6	245	7.0	2.5
3	*warning*	6.16	1	1.94	3	0.049	1	30.6	245	4.5	2.4
4	*evening*	6.16	1	1.94	2	0.049	2	30.6	245	4 0	2.3
5	*duration ^{2} x ln(annual MWh)*	6.16	1	1.94	3	0.049	2	30.6	245	3.0	2.3
6	*finance, insurance & real estate*	6.16	2	1.94	4	0.049	2	30.7	245	5.5	3.4
7	*unknown industry*	6.16	5	1.94	2	0.049	2	30.7	245	5.5	3.6
8	*duration x ln(annual MWh)*	6.16	3	1.94	2	0.049	2	30.7	245	1 5	2.1
9	*public administration*	6.16	2	1.94	3	0.049	4	30.7	245	2 0	2.8
10	*weekday*	6.16	2	1.94	3	0.048	3	30.7	245	3 5	2.9
11	*wholesale & retail trade*	6.16	1	1.94	1	0 049	1	30.9	245	7 5	2.6
12	*services*	6.16	2	1.94	1	0 049	3	30.9	245	2 0	2.0
13	*morning*	6.16	2	1.95	2	0 048	2	31.4	245	4 5	2.6
14	*afternoon*	6.16	1	1.95	2	0 048	1	31.5	245	3 0	1.8
15	*summer*	6.17	1	1.95	1	0 047	1	31.8	245	4 5	1.9
16	*ln(annual MWh)*	6.17	1	1.96	3	0 045	1	32.0	245	3 0	2.0
17	*backupgen and power conditioning*	6.19	2	1.97	1	0 041	1	32.1	246	2 5	1.6
18	*backupgen or power conditioning*	6.20	1	1.98	1	0 036	1	32.1	246	2 0	1.3
19	*manufacturing*	6.22	1	2.00	2	0 029	1	32.1	246	1 5	1.4
20	*construction*	6.24	1	2 01	1	0 023	1	32.2	247	1 0	1.0
21	*duration ^{2}*	6 52	1	2.16	1	-0.089	1	32.8	248	1.0	1.0
22	*duration*	6 32	1	2.13	1	-0.001	1	34.2	251	1.0	1.0

The final model for small C&I customers is shown below:

$$Interruption\ Cost = f(\ln(annual\ MWH), duration, duration^2, summer, industry, backup\ equipment, time\ of\ day)$$

Industry, backup equipment and time of day are the only categorical variables remaining, and many of the categories were removed. Note that as categories are removed, they are relegated to the reference category, so for example the construction binary variable should now be interpreted as the average impact on interruption cost associated with being in the construction industry, relative to all industries other than manufacturing, which is the only other industry that was retained as a binary variable. The categories that remain in the final model are shown in Table 4-2 below.

Table 4-2: Breakdown of Categorical Variables Featured in Final Model – Small C&I

Variable	Categories
industry	Other; Construction; Manufacturing
backup equipment	None; Backup Gen or Power Conditioning; Backup Gen and Power Conditioning
time of day	Other (5 PM to 6 AM); Morning (6 AM to 12 PM); Afternoon (12 to 5 PM)

To confirm that the selection process did not produce an overfitted model, and to estimate the predictive performance of the final model when evaluated on unseen data, Nexant evaluated the final model against the global model using the test dataset, which is the 10% of data that was held out from the backwards stepwise selection process. Both models were fitted to the remaining data, and then the test dataset was used to evaluate their predictive performance. The results are shown in Table 4-3. Note that while the global model outperforms the final model in each metric, the differences between the values are very small. The final model offers a much simpler solution with comparable performance to the global model.

Table 4-3: Test Dataset Predictive Performance Metrics for Final and Initial Models – Small C&I

Model	RMSE (Thousands)	MAE (Thousands)	R-squared
Final	5.50	1.82	0.045
Global	5.49	1.82	0.048

4.2 Model Coefficients

Nexant then estimated the final two-part regression model specification on the full dataset for residential customers. Table 4-4 describes the final probit regression model that specifies the relationship between the presence of zero interruption costs and a set of independent variables that includes interruption characteristics, customer characteristics, and industry designation. Although the purpose of this preliminary limited dependent variable model is only to normalize the predictions from the interruption costs regression in the second part of the two-part model, there are a few interesting results to note (these remain consistent with the original specification):

- All of the coefficients are statistically significant at a less than 1% level;
- The longer the interruption, the more likely that the costs associated with it are positive (the presence of a negative coefficient on the square of duration indicates that this effect diminishes for longer durations);
- Summer interruptions are more likely to incur costs than non-summer interruptions;
- Afternoon interruptions are more likely to incur costs than any other time of day; and
- Manufacturing and construction customers are more likely to incur costs than customers in other industries.

Table 4-4: Customer Regression Output for Probit Estimation – Small C&I

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
duration	0.003	0.000	0.000
duration^2	-1.780E-06	0.000	0.000
summer	0.215	0.030	0.000
morning	0.537	0.022	0.000
afternoon	0.664	0.029	0.000

Variable	Coefficient	Standard Error	P-Value
Customer Characteristics			
ln(annual MWh)	0.124	0.013	0.000
backupgen or power conditioning	0.082	0.025	0.001
backupgen and power conditioning	0.272	0.059	0.000
Industry			
construction	0.261	0.054	0.000
manufacturing	0.176	0.042	0.000
Constant	-1.332	0.048	0.000

Table 4-5 describes the final GLM regression model, which relates the level of interruption costs to customer and interruption characteristics as well as industry designation. A few results of note:

- The longer the interruption, the higher the interruption cost;
- Larger customers (in terms of annual MWh usage) incur larger costs for similar interruptions (however, interruption costs increase at a decreasing rate as usage increases);
- Manufacturing and construction industry customers incur larger costs for similar interruptions than equivalent customers in other industries; and
- Summer interruptions incur lower interruption costs than other times of the year.

Table 4-5: Customer Regression Output for GLM Estimation – Small C&I

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
duration	0.004	0.000	0.000
duration^2	-2.160E-06	0.000	0.000
summer	-0.384	0.073	0.000
morning	-0.057	0.070	0.413
afternoon	-0.032	0.083	0.701
Customer Characteristics			
ln(annual MWh)	0.069	0.035	0.046
backupgen or power conditioning	0.308	0.058	0.000
backupgen and power conditioning	0.538	0.129	0.000
Industry			
construction	0.786	0.153	0.000
manufacturing	0.587	0.104	0.000
Constant	7.000	0.135	0.000

Finally, Table 4-6 shows the average values of the regression inputs for small C&I customers, which are useful for modeling purposes and for assessing marginal effects. Other descriptive statistics are also provided.

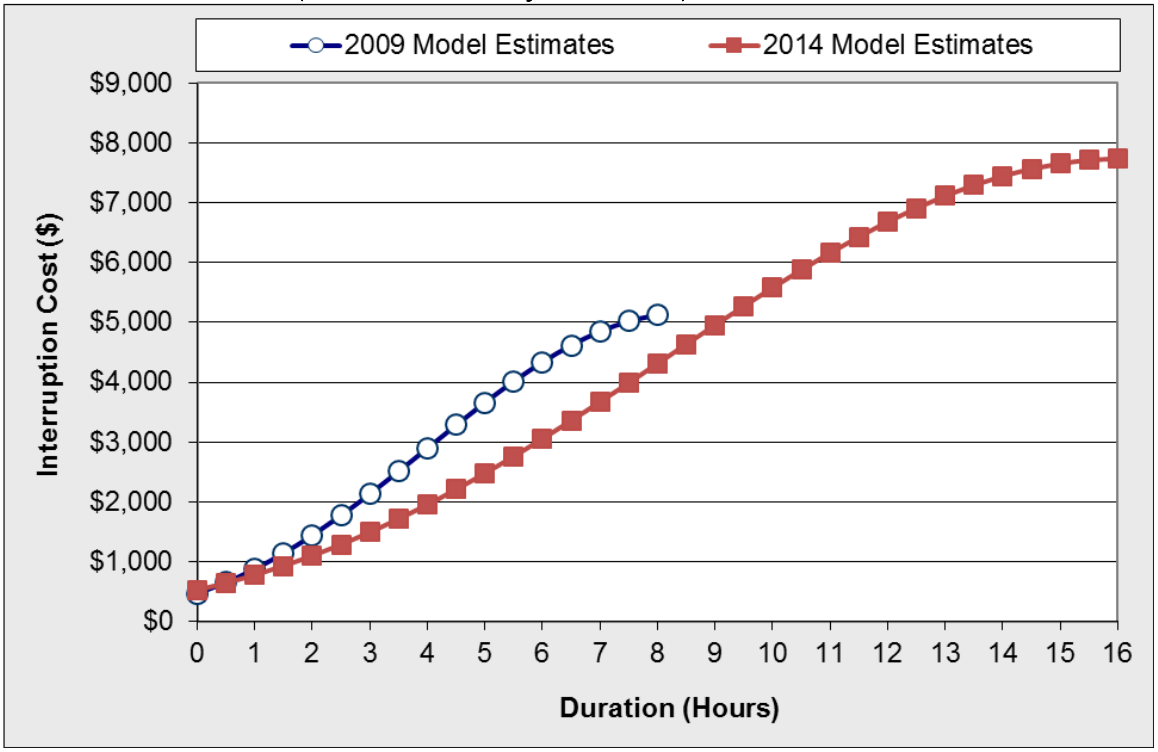
Table 4-6: Descriptive Statistics for Regression Inputs – Small C&I

Variable	N	Average	Minimum	25th Percentile	Median	75th Percentile	Maximum
Interruption Characteristics							
duration	27,751	191	0	60	60	240	1,440
duration^2	27,751	107,425	0	3,600	3,600	57,600	2,073,600
summer	27,751	89.3%	0%	100%	100%	100%	100%
morning	27,751	45.5%	0%	0%	0%	100%	100%
afternoon	27,751	37.6%	0%	0%	0%	100%	100%
Customer Characteristics							
ln(annual MWh)	27,751	2.6	-2.0	2.2	2.8	3.3	3.9
backupgen or power conditioning	27,751	27.1%	0%	0%	0%	100%	100%
backupgen and power conditioning	27,751	3.5%	0%	0%	0%	0%	100%
Industry							
construction	27,751	4.6%	0%	0%	0%	0%	100%
manufacturing	27,751	7.8%	0%	0%	0%	0%	100%

4.3 Comparison of 2009 and 2014 Model Estimates

Figure 4-1 provides a comparison of the 2009 model estimates and the 2014 model estimates by interruption duration, in 2013 dollars. The 2014 model estimates have been extended to 16 hours because the addition of data on 24-hour power interruption scenarios has allowed to model to more reliably predict costs up to 16 hours. As with medium and large C&I customers, the magnitude of the interruption cost estimates is similar between the two small C&I models, but there is a noticeable change in the functional form. This change is attributable to the addition of the longer duration scenarios and to the significant change in the model specification. The functional form is more linear and no longer levels off at 8 hours, which seems more plausible.

Figure 4-1: Estimated Customer Interruption Costs (U.S.2013$) by Duration and Model (Summer Weekday Afternoon) – Small C&I



4.4 Interruption Cost Estimates and Key Drivers

Table 4-7 shows how small C&I customer interruption costs vary by season and time of day. The cost of a summer power interruption is around 9% to 30% lower than a non-summer one, depending on duration, season, and time of day. Interestingly, this is opposite the pattern of medium and large C&I customers, which experience higher interruption costs during the summer. As for how interruption costs vary by time of day, costs are highest in the afternoon and are similarly high in the morning. In the evening and nighttime, small C&I interruption costs are substantially lower, which makes sense given that small businesses typically operate during daytime hours. Considering that the evening/night time period (5 PM to 6 AM) accounts for a majority of the hours of the day, the weighted-average interruption cost estimate is closer to the evening/night estimates. This weighted-average interruption cost estimate is most appropriate to use for planning purposes, unless the distribution of interruptions by season and time of day is known.

Table 4-7: Estimated Customer Interruption Costs (U.S.2013$) by Duration and Timing of Interruption – Small C&I

Timing of Interruption	% of Hours per Year	Interruption Duration					
		Momentary	30 Minutes	1 Hour	4 Hours	8 Hours	16 Hours
Summer Morning	8%	$461	$569	$692	$1,798	$4,073	$7,409
Summer Afternoon	7%	$527	$645	$780	$1,954	$4,313	$7,737
Summer Evening/Night	18%	$272	$349	$440	$1,357	$3,518	$6,916
Non-summer Morning	17%	$549	$687	$848	$2,350	$5,592	$10,452
Non-summer Afternoon	14%	$640	$794	$972	$2,590	$5,980	$10,992
Non-summer Evening/Night	36%	$298	$388	$497	$1,656	$4,577	$9,367
Weighted Average		**$412**	**$520**	**$647**	**$1,880**	**$4,690**	**$9,055**

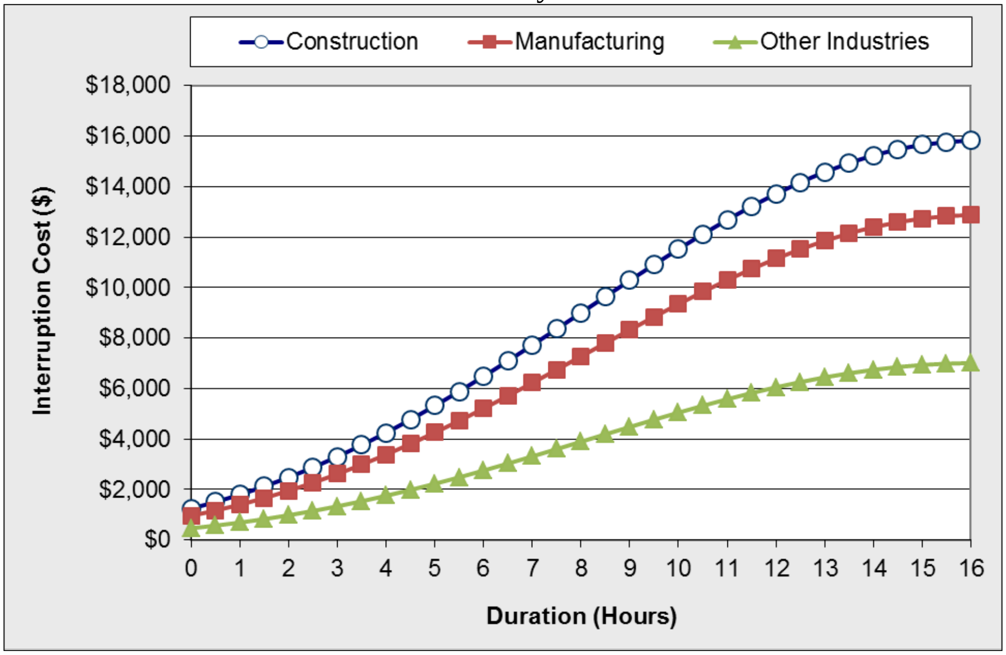
Based on the weighted-average interruption cost estimate, Table 4-8 provides cost per event (equal to the weighted-average interruption cost), cost per average kW, and cost per unserved kWh for small C&I customers. Cost per unserved kWh is relatively high for a momentary interruption because the expected amount of unserved kWh over a 5-minute period is relatively low.

Table 4-8: Cost per Event, Average kW and Unserved kWh – Small C&I

Interruption Cost	Interruption Duration					
	Momentary	30 Minutes	1 Hour	4 Hours	8 Hours	16 Hours
Cost per Event	$412	$520	$647	$1,880	$4,690	$9,055
Cost per Average kW	$187.9	$237.0	$295.0	$857.1	$2,138.1	$4,128.3
Cost per Unserved kWh	$2,254.6	$474.1	$295.0	$214.3	$267.3	$258.0

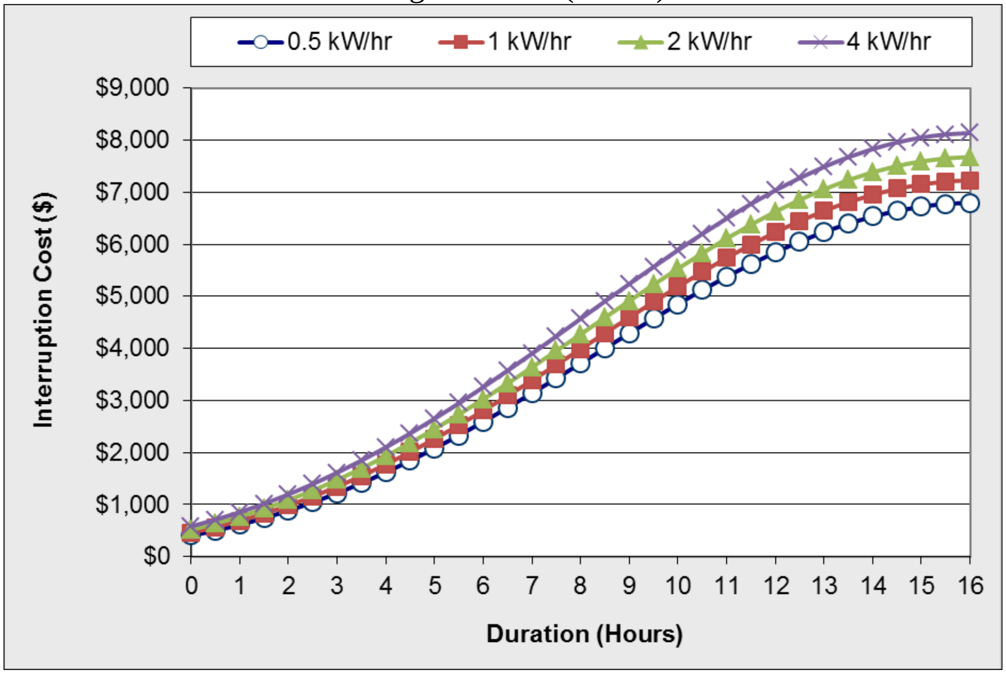
Figure 4-2 shows the small C&I interruption costs in the summer afternoon by industry. As in the 2009 model, interruption costs in the manufacturing and construction sectors are relatively high. At all durations, the estimated interruption cost for manufacturing and construction customers is around double or more the cost for customers in other industries. As in the medium and large C&I customer class, this is a key driver to consider for planning purposes – whether the planning area of interest includes small C&I customers with manufacturing or construction facilities that may be particularly sensitive to power interruptions.

Figure 4-2: Estimated Summer Afternoon Customer Interruption Costs (U.S.2013$) by Duration and Industry – Small C&I



Finally, Figure 4-3 shows the small C&I interruption costs in the summer afternoon for various levels of average demand. Small C&I interruption costs are not highly sensitive to the average demand of a customer. In the figure, each increment in average demand represents a 2-fold increase in usage, but interruption costs only increase by around 10% from one level of average demand to the next.

Figure 4-3: Estimated Summer Afternoon Customer Interruption Costs (U.S.2013$) by Duration and Average Demand (kW/hr) – Small C&I



5. Residential Results

This section summarizes the results of the model selection process and provides the model coefficients for residential customers.

5.1 Final Model Selection

The global model for residential customers is shown below:

Interruption Cost = f(ln(annual MWh), duration, duration², household income, medical equip., backup generation, summer, weekday, outage in last 12 months, # residents 0-6, # residents 7-18, # residents 19-24, # residents 25-49, # residents 50-64, # residents over 64, time of day, housing)

Interruption cost is expressed as a function of various explanatory variables. Note that the dependent variables differ between the probit and GLM models; hence the above equation expresses the two-part model in its most general form. Time of day and housing are categorical variables, and their respective categories are shown in Table 5-1 below. As is typical in indicatory coding, the first category within each categorical variable is not included explicitly as a binary variable, but rather serves as a reference category.

Table 5-1: Breakdown of Categorical Variables Featured in Global Model – Residential

Variable	Categories
time of day	Morning (6 AM to 12 PM); Afternoon (12 to 5 PM); Evening (5 to 10 PM); Late Evening/Early Morning
housing	Detached; Attached; Apartment/Condo; Mobile; Manufactured; Unknown

The global model was successfully parsed down to only key variables. In selecting among variables, categorical variables were not treated as a set (either all or none removed), but rather each binary variable was removed one at a time. This allowed for a particularly important category to remain, while others that might have had a smaller effect were no longer represented. Table 5-2 shows the results of each step in the process. Each iteration represents the exclusion of a variable from the global model, and the variable listed is the one that, when excluded, produces the model with the best performance across various metrics in out-of-sample tests. The model's value and rank (relative to the other possible exclusions) in the metrics is listed, along with its overall rank, which is an average of the individual ranks. Note that iteration zero represents the global model alone, so some metrics that are only meaningful when compared with other models, such as ranks and AICs, are not listed. The highlighted row shows the final exclusion that was made; the rows that follow show the variables that remain in the final model. Ultimately, interruption costs for residential customers can be estimated relatively accurately with variables representing customer usage, household income, and interruption duration, along with some binary variables for interruption timing. A few of the 16 excluded variables show a minor improvement in predictive accuracy, but considering how difficult it can be for ICE Calculator users to find information for some of those inputs, this minor improvement in predictive accuracy was not sufficient to justify keeping those variables in the final model.

Table 5-2: Excluded Variables and Relevant Metrics from Backwards Stepwise Selection Process – Residential

Iteration	Excluded Variable	RMSE		MAE		R2		AIC			Overall Rank
		Value	Rank	Value	Rank	Value	Rank	Probit Value (Thousands)	GLM Value (Thousands)	Rank	
0	-	16.6	-	8.50	-	0.145	-	-	-	-	-
1	*late evening/early morning*	16.5	1	8.49	1	0.147	1	37.3	126	9.5	3.1
2	*mobile housing*	16.5	3	8.48	2	0.148	3	37.3	126	3.5	2.9
3	*outage in last 12 months*	16.5	1	8.48	1	0.149	1	37.3	126	9.5	3.1
4	*# residents 7-18 years old*	16.5	1	8.48	5	0.149	1	37.3	126	6.0	3.3
5	*# residents 25-49 years old*	16.5	2	8.48	3	0.149	2	37.3	126	6.5	3.4
6	*# residents 50-64 years old*	16.5	2	8.48	2	0.149	2	37.3	126	1.0	1.8
7	*manufactured housing*	16.5	2	8.48	2	0.149	2	37.3	126	4.0	2.5
8	*weekday*	16.5	1	8.48	2	0.149	1	37.3	126	5.5	2.4
9	*attached housing*	16.5	1	8.48	1	0.149	1	37.4	126	5.5	2.1
10	*apartment/condo*	16.5	3	8.48	2	0.149	3	37.4	126	1.0	2.3
11	*# residents 19-24 years old*	16.5	1	8.48	2	0.149	1	37.4	126	3.5	1.9
12	*backup generation*	16.5	1	8.48	1	0.149	1	37.4	126	4.0	1.8
13	*# residents 0-6 years old*	16.5	2	8.48	2	0.149	2	37.4	126	1.5	1.9
14	*unknown housing*	16.5	2	8.49	1	0.148	2	37.4	126	1.5	1.6
15	*medical equipment*	16.5	1	8.49	2	0.148	1	37.5	126	2.5	1.6
16	*# residents 65 and over*	16.6	1	8.49	1	0.146	1	37.5	126	2.5	1.4
17	*household income*	16.6	1	8.53	1	0.140	1	37.5	127	2.5	1.4
18	*evening, 5 pm to 8 pm*	16.7	1	8.61	2	0.133	1	38.7	127	3.0	1.8
19	*afternoon, 12 noon to 4 pm*	16.7	1	8.63	1	0.127	1	38.9	127	2.0	1.3
20	*summer*	16.8	1	8.71	1	0.119	1	39.7	127	2.0	1.3
21	*ln(annual MWh)*	17.0	1	8.82	1	0.098	1	39.7	128	1.5	1.1
22	*duration* ^{2}	17.3	1	8.95	1	0.072	1	39.9	128	1.0	1.0
23	*duration*	17.9	1	9.44	1	0.000	1	41.6	130	1.0	1.0

The final model for residential customers is shown below:

Interruption Cost = f(ln(annual MWh), duration, duration^2, household income, summer, time of day)

To confirm that the selection process did not produce an over-fitted model, and to estimate the predictive performance of the final model when evaluated on unseen data, Nexant evaluated the final model against the global model using the test dataset, which is the 10% of data that was held out from the backwards stepwise selection process. Both models were fitted to the remaining data, and then the test dataset was used to evaluate their predictive performance. The results are shown in Table 5-3. Note that while the global model outperforms the final model in each metric, the differences between the values are very small. The final model offers a much simpler solution with comparable performance to the global model.

Table 5-3: Test Dataset Predictive Performance Metrics for Final and Initial Models – Residential

Model	RMSE	MAE	R-squared
Final	17.5	8.34	0.148
Global	17.3	8.28	0.165

5.2 Model Coefficients

Nexant then estimated the final two-part regression model specification on the full dataset for residential customers. Table 5-4 describes the final probit regression model that specifies the relationship between the presence of zero interruption costs and a set of independent variables that includes interruption characteristics and customer characteristics. Although the purpose of this preliminary limited dependent variable model is only to normalize the predictions from the interruption costs regression in the second part of the two-part model, there are a few interesting results to note (these remain consistent with the original specification):

- All of the coefficients are statistically significant at a less than 5% level;
- The longer the interruption, the more likely that the costs are positive (the presence of a negative coefficient on the square of duration indicates that this effect diminishes for longer durations);
- Customers are less likely to have a positive cost for an afternoon or an evening interruption versus any other time of day.

Table 5-4: Regression Output for Probit Estimation – Residential

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
duration	0.003	0.000	0.000
duration^2	-1.130E-06	0.000	0.000
summer	0.541	0.019	0.000
afternoon	-0.266	0.026	0.000
evening	-0.755	0.024	0.000
Customer Characteristics			
ln(annual MWh)	0.038	0.018	0.035
household income	9.660E-07	0.000	0.004
Constant	-0.266	0.051	0.000

Table 5-5 describes the final GLM regression model which relates the level of interruption costs to customer and interruption characteristics. A few results of note:

- All of the coefficients are statistically significant at a less than 5% level;
- The longer the interruption, the higher the interruption cost;

- Customers have lower interruption costs for afternoon and evening interruptions than for those that occur at other times of day;
- Customers experience higher costs for summer interruptions than for non-summer interruptions; and
- Larger customers (in terms of annual MWh usage) have a higher cost for similar interruptions than otherwise equivalent, smaller customers.

Table 5-5: Regression Output for GLM Estimation – Residential

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
duration	0.002	0.000	0.000
duration^2	-9.450E-07	0.000	0.000
summer	0.161	0.029	0.000
afternoon	-0.282	0.041	0.000
evening	-0.095	0.047	0.044
Customer Characteristics			
ln(annual MWh)	0.249	0.028	0.000
household income	1.850E-06	0.000	0.000
Constant	1.379	0.080	0.000

Finally, Table 5-6 shows the average values of the regression inputs for residential customers, which are useful for modeling purposes and for assessing marginal effects. Other descriptive statistics are also provided.

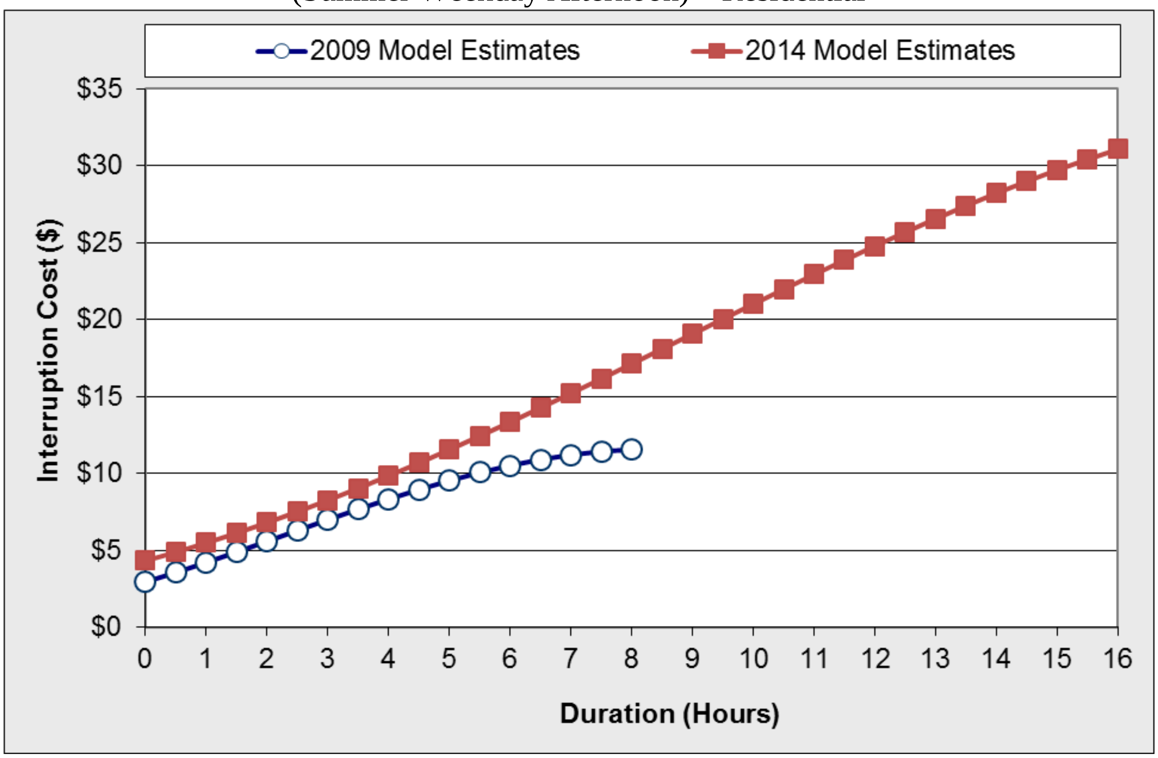
Table 5-6: Descriptive Statistics for Regression Inputs – Residential

Variable	N	Average	Minimum	25th Percentile	Median	75th Percentile	Maximum
Interruption Characteristics							
duration	34,212	168	0	60	60	240	1,440
duration^2	34,212	82,198	0	3,600	3,600	57,600	2,073,600
summer	34,212	73.4%	0%	0%	100%	100%	100%
afternoon	34,212	48.8%	0%	0%	0%	100%	100%
evening	34,212	29.1%	0%	0%	0%	100%	100%
Customer Characteristics							
ln(annual MWh)	34,212	2.4	0.3	1.9	2.4	2.9	4.4
household income	34,212	69,243	5,076	36,846	63,445	97,618	173,611

5.3 Comparison of 2009 and 2014 Model Estimates

Figure 5-1 provides a comparison of the 2009 model estimates and the 2014 model estimates by interruption duration, in 2013 dollars. The 2014 model estimates have been extended to 16 hours because the addition of data on 24-hour power interruption scenarios has allowed to model to more reliably predict costs up to 16 hours. As with C&I customers, the magnitude of the interruption cost estimates is similar between the two small C&I models, but there is a noticeable change in the functional form. This change is attributable to the addition of the longer duration scenarios and to the significant change in the model specification. The functional form is more linear and no longer levels off at 8 hours, which seems more plausible.

Figure 5-1: Estimated Customer Interruption Costs (U.S.2013$) by Duration and Model (Summer Weekday Afternoon) – Residential



5.4 Interruption Cost Estimates and Key Drivers

Table 5-7 shows how residential customer interruption costs vary by season and time of day. The cost of a summer power interruption is substantially higher than a non-summer one, for all durations, seasons, and times of day. As for how interruption costs vary by time of day, costs are highest in the morning and night (10 PM to 12 noon). The weighted-average interruption cost estimate is most appropriate to use for planning purposes, unless the distribution of interruptions by season and time of day is known.

Table 5-7: Estimated Customer Interruption Costs (U.S.2013$) by Duration and Timing of Interruption – Residential

Timing of Interruption	% of Hours per Year	Interruption Duration					
		Momentary	30 Minutes	1 Hour	4 Hours	8 Hours	16 Hours
Summer Morning/Night	19%	$6.8	$7.5	$8.4	$14.3	$24.0	$42.4
Summer Afternoon	7%	$4.3	$4.9	$5.5	$9.8	$17.1	$31.1
Summer Evening	7%	$3.5	$4.0	$4.6	$9.2	$17.5	$34.1
Non-summer Morning/Night	39%	$3.9	$4.5	$5.1	$9.8	$17.8	$33.5
Non-summer Afternoon	14%	$2.3	$2.7	$3.1	$6.2	$12.1	$23.7
Non-summer Evening	14%	$1.5	$1.8	$2.2	$5.0	$10.8	$23.6
Weighted Average		**$3.9**	**$4.5**	**$5.1**	**$9.5**	**$17.2**	**$32.4**

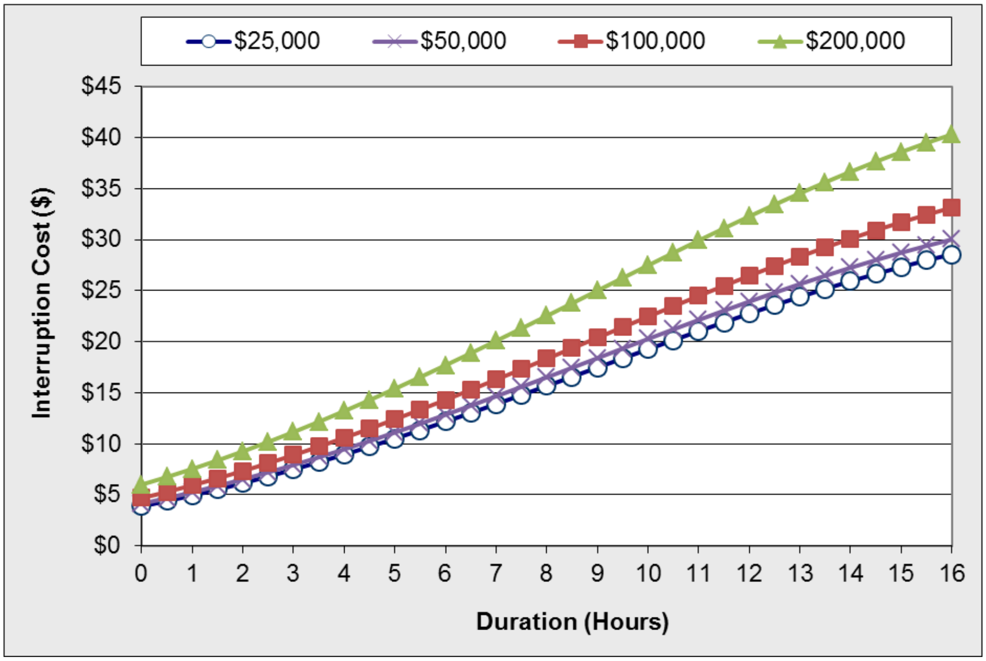
Based on the weighted-average interruption cost estimate, Table 5-8 provides cost per event (equal to the weighted-average interruption cost), cost per average kW, and cost per unserved kWh for residential customers. Cost per unserved kWh is relatively high for a momentary interruption because the expected amount of unserved kWh over a 5-minute period is relatively low.

Table 5-8: Cost per Event, Average kW and Unserved kWh – Residential

Interruption Cost	Interruption Duration					
	Momentary	30 Minutes	1 Hour	4 Hours	8 Hours	16 Hours
Cost per Event	$3.9	$4.5	$5.1	$9.5	$17.2	$32.4
Cost per Average kW	$2.6	$2.9	$3.3	$6.2	$11.3	$21.2
Cost per Unserved kWh	$30.9	$5.9	$3.3	$1.6	$1.4	$1.3

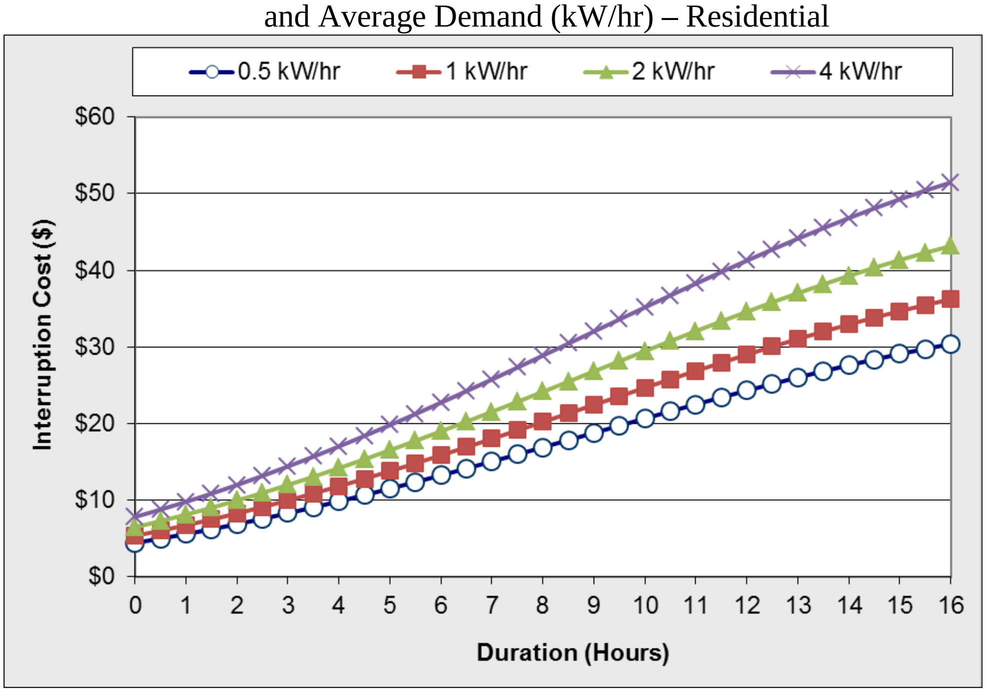
Figure 5-2 shows the residential interruption costs in the summer afternoon by levels of household income. Household income has a relatively modest impact on interruption costs. Between a household income of $50,000 and $100,000, the difference in interruption costs is only around 10% for all durations.

Figure 5-2: Estimated Summer Afternoon Customer Interruption Costs (U.S.2013$) by Duration and Household Income – Residential



Finally, Figure 5-3 shows the residential interruption costs in the summer afternoon for various levels of average demand. Residential interruption costs are not highly sensitive to the average demand of a customer. In the figure, each increment in average demand represents a 2-fold increase in usage, but interruption costs only increase by around 20% from one level of average demand to the next.

Figure 5-3: Estimated Summer Afternoon Customer Interruption Costs (U.S.2013$) by Duration and Average Demand (kW/hr) – Residential



6. Study Limitations

As in the 2009 study, there are limitations to how the data from this meta-analysis should be used. It is important to fully understand these limitations, so they are further described in this section. First, certain very important variables in the data are confounded among the studies we examined. In particular, region of the country and year of the study are correlated in such a way that it is impossible to separate the effects of these two variables on customer interruption costs. Thus, for example, it is unclear whether the higher interruption cost values for the southwest are purely the result of the hot summer climate in that region or whether those costs are higher in part because of the particular economic and market conditions that prevailed during the year when the study for that region was done. The same logic applies to the 2012 west study, which was the only survey to include power interruption scenarios of more than 12 hours, which makes it difficult to separate the effect of region and year from the effect of the relatively long interruption duration.

There is further correlation between regions and scenario characteristics. The sponsors of the interruption cost studies were generally interested in measuring interruption costs for conditions that were important for planning for their specific systems. As a result, interruption conditions described in the surveys for a given region tended to focus on periods of time when interruptions were more problematic for that region. Unfortunately, the time periods when the chance of interruptions is greatest are not identical for all sponsors of the studies we relied upon, so interruption scenario characteristics tended to be different in different regions. Fortunately, most of the studies we examined included a summer afternoon interruption, so we could compare that condition among studies.

A further limitation of our research is that the surveys that formed the basis of the studies we examined were limited to certain parts of the country. No data were available from the northeast/mid-Atlantic region, and limited data were available for cities along the Great Lakes. The absence of interruption cost information for the northeast/mid-Atlantic region is particularly troublesome because of the unique population density and economic intensity of that region. It is unknown whether, when weather and customer compositions are controlled, the average interruption costs from this region are different than those in other parts of the country.

Another caveat is that around half of the data from the meta-database is from surveys that are 15 or more years old. Although the intertemporal analysis in the 2009 study showed that interruption costs have not changed significantly over time, the outdated vintage of the data presents concerns that, in addition to the limitations above, underscore the need for a coordinated, nationwide effort that collects interruption cost estimates for many regions and utilities simultaneously, using a consistent survey design and data collection method.

Finally, as described in Section 1, although the revised model is able to estimate costs for interruptions lasting longer than 8 hours, it is important to note that the estimates in this report are not appropriate for resiliency planning. This meta-study focuses on the direct costs that customers experience as a result of relatively short power interruptions of up to 24 hours at most. In fact, the final models and results that are presented in Sections 3 through 5 truncate the estimates at 16 hours, due to the relatively few number of observations beyond 12 hours (scenarios of more than 12 hours account for around 2% to 3% of observations for all customer classes). For resiliency considerations that involve planning for long duration power interruptions of 24 hours or more, the nature of costs change and the indirect, spillover effects to the greater economy must be considered.[12] These factors are not captured in this meta-analysis.

[12] For a detailed study and literature review on estimating the costs associated with long duration power interruptions lasting 24 hours to 7 weeks, see: Sullivan, Michael and Schellenberg, Josh. *Downtown San Francisco Long Duration Outage Cost Study*. March 27, 2013. Prepared for Pacific Gas & Electric Company.

I/A

Public Staff
Thomas Exhibit 2

Duke Energy Carolinas
Response to
North Carolina Public Staff Data Request
Data Request No. NCPS 133

Docket No. E-7, Sub 1214

Date of Request: **January 3, 2020**
Date of Response: **January 13, 2020**

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Confidential Responses are provided pursuant to Confidentiality Agreement

The attached response to North Carolina Public Staff Data Request No. 133-7, was provided to me by the following individual(s): Karen Ann Ralph, Lead Planning & Regulatory Support Specialist, and was provided to North Carolina Public Staff under my supervision.

Camal O. Robinson
Senior Counsel
Duke Energy Carolinas

North Carolina Public Staff
Data Request No. 133
DEC Docket No. E-7, Sub 1214
Item No. 133-7
Page 1 of 2

Request:

The following questions are related to the DEC Transformer Retrofit cost benefit analysis (titled Oliver_EXH_7_HR_Transformer Retro_DEC-DEP_NC_19-22_vF.xlsx) that was provided in Oliver Exhibit 7.
7. The 'Selection Metric' tab, column C, calculates reliability reductions in rows 74 - 100, generally, by the formula below, where i=year and m=metric.

$$ReliabilityReductions_{i,m} = \frac{AverageOutagesDueToUnretrofittedTfrs_{i,m}}{OverheadTransformerTotalUnitsYE2017} * TotalTransformerRetrofitProgramScopeUnits_{i}$$

Metrics include number of incidents (non-MED), CI (non-MED), CMI (non-MED), number of incidents (MED), CI (MED), and CMI (MED).

Please provide supporting documentation for the Average Outages Due to Unretrofitted Transformers numbers (rows 31-36). In addition to quantitative support for these figures, this response should discuss how these numbers were calculated, the source of the data used, how each outage incident was classified as MED and non-MED, and how each outage was determined to be due to an unretrofitted transformer.
Please confirm that this CBA assumes that retrofitted transformers only protect upstream customers from potential outages.
Duke personnel indicated that they have been retrofitting transformers in this way for "maybe 15 years". Does Duke have any data that indicates if these retrofitted transformers actually experience fewer failures due to external factors (i.e., lightning strikes and animal interference)? If so, please provide a summary of the available data and quantify the reduction in failure rate.

Response:
a) The attached Excel spreadsheet titled "PS DR 133-7(a) DEC & DEP Outages Due To Unretrofitted Transformers" shows the number of events, CI, & CMI by year and MED Type associated with outages due to unretrofitted transformers from 2013 - 2017.

PS DR 133-7 (a) DEC
& DEP Outages Due T

i. The Average Outages Due to Unretrofitted Transformers number used in the CBA is the average of each year’s total events/CI/CMI for NC from 2013 – 2017.
ii. The source of this data is our common outage history database.
iii. MEDs are specific dates where the Daily SAIDI exceeds the MED threshold

calculated per IEEE 1366 – 2012.
iv. A complex Microsoft Access query was used to extract outages from the common outage history database using a combination of codes & contextual searches of comments that determines the outage was an outage due to an unretrofitted transformer.
b) Transformer retrofit benefits both customers served by the transformer and customers upstream from the transformer.
c) The attached Excel spreadsheet titled “PS DR 133-7 (c) DEC Decrease in SAIFI Due To Unretrofitted Transformers 2005 – 2017” show the decrease in SAIFI associated with unretrofitted transformers over time.

PS DR 133-7 (c) DEC
Decrease in SAIFI Due

Public Staff
Thomas Exhibit 3

Duke Energy Carolinas
Response to
North Carolina Public Staff Data Request
Data Request No. NCPS 133

Docket No. E-7, Sub 1214

Date of Request: January 3, 2020
Date of Response: January 13, 2020

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The attached response to North Carolina Public Staff Data Request No. 133-13, was provided to me by the following individual(s): Karen Ann Ralph, Lead Planning & Regulatory Support Specialist, and was provided to North Carolina Public Staff under my supervision.

Camal O. Robinson
Senior Counsel
Duke Energy Carolinas

Request:

13. In a follow up email following the December 17, 2019 meeting, Duke sent a spreadsheet entitled 'DEC NC_SOG Circuits_CI CMI Savings_5 Year Load Projections'. For the following six circuits, please provide a more detailed explanation as to how specifically the Incremental CI Savings and the Incremental CMI Savings were estimated for 2019, 2020, and 2021.
a) This response should address what outage causes were included in historical circuit reliability and what outages were assumed to be mitigated by SOG.
b) If other reliability programs, such as vegetation management, were considered, please describe how they were taken into account.

Circuit ID #	Substation Name	Circuit Name	SOG Year	Incremental CI Savings	Incremental CMI Savings
14142410	FAIRNTOSH RET	Fairntosh Ret 2410	2021	4,317	646,035
14202413	GARRETT RD RET	Garrett Rd Ret 2413	2021	4,467	687,576
09122406	GROOMTOWN RET	Groomtown Ret 2406	2020	4,058	608,308
01012408	HILL ST RET	Hill St Ret 2408	2020	7,953	862,192
01342406	NEWELL RET	Newell Ret 2406	2021	4,771	703,943
11202409	WHITSETT RET	Whitsett Ret 2409	2019	4,483	671,540

Response:

See attachment 'PS DR 133-13_DEC NC_SOG_CI & CMI Savings_Sample Circuits'
The assumptions used to calculate the CI and CMI Savings are shown on the tab entitled 'SOG CI & CMI Assumptions.' This worksheet (tab) steps through a series of different base case scenarios that are typical for Duke Energy distribution circuit profiles. The detailed CI and CMI calculations are shown under each scenario. A key factor in the equations is the 'Faults per Mile' (also called Failure Rate). The Duke Energy enterprise system average faults per mile is based on historical outage events (greater than 5 minutes), excluding Major Event Days (MED's), on substation devices, substation circuit (feeder) breakers, and reclosers, divided by the feeder backbone miles. Any outage greater than 5 minutes, regardless of cause, that impacted the feeder backbone was included. The feeder backbone is defined and illustrated on the worksheet (tab) entitled 'Definition – Feeder Backbone.' The distribution system average Faults per Mile across the Duke Energy enterprise is approximately 0.2. The table at the bottom of the 'SOG CI & CMI Assumptions' tab summarizes the % CI Improvements that are used system-wide based on the current state of a circuit to get to the final SOG state.
Using the logic shown on the 'SOG CI & CMI Assumptions' tab, the Customer

Interruption (CI) Savings due to SOG are calculated on a circuit-by-circuit basis, as shown on the 'DEC NC SOG Calc.' worksheet (tab) in columns 'V' through 'AB.' The failure rate (Faults per Mile) for DEC is approximately 0.24. The current CI is calculated from the existing state of the circuit (base case). Then the projected CI is calculated based on each circuit becoming 100% SOG compliant. The difference is taken between the 2 cases to determine the resulting CI Savings. The CI Savings (CI Improvement) for each SOG circuit is aggregated to determine the total CI Savings for the jurisdiction. The projected CMI is then calculated on a circuit-by-circuit basis assuming a repair time of 180 minutes and switching time of 90 minutes (see 'DEC NC SOG Calc.' tab row 'AD'). The potential CMI Savings (Improvement) is calculated based on the existing state of a circuit and applying the logic from the 'SOG CI & CMI Assumptions' tab. If a circuit is on an existing Self-Healing Network, then the potential CMI Improvement is assumed to be approximately a 30% improvement. If a circuit is not on an existing Self-Healing Network, then the potential CMI Improvement is assumed to be approximately 70% (see 'DEC NC SOG Calc.' tab row 'AD').

a. As stated above, any outage greater than 5 minutes, regardless of cause, that impacted the feeder backbone was included in the SOG assumptions.

b. The current state of a circuit due to other reliability programs was considered in the calculations. If a circuit had some form of existing segmentation (or sectionalization) on the feeder backbone, or was part of an existing Self Healing Network (SHN), then these were taken into account to calculate the % CI and % CMI improvement to get to the final SOG state. See the 'SOG CI & CMI Assumptions' worksheet (tab).

PS DR 133-13_DEC
NC_SOG_CI & CMI S

I/A

Public Staff
Thomas Exhibit 4

Duke Energy Carolinas
Response to
North Carolina Public Staff Data Request
Data Request No. NCPS 179

Docket No. E-7, Sub 1214

Date of Request:	**January 30, 2020**
Date of Response:	**February 6, 2020**

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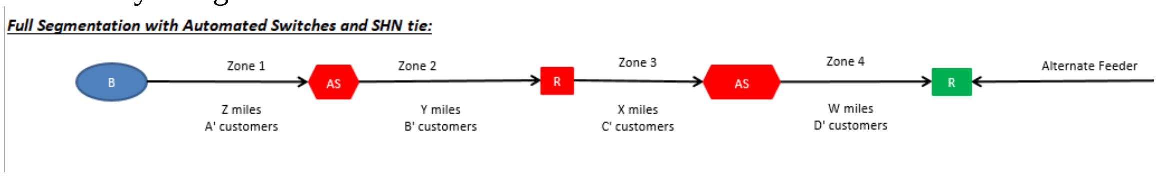
The attached response to North Carolina Public Staff Data Request No. 179-4, was provided to me by the following individual(s): Karen Ann Ralph, Lead Planning & Regulatory Support Specialist, and was provided to North Carolina Public Staff under my supervision.

Camal O. Robinson
Senior Counsel
Duke Energy Carolinas

North Carolina Public Staff
Data Request No. 179
DEC Docket No. E-7, Sub 1214
Item No. 179-4

Request:

4. In its response to PS DR 133-13, DEC provided a spreadsheet showing CI and CMI calculations for SOG circuits. This question refers to the 'SOG CI & CMI Assumptions' tab. When a fault occurs on a fully deployed SOG circuit segment (say, zone 2 from the image below), do customers on other segments (zone 1, 3, and 4) experience a momentary outage?



a) Assuming a fault resulting in a momentary outage in zone 2, please describe the experience of customers in zones 1, 2, 3, and 4 (do they experience a flicker, outage, how many cycles, etc?).
b) Assuming a fault resulting in a sustained outage in zone 2, please describe the experience of customers in zones 1, 2, 3, and 4. (do they experience a flicker, outage, how many cycles, etc?).

Response:

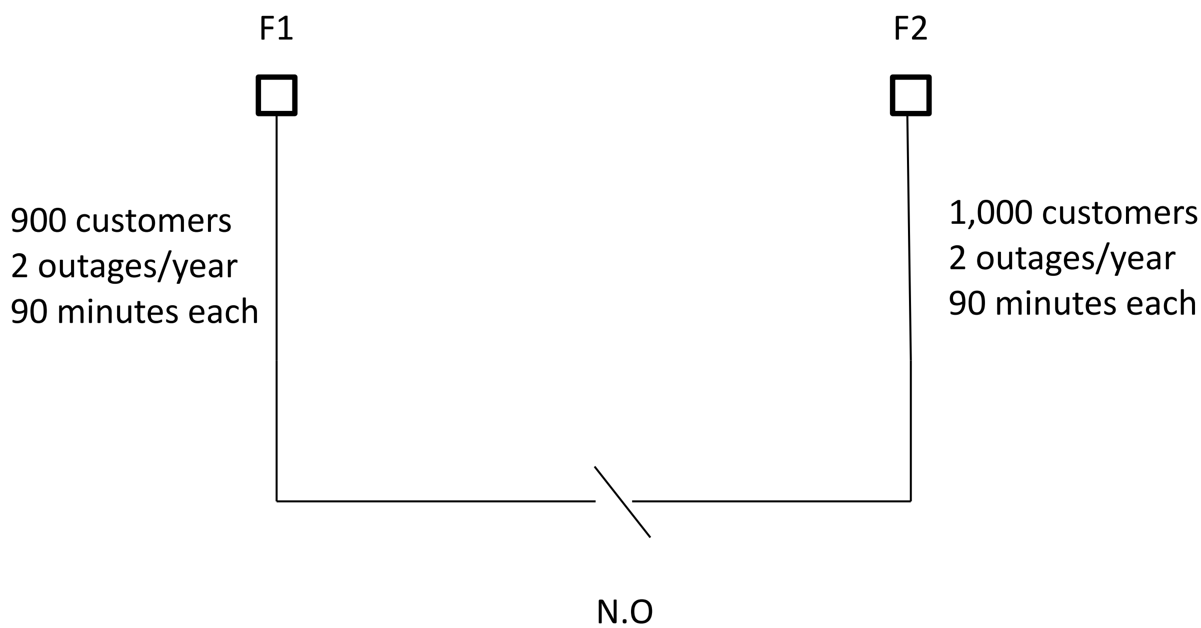
4. Assuming a fault in Zone 2 produces a fault current magnitude & duration greater than the substation breaker relay trip curve then the substation breaker would trip and reclose and as such all customers in zones 1, 2, 3, & 4 would experience a momentary interruption.
a. Assuming a fault in zone 2 produces a fault current magnitude & duration greater than the substation breaker relay trip curve then the substation breaker would trip and reclose (the device between zone 1 & zone 2 is an automated switch so it does not normally operate in a protection mode) and as such all customers in zones 1, 2, 3, & 4 would experience a momentary interruption. The duration of the momentary outage could range from a few cycles to a few of seconds depending on the breaker relay setting, the magnitude of the fault current, and the duration of the fault current.
b. Assuming a fault in zone 2 produces a fault current magnitude & duration greater than the substation breaker relay trip curve then the substation breaker would trip and reclose (the device between zone 1 & zone 2 is an automated switch so it does not normally operate in a protection mode) a number of times based on the relay settings and ultimately lock out. If all YFA criteria are met the following sequence of events would occur in 2 mins or less:
i. The automate switch between zones 1 & 2 would open
ii. The recloser between zones 2 & 3 would open

iii. The recloser between zone 4 and the alternate circuit would close
iv. The substation breaker would close
As stated above, all customers in zones 1, 2, 3, & 4 would experience multiple momentary interruptions as a result of the sustained fault in zone 2 (based on the substation breaker relay settings). After the switching the customers in zones 1, 3, & 4 would be restored in 2 minutes or less. The customers in zone 2 would experience a sustained outage until the outage was restored.

Using the ICE Calculator for FLISR Reliability Improvement Value

Automatic reconfiguration of distribution circuits is a popular way to improve service reliability to electric customers on distribution circuits. This technique is often called self-healing or Fault Location Isolation and Service Restoration (FLISR). It is important to know the reliability improvement value to customers when designing these systems. The ICE Calculator is a widely accepted tool for calculating outage costs and to calculate the value of reliability improvements. It is very important to use the tool properly to avoid over-estimating the value.

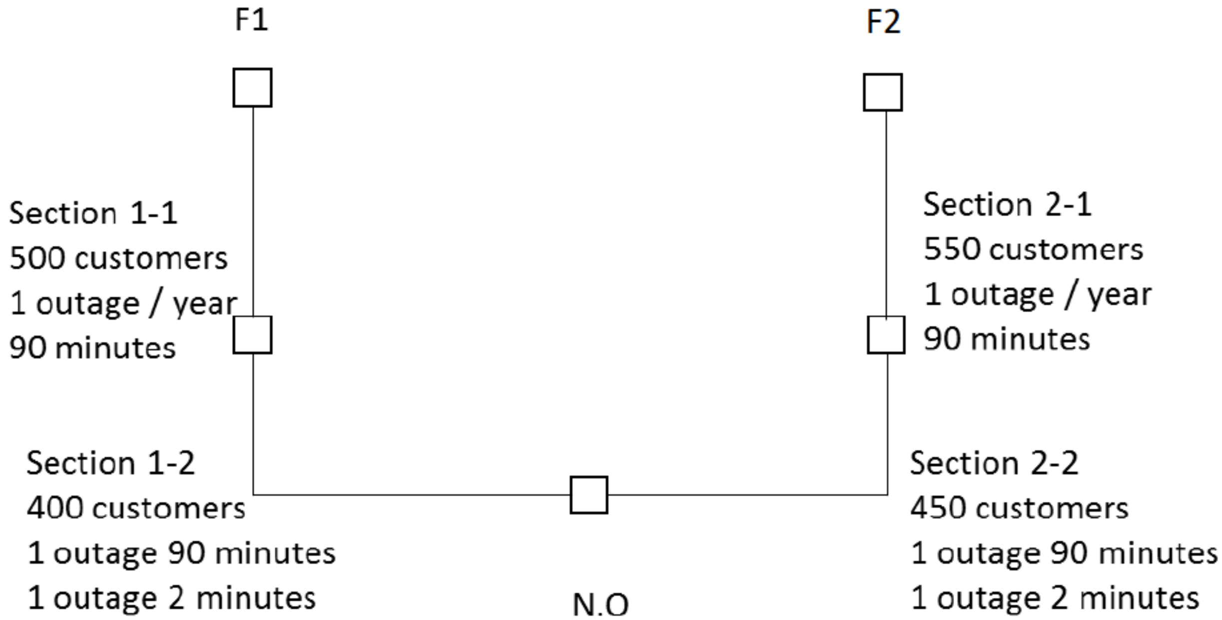
This document provides a very basic example of how to use the ICE tool to accurately calculate the reliability benefits when sustained outages are changed to momentary outages. It normally requires building at least two models and combining the results. Consider this simple example with two feeders, F1 and F2. F1 serves 900 residential customers while F2 serves 1,000 residential customers in the state of Indiana. (We picked Indiana because the ICE calculator needs a state for input.) Each feeder experiences two sustained outages per year. Each of the outages last 90 minutes. They do not experience any momentary outages to simplify the example.



The reliability metrics are shown below

Sections	Customers	SAIFI	SAIDI	CAIDI	MAIFI
F1	900	2.0	180	90	0
F2	1,000	2.0	180	90	0
Total System	1,900	2.0	180	90	0

Now consider FLISR improvements and calculate the net reliability improvement. Reclosers are placed midway along each feeder and at the normally open point. Recloser placement is equal such that each of the four sections will experience one sustained interruption per year. Customers on Sections 1-1 and 2-1 enjoy one less outage per year. The FLISR design will automatically restore service to Section 1-2 from Section 2-2 when problems occur on Section 1-1. Customers on Section 1-2 now see only a 2 minute interruption instead of 90 minutes. Likewise, FLISR will restore service to Section 2-2 from Section 1-2 when problems occur on Section 2-1. Customers on Section 2-2 only see a 2 minute outage instead of a 90 minute outage. This 2 minute duration removes these customer interruptions from the IEEE sustained reliability metrics and places them in the momentary category.



Here are the new reliability numbers after the system improvements

Sections	Customers	SAIFI	SAIDI	CAIDI	MAIFI
1-1 and 2-1	1,050	1.0	90	90	0
1-2 and 2-2	850	1.0	90	90	1
Total System	1,900	1.0	90	90	0.45

Here is how we can use the ICE calculator to estimate the value. Since the ICE calculator does not directly call out MAIFI, the user might be tempted to simply input new SAIDI, CAIDI and SAIDI numbers. However, this substantially overstates the reliability benefit because it assumes there will not be any momentary interruptions. A correct model must separate the customers by their common experience.

The 1050 customers in Sections 1-1 and 2-1 see different reliability improvement compared to the 850 customers in Sections 1-2 and 2-2.

All customers in 1-1 and 2-1 see the same amount of SAIFI and SAIDI improvement so the first step in the calculation can be a simple improvement in sustained interruptions. The ten year benefit per customer turns out to be $57.62 for the default financial inputs.

All customers in 1-2 and 2-2 have the same sustained SAIFI and SAIDI statistics, but they also see a momentary for a total of two outages per year. The true benefit to these customers is not a reduction of outages. The benefit is only a reduction in duration of one outage per year from 90 minutes to 2 minutes. We model this in the ICE Calculator as a duration change only for the sustained 90 minute outage that changed to a 2 minute momentary. So we input SAIFI = 1 before and SAIFI = 1 after. SAIDI changes from 90 minutes to 2 minutes. This benefit is a much lower $14.64 compared to $57.62 if the outage is eliminated.

Here is the more accurate summary of benefits with the total benefit rounded to the nearest hundred dollars.

Sections	Customers	Benefit / Customer	Total Benefit
1-1 and 2-1	1,050	$57.62	$60,500
1-2 and 2-2	850	$14.64	$12,500
Total System	1,900	$38.39	$73,000

Had this not accounted for the momentary outages, a single pass through the ICE Calculator estimates $109,500 benefits for the SAIFI, SAIDI, and CAIDI improvement. This overstates the more accurate amount by $36,500. This is about 50% more benefit than will actually be realized.

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Estimated Value of Service Reliability for Electric Utility Customers in the United States

Prepared for
Office of Electricity Delivery and Energy Reliability
U.S. Department of Energy

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http://eetd.lbl.gov/ea/EMS/EMS_pubs.html

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The authors are solely responsible for any omissions or errors contained herein.

Disclaimer

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Table of Contents

List of Figures and Tables

Acronyms and Abbreviations

C&I – Commercial and Industrial
CDF – Customer Damage Function
EPRI – Electric Power Research Institute
GDP – Gross Domestic Product
GLM – General Linear Model
IQR – Interquartile Range
kW - Kilowatt
kWh – Kilowatt hour
LR Test – Likelihood Ratio Test
MAIFI – Momentary Average Interruption Frequency Index
MWh – Megawatt hour
NLLS – Nonlinear Least Squares
OLS – Ordinary Least Squares
SAIDI – System Average Interruption Duration Index
SAIFI – System Average Interruption Frequency Index
SIC – Standard Industrial Classification
WTA – Willingness to Accept
WTP – Willingness to Pay
VOS – Value of Service

Abstract

Information on the value of reliable electricity service can be used to assess the economic efficiency of investments in generation, transmission and distribution systems, to strategically target investments to customer segments that receive the most benefit from system improvements, and to numerically quantify the risk associated with different operating, planning and investment strategies. This paper summarizes research designed to provide estimates of the value of service reliability for electricity customers in the US. These estimates were obtained by analyzing the results from 28 customer value of service reliability studies conducted by 10 major US electric utilities over the 16 year period from 1989 to 2005. Because these studies used nearly identical interruption cost estimation or willingness-to-pay/accept methods it was possible to integrate their results into a single meta-database describing the value of electric service reliability observed in all of them. Once the datasets from the various studies were combined, a two-part regression model was used to estimate customer damage functions that can be generally applied to calculate customer interruption costs per event by season, time of day, day of week, and geographical regions within the US for industrial, commercial, and residential customers. Estimated interruption costs for different types of customers and of different duration are provided. Finally, additional research and development designed to expand the usefulness of this powerful database and analysis are suggested.

Keywords: electric power reliability; customer value of service reliability; interruption cost; customer damage function.

Executive Summary

One of the guiding principles in evaluating investments designed to improve the reliability of electricity systems is that these investments should be economically efficient. That is, the cost of improving the reliability and power quality supplied by an electric system should not exceed the value of the economic loss to customers that the system improvement is intended to prevent. This approach to utility investment planning is generally referred to as value-based reliability planning.

Value-based planning explicitly balances the incremental costs of improved reliability in generation, transmission, and/or distribution against the incremental benefits of enhanced (or maintained) system reliability with both costs and benefits defined as societal costs and societal benefits. The incremental societal benefits include the customers' added value of service reliability. The customers' added value of service reliability can be quantified by the willingness of customers to pay for service reliability, taking into account the resources (e.g., income) of the residential customer or by a firm's expected net revenues associated with the added reliability. Measures of the added value of service reliability include reported economic losses (net of benefits) and measurements of customer's willingness-to-pay to avoid service unreliability or their willingness-to-accept compensation for it. These measures of the added value of service reliability do not measure all the societal benefits that result from reliability improvements. They do not, for example, account for such benefits as improved public safety or public health that result from avoided widespread electric service interruptions. Such societal benefits must be incorporated separately. A system improvement is considered economically efficient if its marginal societal benefits (the economic value of the improvement in reliability) exceed the marginal societal costs (the cost of the investment, including direct as well as indirect (e.g., environmental) costs).

The cost of system improvements is usually estimated using engineering cost analysis. The economic value of the benefit to customers is estimated as the avoided economic loss that would have occurred if the investment had not occurred. Two components comprise this estimate – the expected improvement in service reliability (in minutes, frequency, un-served load or un-served kWh) and the expected economic losses that customers experience when service is interrupted – usually obtained by surveying representative samples of customers about the economic losses they experience as a result of electric service interruptions or power-quality problems or, alternatively, customers' willingness-to-pay to avoid/willingness-to-accept compensation for such problems.[1]

Value-based reliability planning concepts have been in use for more than 20 years. They have been used in a variety of utility planning and ratemaking applications including:

1. Estimating the cost of electric reliability to the US economy;
2. Establishing the marginal cost of generating capacity for purposes of setting electric rates and establishing economically efficient planning reserve margins;

[1] In this report, we use the term "customer interruption costs" to refer to value of electricity service reliability estimates developed through either surveys of the economic losses customers experience as a result of electric service interruptions or those developed through surveys of customers' willingness-to-pay to avoid/willingness-to-accept compensation for such problems.

3. Assessing the economic costs of additional load on transmission systems associated with wholesale and retail wheeling;
4. Assessing the economic benefits of transmission system reliability reinforcements;
5. Assessing the economic benefits of distribution system reinforcements;
6. Prioritizing distribution system reinforcement alternatives to obtain the optimal set of projects to carry out given limited capital;
7. Evaluating the costs and benefits of alternative substation design standards; and most recently,
8. Establishing the economic worth and cost-effectiveness of investments in Smart Grid.
9. Improving the design of demand response programs that aim to assign limited capacity to those with the highest willingness to pay during supply shortages.

A comprehensive review of publicly available interruption cost estimates was published in 2001 by Eto et. al. In this review they found that analysts had estimated customer interruption costs in a variety of ways. The analysts had studied interruption costs in a number of geographical locations at different points in time; and they had reported results in slightly different metrics. Consequently, it was impossible to use the results of publicly available studies to derive meaningful estimates of customer interruption costs generally.

The published information on customer interruption costs in the US was quite limited. Starting in the mid-1980s, however, a number of utilities in the US conducted a number of customer value of service reliability studies. Because most US utility companies believed these studies could be used by competitors and opponents in the regulatory arena to gain advantage, only summary reports from such surveys were made available to state regulatory bodies and others. Detailed results of most of these studies (i.e., including individual data) were not released to the public domain until about 2003 – and then only under strict confidentiality guidelines.

This paper describes work to assemble a meta-database on electricity customer interruption costs for the US and analyze the resulting data to develop customer damage functions useful for evaluating the economic benefits of electric system reliability reinforcements. This work is an extension of work originally published by Lawton et. al. in 2004. Several important changes have been made to the data and analysis methodology in the original work and the results from this study supersede the prior estimates in both scope and quality. The improvements to the study are as follows:

1. The meta-database has been updated to include results from utilities that previously declined to participate – extending the geographical coverage of the data to the north-central Midwest region and the time period covered by the database to 2005.
2. The interruption costs have been estimated in 2008 dollars by adjusting original estimates using the US Bureau of Economic Analysis GDP deflator.
3. The customer damage functions have been estimated using a two part model which we believe is more appropriate for estimating interruption costs than the Tobit model used by Lawton et. al. (2004)
4. The results have been summarized by customer type and size instead of by customer type only.

The 28 studies comprising the current meta-database were selected for study because they employed a common estimation methodology including: sample designs, measurement protocols, survey instruments, and operating procedures. This common survey methodology is described in detail in the Electric Power Research Institute *Outage Cost Estimation Guidebook* (Sullivan and Keane, 1995). The studies were carried out by major utilities in Southeast, Northwest, West and Midwest.

With the exception of aggregate interruption costs for Duke Energy and Mid-America (see Sullivan, Vardell, and Johnson (1997) and Chowdhury et al (2005)), none of the interruption cost information reported in the previous study and this one were widely available in the public domain before this research began.[2] So, one major benefit from this research is that the results of these important studies are now available in the public domain. Other benefits that arise from combining the data from these studies are:

1. Individual utilities typically represent only one region of the country whereas a combined data set allows interruption cost estimation across regions, observing differences in interruption costs associated with climate, energy prices, and economic conditions.
2. Utility customer populations are heterogeneous, particularly in the commercial and industrial (C&I) sectors; and combining data from a number of studies enlarges the number of cases considered from all businesses, allowing for the analysis of differences in interruption costs for different business segments.
3. All of the studies examined used a survey method in which customers were asked to state their costs for interruptions that could occur under varying conditions (e.g., time of day, duration, season extent of notice, etc). Several of these “scenarios” were common to all surveys, while others were unique to specific studies. So, the combined data from the studies allows both the comparison of customer interruption costs across the country for similar circumstances and estimation of the effects of specific circumstances that may have been studied on only one occasion.
4. Because several of the contributing utilities repeated their VOS surveys using exactly the same methodology at two points in time, it is possible to carefully analyze the change in interruption cost that occurred over a time.
5. The resulting regression models can be used to predict interruption costs for regions or utilities that do not have or plan to conduct VOS surveys.

The Methodology for Estimating Customer Damage Functions

The meta-analysis consists of two steps. The first step is to combine the results from the various studies into a single data base with common variable definitions. In this way the results from all of the studies are combined into one large data base consisting of responses of 11,970 firms and 7,693 households. Once this has been done, the second step in the meta-analysis is to analyze the data using statistical regression techniques to identify the best fitting customer damage functions for the data. Our procedures in carrying out these steps are discussed below.

[2] Many utilities routinely submit the full report from their value of service reliability studies to their state utility commissions and, in some but not all cases, these studies are accessible publicly from these commissions.

Combining Data Sets

Digital files and documentation describing the results of the 28 interruption-cost surveys were obtained from all of the participating utilities, in return for assurances that detailed data describing their customers would not be disclosed. Utilities that provided data included: Bonneville Power Administration, Cinergy (Now Duke Energy), Duke Energy, Mid America Power, Pacific Gas and Electric Company, Puget Sound Energy, Salt River Project, Southern California Edison, and Southern Company.

While the survey instruments and procedures were very similar in all of the above cases, the data was provided in varying digital formats with differing variable names. The first step in the process of consolidating the data was to convert the information in these 28 files into a common format with common variable definitions and names.

Meta-data sets were created for three customer groups: Small Commercial and Industrial customers (those operating facilities with less than 50 thousand annual kWh usage); Medium and Large Commercial and Industrial customers (i.e., those operating facilities with more than 50 thousand annual kWh usage); and, residential customers. The studies collected interruption cost data by describing hypothetical interruptions and asking customers to estimate the costs that would occur if they experienced interruptions of varying duration, at different times of the day and during different seasons. Residential customers were asked to indicate the amount they would be willing to pay to avoid interruptions occurring under the same conditions. Respondents were typically asked to estimate their costs for between four and eight hypothetical interruptions -- varying the onset times, durations, seasons, etc as described above. [3]

To adjust for the fact that these studies were conducted over a 16-year period, the interruption-cost estimates were adjusted for inflation to 2008 dollars using the US Bureau of Economic Analysis GDP Deflator.

Finally, we dealt with the significant outliers in the interruption cost data. Statistics derived from data sets that include outliers can be extremely misleading. Outliers can occur by chance in any distribution, but they are often indicative either of measurement error or that the population has a long-tailed distribution. In the former case outliers should be discarded or statistics should be used that are robust to outliers. In the latter case outliers indicate that the distribution has high kurtosis and that one should be very cautious in making the assumption of normality. A

[3] There has been a long simmering debate about the validity and reliability of customer reported interruption costs measured using survey techniques. There are two central criticisms of the use of survey methods to estimate customer interruption costs. The first applies generally to interruption cost surveys that use hypothetical interruptions as a framework within which to ask questions about interruption costs. In particular, there is concern that cost estimates based on hypothetical circumstances may over or under estimate the costs that occur under real conditions. There is no empirical evidence one way or another as to whether this concern is justified. A second concern applies principally to the measurements of interruption costs for residential customers that rest on what are called contingent valuation methods or stated preference methods. Contingent valuation studies have been the subject of considerable controversy – particularly as applied to the measurement of damage arising from environmental problems. The validity and reliability of various approaches to damage cost measurement using contingent valuation have been discussed at length in the literature. We cannot do it justice in the space available in this format. Those interested in this debate should see Mitchell and Carson (1989) or Horowitz and McConnell (2002).

common cause of the outlier problem is that that the so-called outliers belong to a different population than the rest of the sample set. For example, for medium and large C&I customers the top five values for a 1 hour interruption are greater than 100 million dollars, and the highest interruption cost reported in the distribution is 112,000 times the mean interruption cost. Whether these observations are due to measurement error or are a totally distinct population of customers is unknown in this case. Careful inspection of the data for the above described statistical outliers suggests that the costs they are reporting are plausible. They are reported by customers operating extremely large and complicated industrial facilities with very high energy use. Nevertheless, meaningful statistical modeling cannot be developed to take account of the interruption costs experienced by this numerically small but potentially important class of customers. Extreme outliers were therefore excluded.[4] Outliers were eliminated after first transforming the data to a lognormal scale (see the detailed discussion in Section 3.4 below). The total number of observations eliminated is approximately 2.8%.

Estimating Customer Damage Functions

Customers' economic losses as a result of reliability and power-quality problems can be summarized by what is called a customer damage function (CDF). This idea was first suggested in 1994 by Goel and Billinton (1994). They described the customer damage function as a simple linear equation relating average interruption cost to the duration of an interruption. They used data collected from customers to describe this function. In 1995, Keane and Sullivan suggested a more general form of the CDF – that could be used to predict interruption cost values from a number of variables that have been shown in interruption cost surveys to influence customer interruption costs. Their form of the CDF appears below:

Loss = f {interruption attributes, customer characteristics, environmental attributes}. *(1)*

The interruption cost (Loss) in Eq. 1 is expressed in dollars per event, per customer. The factors (*f*) on which interruption costs depends are defined as follows:

- *Interruption attributes* are factors such as interruption duration, season, time of day, and day of the week during which the interruption occurs.
- *Customer characteristics* include factors such as: customer type, customer size, business hours, household family structure, presence of interruption-sensitive equipment, and presence of back-up equipment.
- *Environmental attributes* include: temperature, humidity, storm frequency, and other external/climate conditions.

In the work described in this report, regression analysis techniques are used to study alternative specifications of the customer damage functions for commercial and residential customers and ultimately to summarize the impacts of interruption attributes, customer attributes, and environmental conditions on the economic losses that customers said would occur as a result of electric interruptions in numerous studies.

[4] It is also possible that such observations represent strategic responses designed to bias the results.

The ideal statistical framework for analyzing the above-described data is multiple regression. However, the use of an ordinary-least squares (OLS) approach to parameter estimation in regression is inappropriate because large percentages of respondents to interruption cost surveys report “0” (zero) interruption costs for short-duration interruptions.
To solve the above problem a two-part regression model was used to estimate the customer damage functions in this study. The two-part model assumes that the zero values in the distribution of interruption costs are correctly observed zero values. That is they are not errors. In the first step, a limited dependent model is used to predict the probability that a particular customer will report a value of zero versus any positive value for a particular interruption scenario, based on a set of independent variables which describe the nature of the interruption as well as customer characteristics. The predicted probabilities from this first stage are retained. In the second step, interruption costs for only those customers who report positive costs are related to a set of independent variables (which may or may not be the same as the independent variables used in the first stage). Predictions are made from this model for all customers, including those who reported zero interruption costs. Finally, the predicted probabilities from the “first part” are multiplied by the estimated interruption costs from the “second part” to generate the final interruption cost predictions.

The functional form for the second part of the two-part model, must take account of the fact that the interruption cost distribution is bounded at zero and extremely right skewed (i.e. has a long tail in the upper end of the distribution). OLS is not an appropriate functional form given these conditions. A simple way to define the customer damage function given the above constraints is to estimate the mean interruption cost, which is linked to the predictor variables through a logarithmic link function.

The values of the parameters in the two-part model cannot be directly interpreted in terms of their influence on interruption costs because the relationships are among the variables in their logs. However, the estimated model produces a predicted interruption cost, given the values of variables in the models. To analyze the magnitude of the impact of variables in the CDF on interruption cost, it is necessary to compare the predictions made by the function under varying assumptions. For example, it is possible to observe the effects of duration on interruption cost by holding the other variables constant at their sample means. In this way, one can predict average customer interruption costs of varying durations holding other factors constant statistically.

Results

Table ES- 1 displays estimated average electricity customer interruption costs for 2008 expressed in costs per event, costs per average kW demand and costs per annual kWh sales. Cost estimates are provided for three customer segments and for durations ranging from < 5 minutes (momentary) to 8 hours. They are reported for three customer classes defined as follows: Medium and Large Commercial and Industrial (all non-residential customers with sales > 50,000 kWh per year); Small Commercial and Industrial Customers (all non-residential accounts with sales <= 50,000 kWh per year); and residential customers.

The values in the table have been calculated using the general customer damage functions described in Sections 4-6 of this report. These chapters describe the development of three customer damage functions – one for each customer type (i.e., medium and large commercial and industrial customers, small commercial and industrial customer and residential customers). These customer damage functions provide estimates of the costs of interruptions of varying duration; occurring at different times of day (morning, afternoon and evening), days of week (weekends or weekdays) and season (summer and winter. They also provide estimates of interruption costs for customers of different size; and in the case of business customers, by business type (i.e., retail, utilities, construction, etc.). It is possible to estimate costs for planned as opposed to unannounced interruptions and for customers with and without backup generation. Thus by inserting reasonable assumptions about the interruption characteristics and customers into the customer damage functions, it is possible to use them to estimate the cost of a wide range of interruptions for a wide range of customers.

Table ES- 1. Estimated Average Electric Customer Interruption Costs US 2008$ by Customer Type and Duration (Summer Weekday Afternoon)

Interruption Cost	Interruption Duration				
	Momentary	30 minutes	1 hour	4 hours	8 hours
Medium and Large C&I					
Cost Per Event	$11,756	$15,709	$20,360	$59,188	$93,890
Cost Per Average kW	$14.4	$19.3	$25.0	$72.6	$115.2
Cost Per Un-served kWh	$173.1	$38.5	$25.0	$18.2	$14.4
Cost Per Annual kWh	$1.65E-03	$2.20E-03	$2.85E-03	$8.29E-03	$1.31E-02
Small C&I					
Cost Per Event	$439	$610	$818	$2,696	$4,768
Cost Per Average kW	$200.1	$278.1	$373.1	$1,229.2	$2,173.8
Cost Per Un-served kWh	$2,401.0	$556.3	$373.1	$307.3	$271.7
Cost Per Annual kWh	$2.28E-02	$3.18E-02	$4.26E-02	$0.1403	$0.2482
Residential					
Cost Per Event	$2.7	$3.3	$3.9	$7.8	$10.7
Cost Per Average kW	$1.8	$2.2	$2.6	$5.1	$7.1
Cost Per Un-served kWh	$21.6	$4.4	$2.6	$1.3	$0.9
Cost Per Annual kWh	$2.06E-04	$2.48E-04	$2.94E-04	$5.81E-04	$8.05E-04

The most widely used (and desired) metric for expressing interruption costs is the expected cost of un-served energy. Estimates of the expected cost per un-served kWh are presented in Table ES-1 and Table ES-5 below. This estimate was derived by dividing the interruption cost per event by [(annual kWh/8760) times the interruption duration]. While we recognize this calculation oversimplifies the estimation of un-served kWh, the data available concerning the distribution of customer loads and energy use across time is quite limited (i.e., annual kWh and in some cases annual maximum demand). It may be possible to derive more precise estimates of kWh un-served in future efforts, but the resources available to the current project did not permit exploration of the alternative ways that may be available (e.g., using load research data to develop hourly customer load shapes by season and customer type and then allocating annual kWh across the hours of the year).

The interruption costs in Table ES- 1 are for the average sized customer in the meta-database for interruptions originating on summer afternoons without advance notice. The average annual kWh usages for the respondents in the meta-database were as follows:

Sector	Annual kWh
Medium and Large C&I	7,140,501
Small C&I	19,214
Residential	13,351

The interruption cost estimates in Table ES- 1 describe the impact of duration on interruption costs for different types of customers and illustrate the dramatic differences in interruption costs for different type customers. These interruptions costs are appropriate for application to customers anywhere in the US within customer type. However, since the mixture of customers by type varies by geographical location, readers are advised to calculate location specify interruption costs using the equations described in chapters 4-6 taking account of locally available information about usage and business type to the extent that this information is available. The different interruption cost metrics in ES-1 can be used to calculate interruption costs using information about interruption frequency (i.e. cost per event), for kW un-served (cost per average kW demand) and for different quantities of un-served load per hour (i.e., cost per un-served kWh).

Table ES-2 through ES-5 display estimated customer interruption costs calculated for different kinds of interruptions and different kinds of customers for the US for interruptions occurring on summer weekday afternoons.

Table ES-2 displays the interruption cost per event for summer afternoon interruptions for non-residential customers of different business types. This table illustrates the wide variation in interruption costs that occur for different business types within medium and large and small firms. For medium to large sized firms, interruptions of one hour duration range in cost from about $8,000 for agricultural firms to about $47,000 thousand for manufacturing firms – a factor of almost 6. For small commercial and industrial customers, interruption costs vary from a low of about $461 per event for Public Administration to about $1,900 for Construction – a factor of about 4.

Table ES- 2. Estimated Average Electric Customer Interruption Costs Per Event US 2008$ by Duration and Business Type (Summer Weekday Afternoon)

Interruption Cost	Interruption Duration				
	Momentary	30 minutes	1 hour	4 hours	8 hours
Medium and Large C&I					
Agriculture	$4,382	$6,044	$8,049	$25,628	$41,250
Mining	$9,874	$12,883	$16,366	$44,708	$70,281
Construction	$27,048	$36,097	$46,733	$135,383	$214,644
Manufacturing	$22,106	$29,098	$37,238	$104,019	$164,033
Telecommunications & Utilities	$11,243	$15,249	$20,015	$60,663	$96,857
Trade & Retail	$7,625	$10,113	$13,025	$37,112	$58,694
Fin., Ins. & Real Estate	$17,451	$23,573	$30,834	$92,375	$147,219
Services	$8,283	$11,254	$14,793	$45,057	$71,997
Public Administration	$9,360	$12,670	$16,601	$50,022	$79,793
Small C&I					
Agriculture	$293	$434	$615	$2,521	$4,868
Mining	$935	$1,285	$1,707	$5,424	$9,465
Construction	$1,052	$1,436	$1,895	$5,881	$10,177
Manufacturing	$609	$836	$1,110	$3,515	$6,127
Telecommunications & Utilities	$583	$810	$1,085	$3,560	$6,286
Trade & Retail	$420	$575	$760	$2,383	$4,138
Fin., Ins. & Real Estate	$597	$831	$1,115	$3,685	$6,525
Services	$333	$465	$625	$2,080	$3,691
Public Administration	$230	$332	$461	$1,724	$3,205

Table ES-3 displays estimated utility customer interruption costs by customer type, for interruptions occurring during different seasons and days of the week. Average interruption costs vary by season and by time of day for each customer type. Interruptions in winter are generally less costly than interruptions occurring in summer. Interruptions are between 30% and 70% less costly on weekends than they are on weekdays for business customers. For residential customers, weekend interruptions are about 15% more costly than weekday interruptions. The difference between weekday and weekend interruption costs increases with interruption duration for both businesses and residential customers.

Table ES- 3. Estimated Average Electric Customer Interruption Costs Per Event US 2008$ by Customer Type, Duration, Season and Day Type

	Outage Duration				
Outage Cost	Momentary	30 minutes	1 hour	4 hours	8 hours
Medium and Large C&I					
Summer Weekday	$11,756	$15,709	$20,360	$59,188	$93,890
Summer Weekend	$8,363	$11,318	$14,828	$44,656	$71,228
Winter Weekday	$9,306	$12,963	$17,411	$57,097	$92,361
Winter Weekend	$6,347	$8,977	$12,220	$42,025	$68,543
Small C&I					
Summer Weekday	$439	$610	$818	$2,696	$4,768
Summer Weekend	$265	$378	$519	$1,866	$3,414
Winter Weekday	$592	$846	$1,164	$4,223	$7,753
Winter Weekend	$343	$504	$711	$2,846	$5,443
Residential					
Summer Weekday	$2.7	$3.3	$3.9	$7.8	$10.7
Summer Weekend	$3.2	$3.9	$4.6	$9.1	$12.6
Winter Weekday	$1.7	$2.1	$2.6	$6.0	$8.5
Winter Weekend	$2.0	$2.5	$3.1	$7.1	$10.0

Table ES-4 displays the interruption cost per event for summer afternoon interruptions for non-residential customers of different business types. This table illustrates the wide variation in interruption costs that occur for different business types within medium and large and small firms. For medium to large sized firms, interruptions of one hour duration range in cost from about $8,000 for agricultural firms to about $47,000 thousand for manufacturing firms – a factor of almost 6. For small commercial and industrial customers, interruption costs vary from a low of about $461 per event for Public Administration to about $1,900 for Construction – a factor of about 4.

Table ES- 4. Estimated Average Electric Customer Interruption Costs Per Event US 2008$ by Customer Type, Duration and Time of Day

Interruption Cost	Interruption Duration				
	Momentary	30 minutes	1 hour	4 hours	8 hours
Medium and Large C&I					
Morning	$8,133	$11,035	$14,488	$43,954	$70,190
Afternoon	$11,756	$15,709	$20,360	$59,188	$93,890
Evening	$9,276	$12,844	$17,162	$55,278	$89,145
Small C&I					
Morning	$346	$492	$673	$2,389	$4,348
Afternoon	$439	$610	$818	$2,696	$4,768
Evening	$199	$299	$431	$1,881	$3,734
Residential					
Morning	$3.7	$4.4	$5.2	$9.9	$13.6
Afternoon	$2.7	$3.3	$3.9	$7.8	$10.7
Evening	$2.4	$3.0	$3.7	$8.4	$11.9

The variations in interruption cost estimates in the foregoing tables are not random. Interruptions of different duration result in very different costs. Interruptions for some types of customers are very much more expensive than for others. Interruptions occurring during different seasons, days of the week and times of day all result in significantly different costs.[5] The differences are systematic and reflect the fact that different kinds of customers are differentially affected by different kinds of service interruptions. This inherent variation in the cost of service interruptions is an empirical fact that should not be ignored for purposes of computational convenience. That is, it is not appropriate to just pick one of the interruption costs (for a specific season, day of the week and onset time of day).

Of course, it is often the case that the variation in the reliability of the system with respect to season, day of week, and time of day is unknown. In such situations it is useful to apply what might be termed an "anytime" interruption cost. This is an average interruption cost that has been weighted so that it properly reflects the costs of interruptions in different seasons, on different days of the week and at different times of day. This cost is obtained by weighting the interruption costs for different time periods (in the customer damage functions) in such a way that differences in interruption cost by season, time of day and day of week are properly reflected in to the calculated average.

[5] Because of the large numbers of observations in the models used to estimate the customer damage function, the parameters in these models indicating the effects of season, time of day, customer type and duration are highly statistically significant. The statistical significance for each of these parameters is presented in the subsequent tables. P-values for the parameters generally exceeded significance at 99% or higher.

Table ES-5 displays the anytime average customer interruption costs for the US. The reader will note that these costs are significantly lower than the costs displayed in Table ES-1. In essence, the anytime interruption costs have been deflated to take account of the fact that many hours in the year (e.g., night time and on weekends) represent periods when customer interruption costs are relatively low – compared with the costs of interruptions during times when customers are using electricity. This is done by simply calculating the average interruption cost weighted for the amount of hours within a year by season, day of the week and time period during the day. In this way the wide variations that occur in customer interruption costs resulting in the different impacts of seasons, times of day and day of week can be taken account of in future cost benefit calculations. The anytime costs in Table ES-5 can be reasonably applied to indicators like SAIDI and SAIFI for purposes of calculating the impacts of system improvements that are expected to impact these indicators.[6]

Table ES- 5. Estimated Average Electric Customer Interruption Costs US 2008$ Anytime By Duration and Customer Type

Interruption Cost	Interruption Duration				
	Momentary	30 minutes	1 hour	4 hours	8 hours
Medium and Large C&I					
Cost Per Event	$6,558	$9,217	$12,487	$42,506	$69,284
Cost Per Average kW	$8.0	$11.3	$15.3	$52.1	$85.0
Cost Per Un-served kWh	$96.5	$22.6	$15.3	$13.0	$10.6
Cost Per Annual kWh	9.18E-04	1.29E-03	1.75E-03	5.95E-03	9.70E-03
Small C&I					
Cost Per Event	$293	$435	$619	$2,623	$5,195
Cost Per Average kW	$133.7	$198.1	$282.0	$1,195.8	$2,368.6
Cost Per Un-served kWh	$1,604.1	$396.3	$282.0	$298.9	$296.1
Cost Per Annual kWh	1.53E-02	2.26E-02	3.22E-02	$0.137	$0.270
Residential					
Cost Per Event	$2.1	$2.7	$3.3	$7.4	$10.6
Cost Per Average kW	$1.4	$1.8	$2.2	$4.9	$6.9
Cost Per Un-served kWh	$16.8	$3.5	$2.2	$1.2	$0.9
Cost Per Annual kWh	1.60E-04	2.01E-04	2.46E-04	5.58E-04	7.92E-04

Ideally, in calculating the interruption costs arising from the historical reliability of a given electrical system or part of an electrical system one must take into account the historical distribution of unreliability with respect to time on the circuit(s) of interest. Interruptions on circuits that are primarily composed of residential customers will result in very different

[6] For a discussion of the properties of these indices and the factors that influence their values see: "Tracking the Reliability of the U.S. Electric Power System: An Assessment of the Publicly Available Information Reported to State Public Utility Commissions", by Joe Eto and Kristina Hamachi LaCommare (2008).

customer interruption costs than interruptions on circuits with significant business customer loads. If the interruptions are concentrated in the afternoon (because of temperature or thunder storms) the costs of interruptions will be different than if they are concentrated in the early morning (because of animal contacts with equipment).

It is possible to build interruption cost estimation models that take account of these variations using the customer damage functions outlined in this paper in combination with detailed historical information about the temporal distribution of unreliability and the distribution of sales to customers of different types on the circuit(s) of interest. In essence, this involves estimating the economic cost that customers on the circuit(s) must have experienced (or will experience) based on the number of customers interrupted by type, for how long, during what season, time of day and day of week. While computationally intensive, this calculation is not particularly difficult to accomplish.

Concluding Remarks

This paper describes research designed to merge the results from 28 previously confidential or not widely available interruption cost surveys into several large, integrated data sets (for different customer types) that can be used to estimate electricity customer interruption costs for the US. The principal benefit of this work is the development of reliable estimates of customer interruption costs for populations of industrial, commercial, and residential customers in the US derived from a rich database of responses to customer interruption cost surveys. The interruption costs reported in this paper illustrate the usefulness of the customer damage functions that have been estimated using the meta-database assembled for this research.

Although customer damage functions reported in this paper represent a significant improvement over past information about customer interruption costs, there are limitations to how the data from this meta-analysis should be used. First, certain very important variables in the data are confounded among the studies we examined. In particular, region of the country and year of the study are correlated in such a way that it is impossible to separate the effects of these two variables on customer interruption costs. Thus, for example, it is unclear whether the higher interruption cost values for the southwest are purely the result of the hot summer climate in that region or whether those costs are higher in part because of the particular economic and market conditions that prevailed during the year when the study for that region was done.

There is also some correlation between regions and scenario characteristics. The sponsors of the interruption-cost studies were generally interested in measuring interruption costs for conditions that were important for planning for their specific systems. As a result, interruption conditions described in the surveys for a given region tended to focus on periods of time when interruptions were more “problematic” for that region (e.g., summer peak or months when thunderstorms are common). Unfortunately, the time periods when the chance of interruptions is greatest are not identical for all sponsors of the studies we relied upon, so interruption scenario characteristics tended to be different in different regions. Fortunately, most of the studies we examined included a summer afternoon interruption, so we could compare that condition among studies.

A further limitation of our research is that the surveys that formed the basis of the studies we examined were limited to certain parts of the country. No data were available from the northeast/mid-Atlantic region, and limited data were available for cities along the Great Lakes. The absence of interruption cost information for the northeast/mid-Atlantic region is particularly troublesome because of the unique population density and economic intensity of that region. It is unknown whether, when weather and customer compositions are controlled, the average interruption costs from this region are different than those in other parts of the country.

This paper has removed an important barrier to the widespread use of value based reliability planning in regulation and utility system planning – the availability of reasonable estimates of customer interruption costs. There are others. Additional work that needs to be done includes:

1. Additional interruption cost surveying should be carried out in regions where information on customer interruption costs is currently unavailable (i.e., the Northeast Corridor and the Northern Tier of the Mid-West)
2. An easy to use interruption cost calculator should be developed driven by the customer damage functions described in this paper.
3. Additional work should be carried out to develop the ability to model uncertainty in interruption cost estimates
4. Robust examples of the use of customer interruption costs to assess the benefits arising from different kinds of reliability reinforcements and regulatory decisions should be developed and published
5. Additional basic research is needed to develop reasonable ways of using customer interruption cost information with currently used indicators of reliability performance (e.g., SAIFI and SAIDI); estimate partial interruption cost; and develop modern and less expensive techniques for estimating customer interruption costs.

1. Summary of Data and Overview of Analysis

The discussion of the background for this research and the basic approach to database assembly was presented in the report provided by Lawton et. al. in 2004. It is repeated and updated here for the convenience of the reader.

Ensuring reliability has and will continue to be a priority for electricity industry expansion and restructuring. Reliable electric power delivered on demand is a cornerstone of electricity's ubiquitous adoption and use. A central feature in electricity's value to consumers, whether they are individual households or large industrial complexes, is the infrequent occurrence of interruptions or other power disturbances that interrupt the use of appliances, motors, electronics, or any of the other myriad of end uses for which electricity is the primary energy source.

While no one disagrees that customers seek reliable power, ensuring reliability is a complex and multi-faceted problem. The strategies available to meet that goal are numerous and the price tags associated with them vary greatly. Most important of all, reliability has always been a shared responsibility because it is a public good. Therefore, who pays and who benefits from increased reliability has always been an important question for both private and public decision makers.

Underlying any strategy is assumptions about the value end-use customers place on reliability. During times of crisis caused by either short-term events, a common (yet, we believe inappropriate) assumption is that customers will pay almost any price for reliable power. In contrast, during periods of reliable power delivery but accompanied by rising rates or rising taxes, there are frequent charges that the system is being overbuilt and designed to a higher standard of reliability than customers are willing to pay.

A general framework for addressing this planning problem has been the application of value-based planning. For example see: (Munasinghe, 1979), (Burns and Gross, 1990), (Sanghvi et al., 1991), (Allan and Billinton, 1992), (Sullivan et al., 1996), (Sullivan and Keane, 1995), (Vojdani et al., 1996), (Wacker et al., 1983), (Wojczynski et al., 1983), (Woo and Train, 1988), (Matsukawa and Fujii, 1994), (Dalton et al., 1996), (de Nooij et al, 2006) and 2008), (Ghajar and Billinton, 2005), (Billinton et al., 1983), (Wangdee and Billinton, 2004), (Reitz and Sen, 2006) and (Rose et al, 2007) (LaCommare and Eto, 2006)

Value-based planning is designed to match the level of investment in reliability with the societal benefit of the improvement in reliability. The use of value-based planning requires a method for estimating customers' economic value of service reliability. Historically, generation, transmission, and distribution systems investments have been planned using engineering criteria that do not consider the economics of the decision. With value-based planning, it is assumed that customer preferences for service reliability can be measured and that these preferences can be used to establish economically justified reliability targets for generation, transmission, and distribution investments.

In the application of value-based planning, the value of service reliability to customers has been conceptualized as equal to the economic losses that customers would experience if a given interruption occurred.[7] The economic losses experienced by customers as a result of reliability or power quality problems can be described by a Customer Damage Function (CDF)[8]. The general form of a CDF is:

Loss = f{interruption attributes, customer characteristics, geographical attributes}.

The dependent variable of economic loss is expressed as a loss in dollars per event, per kWh of un-served energy, per kWh of annual energy consumption or per kW of annual peak demand. The equation predicts the economic loss from factors that influence interruption costs.[9] The interruption attributes might include duration, season, time of day, advance notice and day of the week. The customer characteristics could include annual kWh usage, kW demand, type of business, type of household, presence of various interruption sensitive equipment, presence of backup equipment, and other firmographic or demographic characteristics. Finally geographical attributes might include temperature, humidity, frequency of storms and other geographical conditions affecting economic losses from interruptions.

Customer damage functions are useful for reliability planning in several ways. First, the customer damage function provides a framework for conceptualizing and estimating the factors that influence customers' interruption costs for particular types of interruptions. Second, the use of a customer damage function allows for analysis of the isolated effects of different attributes of interruptions such as duration or time of day. Third, it can be used to quantify the economic losses from different electricity system reliability investments by multiplying appropriately defined customer damage functions by the un-served energy expected under different system investment options. These calculations then become the basis for comparing different reliability solutions and evaluating whether the economic benefits to customers are justified by the costs of the investment options.

The use of customer damage functions and value of service reliability estimates applies to many investment decisions facing utility planners, regulators, and policy makers. To compare alternatives in a planning framework, the calculations may focus on the economic costs or benefits of changes in un-served energy, the frequency of key events like momentary interruptions or voltage sags), or other aspects of the economic value of reliability. A few examples serve to illustrate:[10]

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[7] In practice, for residential customers the surveys in this study rely on willingness-to-pay and/or willingness-to-avoid questions. These are taken to be alternatives to direct measurements of measuring residential customers' value of service reliability. Some additional analysis of the relationship between the WTP/WTA responses and the direct interruption cost measures would be of interest in assessing the difference between the two measurement approaches, however budget limitations precluded us from pursuing it at this time.

[8] For a discussion of the application of such functions to electric power supply reliability planning see "Prediction of Customer Load Point Service Reliability Worth Estimates in an Electric Power System," L. Goel and R. Billinton, 1994, IEEE Proc.-Gener, Tans, Dist, Vol.141, No. 4, July 1994.

[9] In this report, we use the term "customer interruption costs" to refer to value of electricity service reliability estimates developed through either surveys of the economic losses customers experience as a result of electric service interruptions or those developed through surveys of customers' willingness-to-pay to avoid/willingness-to-accept compensation for such problems.

[10] Detailed examples of the use of interruption costs in various generation, transmission, and distribution planning situations are provided in "Outage Cost Estimation Guidebook", M. Sullivan and D. Keane, TR-106082, Electric Power Research Institute, Palo Alto, CA: December , 1995.

- Generation planning: As utilities add capacity, the probability of a generation capacity shortfall declines and the cost of un-served energy at the time of peak demand declines. Reducing the amount and hence cost of un-served energy is valuable to customers, the question is whether these benefits outweigh the costs of obtaining them. By analyzing how the benefits from reducing un-served energy are distributed across customer classes and by knowing the economic value of that un-served energy has for different customers, planners can determine whether costs to improve system generation reliability are balanced with the value of the improvement to customers.
- Transmission planning: Transmission planners analyze the reliability of transmission lines to assure sufficient capacity exists to serve customers under different failure contingencies. With value-based planning, the failure scenarios can be examined based on the number and frequency of voltage sags or power quality events they create and the costs to reinforce the system to reduce these power quality problems. By comparing these costs to the economic value to customers of the reduction in power quality problems, decisions can be made as to whether system reinforcement creates sufficient net benefits to justify these added costs. The customer damage functions, combined with the estimates of the frequency with which certain events might occur, serve as the basis for calculating the economic value of various options.
- Distribution planning: Customers on a distribution circuit can be served with different circuit design configurations (e.g., radial, loop, networked, with or without different Smart Grid). Each configuration varies in its cost to implement and each has different implications for the expected frequency and duration of interruptions to customers served by these circuits. Planners can compare options by calculating the expected un-served energy from various circuit designs and by examining the types of customers currently on the circuit and forecasted to locate near the circuit through time. They can also compare designs on the likelihood of various power quality problems. Using a customer damage function, the economic value of the reliability improvements can be calculated for specific groupings of customer types and for the specific reliability problems/improvements anticipated for a given circuit. This economic value can be compared to the cost of various options to balance the costs with the anticipated benefits.

Value-based planning concepts have been around for 20 or more years. Over this period, there have been numerous studies to quantify the value of reliability as a basis for both public policy and private investment, and for operating decisions regarding generation, transmission, distribution, and retail offerings. Efforts have been made to measure interruption costs or value of service using a range of methods and techniques. See for example: (Lawton et. al. 2004), (Keane and Woo, 1992), (Sullivan et. al. 1996), (Woo and Train, 1988), Matsuaka and Fujii, 1994), Wacker, Wojczynski and Billinton (1983), (Billinton, Tollefson and Wacker, 1992), (Caves et. al. 1992), (Beenstock et. al. (1997), (Doane, Hartman and Woo, 1988), (Hartman, Doane and Woo, 1991), (Woo and Pupp, 1992), (Balducci et. al, 2002), (Gilmer and Mack, 1983).

Despite these efforts, Eto, et al. (2001) noted that there were few estimates of the aggregate cost of unreliable power to the U.S. economy, and the estimates that were available were poorly documented or based on questionable assumptions. Costs of large-scale interruption events (e.g., State- or region-wide power interruptions) were not well documented and were mostly based on natural disasters for which it is difficult to separate costs of electric interruptions from damages caused by other disaster features (e.g., property damage from wind or water). Studies of hypothetical interruptions obtained from interruption cost surveys could be used to prepare aggregate estimates of interruption costs. However, there are important differences in the survey and statistical methodologies used in the studies that must be addressed in any meta-analysis relying upon them. Finally, very little information was available in the public domain regarding the costs of power quality problems – an increasingly important aspect of service reliability.

In 2002 LBNL sponsored an effort to assemble the data from a large number of studies for which results had never been reported in the public domain and prepare a statistical meta-analysis designed to estimate customer damage functions for utility customers in the US. See Lawton et. al. (2004).

The research effort assembled respondent level data from 24 studies carried out by 8 major US utilities over the course of 13 years. These studies were based on carefully executed customer interruption cost surveys of residential, commercial and industrial customers. This report describes the expansion and continuation of that research effort and incorporates a number of improvements in the data processing and econometric techniques designed to estimate general customer damage functions.

The credibility of the estimates rests to a large extent on an understanding of how interruption costs were estimated in the various studies and how they have been combined. The studies chosen for this research were selected because they employed a common survey methodology including sample designs, measurement protocols, and survey instruments and operating procedures. This methodology is described in detail in EPRI's *Outage Cost Estimation Guidebook* (Sullivan and Keane, 1995). A brief discussion of this methodology can be found in Appendix B.

The 28 studies used in this research include observations from virtually all the Southeast, most of the western U.S. (including almost all of California, rural Washington and Oregon, and the largest metropolitan areas in Arizona and Washington), and the Midwest south of Chicago. The time frame covered by the studies ranges from 1989 to 2005 – a period of 16 years. Several studies examined interruption costs for similar customer populations (e.g., residential customers) at roughly the same time using nearly identical measurement protocols, but were conducted by utilities located in different parts of the country. Moreover, more than one of participating utilities had measured customer interruption costs using the same instruments and procedures at different points in time – one after five years and another after 12 years. In almost all of the studies, detailed demographic and firmographic information was collected from study respondents and incorporated into the database of results.

While each individual study was extensively analyzed by the utility that conducted the study for their own use, until this research was undertaken in 2002 there had been no efforts to combine the data from the studies into a single database. The value of combining the data and developing a set of meta-models is the prospect of extending the results of the individual studies in several ways:

- Individual utilities typically represent only one region of the country, whereas a combined dataset provides an opportunity to evaluate value of service across regions that will include differences in temperature, humidity, energy rates, and regional economic conditions.
- Utility customers are heterogeneous, particularly in the commercial and industrial sectors. Combining the data provides additional cases to examine value of service for important sub-segments (i.e., business types).
- Most of the studies examined here use a survey method in which customers responded to various interruption scenarios. By combining the data across studies, a broader range of scenarios can be used to estimate the impacts of time of day, duration, season, and certain special conditions, such as receipt of advance notice.
- Because some of the studies were carried out at different times for the same geographical area, it is possible to assess how customer interruption costs are changing for different customer types as time passes.

Combining the data has several positive features, but there are also limitations with which to contend. First, because the studies were conducted for specific utilities at specific points in time some variables of interest are "collinear" with each other. Consequently, it is impossible to develop a model that separates the impacts of time and geography. Second, the studies chosen for this combined dataset used similar methods for collecting the data but they did not necessarily use identical methods. As a result, it is important to consider that some effects identified in the data may be the result of "methods" effects rather than substantive effects of different variables.

1.1 Data Update

The major objective of this project was to identify, gather, and combine the data from prior utility value of service or interruption cost studies into separate databases containing the findings for three distinct customer groups: residential, small commercial and industrial (C&I), and medium and large C&I. As part of the initial review of past studies, 12 utilities were identified that had measured customer interruption costs using survey-based methods for one or more of these three customers groups. Altogether, 28 datasets from 10 companies were ultimately acquired, standardized, and then merged. While each dataset presented certain issues (see Appendix A), it was possible in most cases to develop rules for combining the data from the separate studies into meaningful meta-datasets based on common questions and metrics.

The following steps were taken in creating the databases:

1. Contact the utilities that had conducted customer interruption cost (or Value of Service or interruption cost) studies;
2. Negotiate agreement(s) to participate in the study, including agreements not to disclose customer-specific information or present information that could be attributed to an individual firm;
3. Obtain the datasets, codebooks, and original survey questionnaires;
4. Standardize each dataset in terms of variable selection and construct;
5. Merge the datasets;

6. Normalize interruption costs to a common base year (2008), using the GDP deflator; and,
7. Review the data and exclude outliers and other data anomalies.

The core elements of this process are described in this chapter. Additional details are provided in Appendix A.

First, all variables were standardized using common metrics. For example, some studies may have described the interruption duration in hours (e.g., a 1 hour interruption) while others may have used minutes (e.g., a 30 or 60 minute interruption). In this instance, the results for both studies were converted to minutes. Although the survey instruments for the various studies may have used slightly different wordings, each study measured the same basic underlying concepts. These included:

- Attributes of the Interruption (e.g., duration, frequency, season, time of day)
- Summary of Costs (e.g., labor costs, material costs, damage costs)
- Customer Characteristics (e.g., company size, household income)

Second, all of the scenarios were hypothetical. This is both a strength and weakness of this body of studies. The goal in presenting customers with hypothetical interruption scenarios is that they can respond to the same stimulus (a carefully controlled description of a series of interruptions). This simplifies associating costs and customer characteristics with attributes of interruptions like duration and time of day. However, because these are hypothetical, customers do not provide actual costs for actual events. Instead, they are asked to carefully estimate their costs for the hypothetical situations, regardless of previous interruption experiences. We cannot determine, prime facie, the biases inherent in such self-reports of cost estimates associated with hypothetical interruption scenarios.

Third, the interruption scenarios varied in several ways, including

- duration,
- onset time of day
- onset day type (weekday or weekend)
- season (summer or winter)
- Extent of advance notice of upcoming interruption

Because planners are typically interested in interruptions occurring under specific system conditions, many interruption scenarios described interruptions associated with system peak conditions. For example, studies conducted in northern climates were focused primarily on winter interruptions, while those in southern climates were focused primarily on summer interruptions. Some studies measured interruption costs for momentary interruptions, while others did not. Some studies measured costs for long interruptions (i.e., 8-12 hours), while the maximum interruption duration was limited to 4 hours in others. The most commonly used interruption scenarios involved interruptions of one- and four-hour durations occurring on summer afternoons. Most of the studies included a common 1-hour interruption occurring at time of system peak for all observations.

Fourth, the studies were conducted over a 16-year period. The results from each study are appropriate for the time period during which the data were originally collected. To compare the results across time it was necessary to take account of inflation and changes in the cost of living. Accordingly, all of the cost data have been adjusted to 2008 dollars using the US Bureau of Economic Analysis GDP Deflator.

The strategy used to collect interruption cost data in most of these studies involved presenting customers with a series of hypothetical interruptions and asking them to describe their costs (or to respond to a willingness to pay to avoid their costs) to each one. Each respondent provided cost estimates for more than one scenario (in some cases, up to 8 scenarios). Statistical power of the results was enhanced by organizing the data so that the responses for each scenario in a survey were treated as independent observations or records. For example, if one respondent provided separate cost estimates for each of 3 scenarios, then these results were converted into three separate records in the meta-database. The common variables, e.g., firmographic information such as SIC code, were appended to each record.

As explained above, meta-datasets were created for three customer groups: residential, small C&I (50 thousand annual kWh or less) and medium and large C&I (more than 50 thousand annual kWh). The commercial and industrial datasets include the following information on each observation:

1. Season
2. Onset time of day
3. Onset day of week
4. Interruption duration
5. Whether advanced warning was received
6. Year interruption cost study was completed
7. Estimated interruption cost;
8. Customer's SIC code
9. Customer's business type
10. Number of employees
11. Whether company has back-up generation
12. Customer's annual kWh consumption

The residential customers' survey included similar interruption scenario information (items #1-7, above) but also included:

1. Willingness to pay measure (WTP)
2. Willingness to accept credit (WTA)
3. Type of housing
4. Home ownership
5. Household income
6. Whether household has sickbed resident
7. Whether household uses medical equipment in the home
8. Whether household has a home business

The commercial and industrial, and the residential datasets are also differed from one another in other important respects, as described below.

1.2 Commercial and Industrial Datasets

Development of commercial and industrial sector databases involved creating separate databases for the medium and large C&I and small C&I data. Each includes enterprises involved in all aspects of commercial and industrial activity as well as government services. Although utilities use slightly different criteria for defining small, medium and large customer classes, we used common criteria to assign customers to either small versus medium and large C&I. The small commercial and industrial customer was defined as a one using 50 thousand kWh annually or less. The medium and large C&I customer was defined as a customer using more than 50 thousand kWh annually.

For both commercial and industrial customers, all of the studies employed the same interruption cost estimation methodology – direct worth or direct cost estimation (see Appendix C). In the direct worth estimation methodology, customers were asked to estimate the losses they would experience under varying assumptions about the timing, duration and extent of electric interruptions. In most cases, the estimation involved customers completing a worksheet for each scenario in which they reported various types of costs and various types of savings. These costs and savings were then summed to calculate a net cost of the interruption. Customers were generally asked to provide estimates for four to ten scenarios (i.e., combinations of onset time, duration, extent of advance warning, season and day of the week). Thus, these studies produced a range of estimated interruption costs for each customer – one for each combination of interruption conditions on which they were asked to report. It is not uncommon for some of the customers within a given study to receive one randomly chosen set of interruption conditions, while others receive a somewhat different randomly chosen set.

For the two commercial and industrial datasets, the primary dependent variable is total cost of the interruption on a per event basis. In most cases, demand and usage information for each customer was also available and, for reporting purposes, was used to express interruption cost on a per average kW[11] and per annual kWh basis.

1.3 The Residential Dataset

Unlike the commercial and industrial customers where costs associated with an interruption can be converted into an economic loss based on lost profits or costs over savings, the costs of interruptions to residential customers are often more intangible. Residential customers tend to describe their costs in terms of the "hassle" or "inconvenience" of an interruption rather than in terms of specific labor or material costs. For this reason, most of the residential interruption cost studies in this meta-analysis use some form of 'willingness to pay' (the amount the household respondent would be willing to pay in order to avoid an interruption of a certain scenario) as the

[11] The use of average kW in this report is different from many previous studies where maximum kW demand is used. Maximum kW is not used in this report because it is not included in many of the datasets. Instead, average kW is calculated by dividing annual kWh by 8760 hours/year. If necessary, maximum kW can be estimated by dividing average kW by an assumed load factor.

dependent variable (rather than rely on estimation of direct costs)[12]. The meta-analysis described here focuses on these ‘willingness to pay’ measures.

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[12] Some of the studies measured willingness to pay, willingness to accept and direct worth interruption cost estimates. Willingness to accept and direct worth measurements were not analyzed in developing the customer damage functions reported in later sections.

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[14] The validity and reliability of various approaches to damage cost measurement using contingent valuation have been discussed at length in the literature. We cannot do it justice in the space available in this format. Those interested in this debate should see Mitchell and Carson (1989) or Horowitz and McConnell (2002).

2. Methodology

2.1 The Nature of Interruption Cost Data

The distribution of reported interruption costs has at least three characteristics which present significant challenges to the modeling exercise contemplated here. First, a significant portion of the observations have a value of zero. For example, 33.3% of reported interruption costs for medium and large C&I customers are zero. Second, the nonzero interruption costs are significantly right-skewed (for most of this range, interruption costs are approximately lognormal). Third, the right tail of the distribution deviates substantially from log normality due to excess kurtosis.[15] For example, for medium and large C&I customers, the value of the distribution of interruption costs at the 95th percentile is more than 1,000 times larger than the figure at the 5th percentile. In addition, there are a small number of large customers whose interruption costs are several orders of magnitude higher than other respondents. Given these characteristics, it is likely that standard regression techniques (e.g. OLS) will produce extremely unreliable results, subject to serious bias and inflated error variances.

There is a significant literature dealing with analysis of data on healthcare expenditures which has similar properties (See Jones (2000) for an overview). For example, annual data on healthcare expenditures is characterized by a large cluster of data at 0 and a right skewed distribution of the remaining outcomes. For instance, people who do not get sick generally use $0 of medical care in a given year. Of those who do get sick, most are not seriously ill, but there will be a subset of the population who will incur significant medical expenses. In addition, there will be a small number of outliers with extremely expensive medical care. From an applied statistical perspective, how should one take these characteristics into account? These issues are addressed below.

2.2 Outliers

The distribution of interruption costs contains significant outliers. For example, as indicated above for medium and large C&I customers the top five values for a 1 hour interruption are greater than 100 million dollars, and the highest interruption cost reported is 112,000 times that of the mean interruption cost. Outliers are generally classified as mild outliers or extreme outliers. In statistical terms a value X is an extreme outlier if:

$$X<Q1-3*IQR \qquad (1)$$

$$X>Q3+3*IQR \qquad (2)$$

Mild outliers are any data values which lie between 1.5 times and 3.0 times the interquartile range below the first quartile or above the third quartile. We computed the implied cutoff values based on the medium and large C&I survey responses for a 1-hour interruption. The results are described below:

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[15] For example, for the data on medium and large C&I customers, the test for normality fails to reject the null hypothesis of normality for the skew of the distribution, but easily rejects the null based on excess kurtosis.

	Low	High
Mild Outlier cutoff points	-6,448.3	11,451.9
# mild outliers	0	578
% mild outliers	0.00%	4.05%
Severe Outlier cutoff points	-13,160.8	18,164.4
# severe outliers	0	1618
% severe outliers	0.00%	11.34%

Unfortunately, the extreme kurtosis of the data leads the standard method to reject a substantial fraction of the dataset (15%) as outliers. However, because the data are approximately lognormal over a most of the distribution, and the form of the primary interruption cost regression is logarithmic, it appropriate to examine the data in log form. In natural logarithms, the outlier diagnostics provide much more reasonable results:

	Low	High
Mild Outlier cutoff points	1.794	13.440
# mild outliers	4	51
% mild outliers	0.04%	0.55%
Severe Outlier cutoff points	-2.573	17.810
# severe outliers	0	0
% severe outliers	0.00%	0.00%

For the regression analyses presented in this report, both the mild and severe outliers were eliminated using the above procedure, except that these criteria were applied within industry and duration for log interruption costs and within industry for log annual kWh usage. For all C&I data combined, approximately 2.8% of cases are excluded owing to outliers and missing data, leaving 51,741 cases available for calculating total cost. For the residential dataset, approximately 2.7% of cases are excluded owing to outliers and missing data, leaving 26,026 cases available for calculating total cost.

2.3 Functional Form and Transformation

Excluding the zeros and outliers, the distribution of interruption costs is approximately lognormal. For such distributions, estimation using logged estimates will often yield more precise and robust results than direct analysis of unlogged dependent variable. As such, one might propose the following simple loglinear specification for interruption costs, where C_i represents reported interruption costs for each scenario and X_i represents a vector of scenario-related and firmographic variables:

$$c_i = \ln(C_i) \qquad (3)$$

$$x_i = \ln(X_i) \qquad (4)$$

$$c_i = \beta \cdot x_i + u_i \qquad (5)$$

Of course, we are not interested in log scale results per se. The question then arises how to derive the desired predictions of raw interruption costs $\hat{C}_i$ from the estimated equation above. Note that taking the antilogarithm of the predicted values from the loglinear equation above will *not* yield the desired predictions, i.e., $\exp(\hat{C}_i) \neq \hat{C}_i$. Indeed, given the nature of the data on interruption costs, the results of that procedure are likely to be far from the correct values.

Many economic models specify loglinear relations between variables, which means that after a log-transformation of the dependent variable, and possibly independent variables, the model is a standard linear regression model in the transformed variables. The transformed model can therefore be estimated by OLS and optimal predictors for the transformed dependent variables are easily obtained. However, one is generally interested in predicting the original variables, not the variables in logs. One solution is just to take the inverse transform of the optimal predictor in the transformed model, i.e. take the exponential of the optimal predictor from the loglinear model. This solution is not optimal for the original variable because the nonlinear (inverse) transformation results in a biased predictor, due to both the distribution of the estimator and the random nature of the disturbance term. The problem is one of relating (conditional) expectations before and after a nonlinear transformation. This relation is trivial in linear models but for nonlinear models the problem cannot usually be solved analytically.

If the error term u_i is both normal and homoskedastic, then the predicted values can be recovered via the following relation:

$$E[C_i \mid X_i] = e^{\beta \cdot x_i + \frac{\sigma^2}{2}} \qquad (6)$$

Where σ^2 is the variance of the error u. Of course, the assumption of normality and homoskedasticity is unlikely to hold in general and in particular is extremely unlikely to hold for the interruption cost data at issue here. If the data are nonnormal, another option is the "smearing" estimator of Duan (1983), where the $\sigma^2/2$ factor is replaced by the mean of the antilog of the residuals, however this estimator also assumes homoskedasticity.[16]

The fundamental issue here is not one of simply transformation but a broader question of functional form. Of course, one simple approach would be (despite the characteristics of the data described above) to use OLS on the raw interruption cost data. The advantage of this approach is simplicity – there is no retransformation issue with a purely linear model and the effects of various factors on interruption costs can be clearly observed. The disadvantages, however, are numerous and fatal. First, the high skew of the underlying data means that the results are not robust to smaller data sets, i.e., the results from one dataset may provide poor predictions for another dataset. OLS can also produce negative interruption costs. OLS will be extremely inefficient in the statistical sense due to the enormous residual variance

A simpler way to address the issue is to abandon the goal of estimating E[log(Y)|X], in favor of estimating log(E[Y|X]). In other words, we estimate the mean interruption cost, which is linked to the predictor variables through a log function, while the loglinear approach models the mean $\log(C_i)$. Another way of thinking about the difference between these two models is that the GLM

[16] See Ai and Norton (2000).

approach models the arithmetic mean of interruption costs, while the standard loglinear approach models the geometric mean of the interruption cost. Of course, the estimated parameters will then be arithmetic means instead of geometric means, but in our case the primary goal is the generation of accurate interruption cost predictions under various scenarios, rather than the interpretations of individual parameters per se. Another advantage of the GLM approach is that arithmetic means are still even when the outcome is zero, and thus such an approach could be used to model interruption costs including the zero values (although the use of the two-part model obviates the need to do so).

Following the approach laid out by Manning and Mullaly (1999), the GLM framework is specified by two relationships. The first specifies the mean function for the observed raw-scale variable C_i (interruption costs in our case) conditional on a set of independent variables X_i:

$$\ln(E[C_i]) = \beta \cdot X_i \qquad (7)$$

or

$$E[C_i] = \mu(\beta \cdot X_i) = e^{\beta \cdot X_i} \qquad (8)$$

The second relationship relates the variance function for Y to X:

$$Var(C_i) = \sigma^2 \cdot v(X_i) \qquad (9)$$

It is useful to consider a general class of variance functions of the form:

$$V(C_i) = \kappa(\mu(\beta \cdot X_i))^\gamma \qquad (10)$$

where γ must be finite and non-negative. In the case γ=0, we obtain the usual nonlinear least squares estimator. In the case γ=1, we obtain the Poisson like class, where the variance is proportional to the mean, which is itself a function of X. In the case of γ=2 we get the gamma family of distributions, from which the lognormal, Weibull, and Chi-squared are variants depending on the shape parameters. Manning and Mullaly (1999) note that the family of gamma models (γ=2) are in some respects a natural "baseline" specification, since if the true model is actually C= exp(X·β)*u, then it is natural to suggest that Var[C|X] is proportional to the mean E[C|X] squared. Deb, Manning and Norton (2006) suggest the use of the GLM Family Test (a variant of the Park test) to identify the correct value of gamma. The purpose of the GLM Family Test is to determine the relationship between the mean and variance as specified in the last equation above. The procedure for implementing the test is as follows:[17]

1. Regress interruption costs C_i (raw scale) on X_i (using either OLS or GLM)
2. Save the raw scale residuals $\hat{u}_i$ and $\hat{C}_i$, the predicted values of C_i
3. Regress the log of the estimated residuals on the log of the predicted values. The estimated coefficient $\hat{\gamma}$ from this regression gives the family:

[17] See Pregibon (1980).

If $\hat{\gamma}=0$, Gaussian NLLS (variance unrelated to mean)
If $\hat{\gamma}=1$, Poisson (variance equals mean)
If $\hat{\gamma}=2$, Gamma (variance exceeds mean)
If $\hat{\gamma}=3$, Wald or inverse Gaussian

The estimated values of gamma for the three customer groups are presented below:

	Estimate of Gamma	Standard Error
Medium and Large C&I	1.919	0.00608
Small C&I	1.844	0.01083
Residential	1.654	0.02997

Although the high number of observations and resulting low standard errors lead to a rejection of the null hypothesis that gamma=2 in each case, the fact that the values are close to 2 strongly favors the use of the gamma family of errors. Thus the decision was made to employ GLM with a logarithmic link function with gamma distributed errors.

Because the total number of observations represent the answers to multiple scenarios (up to 6), the standard errors presented in all of the regression estimates contained in the report are adjusted to reflect clustering by respondent.[18]

2.4 The Regression Specification

Previous literature has dealt with the peculiarities of interruption cost data using a variety of regression specifications, many of which can be described under the general rubric of switching regressions.[19] The most general setting is as follows:

Regime 1: $y_i = \beta_1' X_{1i} + u_i$ if and only if $\gamma' Z_i \geq u_i$

Regime 2: $y_i = \beta_2' X_{2i} + u_i$ if and only if $\gamma' Z_i < u_i$

The first term in each of the two regime descriptions above, where the presumed variable of interest y_i is related to a set of determinants ($\beta_1' X$) is sometimes referred to as the outcome equation. The second term ($\gamma' Z$) which specifies the determination between the two regimes is sometimes referred to as the selection equation.

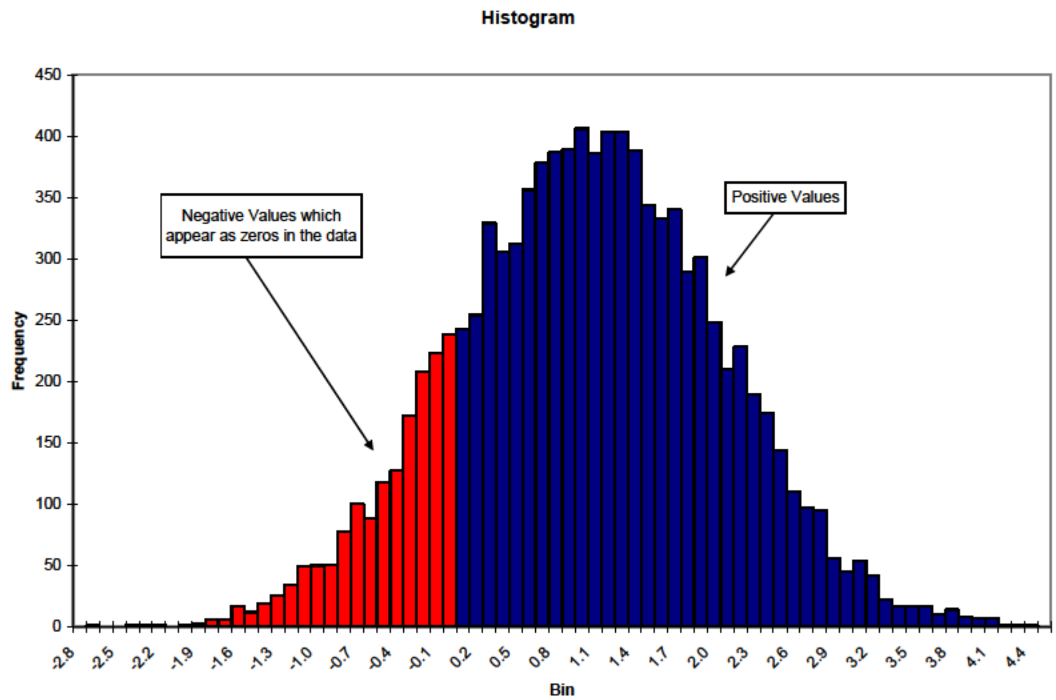
[18] See the svy command in the Stata reference manual.
[19] Although the terms switching regression and selection model are sometimes used interchangeably, technically selection models as well as both endogenous and exogenous switching models are distinct classes depending on which of the two regimes are observed versus unobserved and whether the selection equation is linked to the outcome equation. As is explained below, because we assume that both regimes are observed (whether or not interruption costs are positive) and that the regime indicator has no effect on the outcome (interruption costs), the distinction is moot with regard to our analysis.

Censored and truncated models, selection models (such as the Heckman two-step model), and the two-part model employed here are all particular applications of switching regressions. In censored or truncated models, the outcome variable y_i is only observed in one regime state. Matters may be further complicated when the same factors that determine the regime affect the outcome variable. With respect to interruption costs, the selection model determines whether or not respondents report positive interruption costs for the scenario in question. The outcome model relates interruption costs to the scenario-related and firmographic variables, conditional on the fact that interruption costs are indeed positive.

Although an interruption cost which is reported as zero may indeed be some small positive number which is too troublesome to compute exactly, there is no issue of truncation or censoring. That is the zeros do not represent values below zero that have somehow been censored. The standard Tobit model assumes that the observations are left-censored at zero, that is, that values which are zero are actually negative. Figure 1 displays a graphic comparison of a distribution that corresponds with the form for which the Tobit model is appropriate and the actual distribution of interruption costs observed in this study for Medium and Large Commercial and Industrial Customers. In the figure it is evident that the distribution of interruption costs is not at all similar to the distribution that is left censored.

Figure 2-1, shows that the distribution of interruption costs increases uniformly as the value of interruption costs decrease, until the point mass at zero is reached. Although interruption costs may decrease for some time over some duration, by definition net interruption costs cannot be negative, and in addition to reported interruption costs of zero there are many values near zero.

As in the general case, a potential endogeneity in the estimation of interruption costs arises from the linkage between the parameters of the outcome equation and the selection equation. The presence of this endogeneity determines the appropriateness (or inappropriateness) of the statistical model chosen. In practical terms, the question is whether the factors that determine whether the interruption costs are zero <u>also</u> determine the magnitude of interruption costs. We assume that endogeneity is not an issue with respect to interruption costs, and that a model which accounts for this assumption explicitly presents the best approach from a statistical perspective. Consider as an example the Heckman selection model, where the log odds ratio from the selection model appears in the outcome model to account for the presumed endogeneity. The presence of the correction is due to the potential correlation between the error term in the selection model and the error term in the (conditional) outcome model. On the one hand, if the conditional outcome model does not have the correction term, it may be under-specified, leading to estimation bias. On the other hand, if the correction term does not belong, the outcome model will underpredict interruption costs, perhaps significantly. The correct choice between these two approaches is discussed in detail in Duan and Manning (1983). In the following section we introduce our preferred approach and offer an empirical evaluation of its performance vis-à-vis other switching regressions.



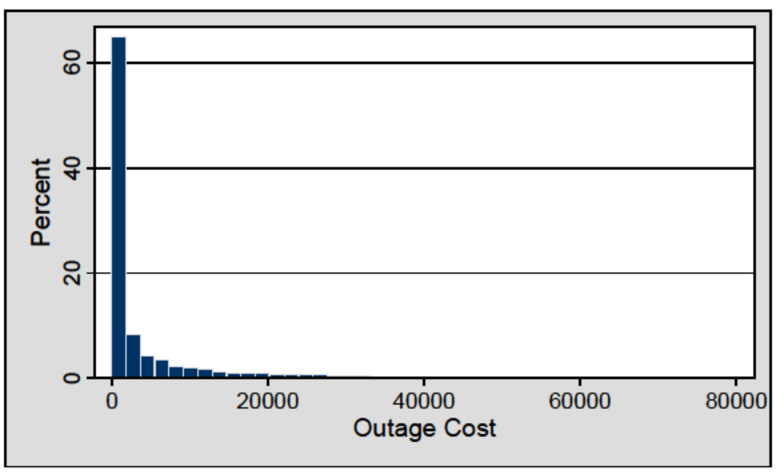


Figure 2-1. Comparison of Censored Distribution with the Actual Distribution of Interruption Costs for Medium and Large Commercial and Industrial Customers Histogram of Interruption Costs (0 to 95th Percentile)

2.5 The Two-Part Model

Unlike sample selection models, the two-part model assumes that the selection equation and the outcome equation are completely independent from one another. In the first step, a limited dependent model is used to assess the probability that a particular customer will indeed report a value of zero versus any positive value for a particular interruption scenario, based on a set of independent variables which describe the nature of the interruption as well as customer characteristics. The predicted probabilities from this first stage are retained. In the second step, interruption costs for only those customers who report positive costs are related to a set of independent variables (which may or may not be the same as the independent variables used in the first stage). Predictions are made from this model for all customers, including those who reported zero interruption costs. Finally, the predicted probabilities from the "first part" are multiplied by the estimated interruption costs from the "second part" to generate the final interruption cost predictions. Heuristically, the model can be described as follows, where C_i represents interruption costs for customer i, Z_i and X_i represent vectors of customer characteristics as well as interruption scenario parameters for customer i, γ and β represent parameter vectors, and u_i and ε_i represent disturbance terms:

Part I: $\Pr(C_i > 0) = F(Z_i'\gamma, u_i)$ *(11)*

$\hat{P}_i = F(Z_i'\hat{\gamma})$ *(12)*

Part II: $C_i = f(X_i, \beta, \varepsilon_i), \quad C_i > 0$ *(13)*

$C_i = f(X_i, \beta)$ *for all i* *(14)*

$\tilde{C}_i = \hat{P}_i \times \hat{C}_i$ *(15)*

Presumably the nomenclature "two-part" is employed rather than "two-stage" to emphasize the fact that the two parts of the model are not related in any way. The choice of independent variables and functional form are totally at the discretion of the researcher, and there is no linkage between the two equations.

In order to evaluate the validity of our assumption regarding the appropriateness of the two-part model versus the Tobit or the Heckman selection model, an in-sample test of forecasting accuracy was performed. The three different specifications were each used to estimate the interruption costs for 20% of the sample held back from the model parameter estimation exercise. Model parameters were estimated for all three customer groups: Small C&I customers, medium and large C&I customers, and residential customers. The models were estimated using a randomly selected group of respondents representing 80% of the total respondents. The estimated model was then used to predict interruption costs for the remaining 20% of the sample. The results of this in-sample validation exercise are presented in Table 2-1 through Table 2-3 below. The results indicate that the Two Part regression procedure produces much more accurate predictions of customer interruption costs than either of the other model specifications.

Table 2-1. Reported and Predicted Interruption Costs Across Three Regression Specifications, Small C&I Customers

Variable	Reported Interruption Costs	Predicted Interruption Costs (Two-part model)	Predicted Interruption Cost (Tobit)	Predicted Interruption Cost (Heckman Two-step model)
Duration				
Voltage Sag	$210	$372	-$1	$1,703
Up to 1 Hour	$738	$653	$0	$2,418
2 to 4 hours	$3,236	$2,322	$34	$5,623
8 to 12 hours	$3,996	$3,971	$217	$7,697
Industry (1-hour duration)				
Agriculture	$302	$531	-$1	$1,351
Mining	$3,161	$1,357	$0	$1,930
Construction	$1,577	$1,128	$1	$3,235
Manufacturing	$1,027	$869	$1	$3,325
Telco. & Utilities	$665	$896	$1	$2,968
Trade & Retail	$623	$564	$1	$2,114
Fin., Ins. & R. E.	$1,039	$886	$0	$3,029
Services	$563	$488	$0	$2,234
Public Admin.	$139	$291	-$1	$1,629
Average kW/hr (1-hour duration)				
0-1 kW/hr	$449	$575	$1	$1,723
1-2 kW/hr	$843	$636	$0	$2,429
2-3 kW/hr	$804	$707	$0	$2,583
3-4.5 kW/hr	$752	$676	$0	$2,676
Over 4.5 kW/hr	$617	$741	$1	$2,984
Region (1-hour duration)				
Midwest	$474	$493	$0	$1,855
Northwest	$335	$491	-$1	$2,313
Southeast	$820	$762	$0	$2,629
Southwest	$1,136	$511	-$1	$2,591
West	$867	$791	$2	$2,286
Time of Day (1-hour duration)				
Night	$226	$495	-$1	$2,781
Morning	$659	$622	$0	$2,268
Afternoon	$1,087	$770	$2	$2,347
Evening	$349	$469	-$1	$4,382

Table 2-2. Reported and Predicted Interruption Costs Across Three Regression Specifications, Medium and Large C&I Customers

Variable	Reported Interruption Costs	Predicted Interruption Costs (Two-part model)	Predicted Interruption Cost (Tobit)	Predicted Interruption Cost (Heckman Two-step model)
Duration				
Voltage Sag	$7,331	$8,439	$108	$5,075
Up to 1 Hour	$16,347	$12,566	$319	$8,371
2 to 4 hours	$40,297	$38,757	$5,400	$37,523
8 to 12 hours	$46,227	$43,068	$7,886	$44,404
Industry (1-hour duration)				
Agriculture	$1,646	$1,096	$5	$640
Mining	$33,925	$14,972	$896	$12,347
Construction	$3,091	$5,987	$23	$2,436
Manufacturing	$46,004	$31,839	$1,004	$23,207
Telco. & Utilities	$5,942	$7,032	$38	$2,452
Trade & Retail	$3,074	$2,875	$52	$2,199
Fin., Ins. & R. E.	$5,760	$8,710	$49	$3,144
Services	$3,868	$4,512	$29	$2,604
Public Admin.	$19,784	$9,402	$52	$3,406
Average kW/hr (1-hour duration)				
0-25 kW/hr	$1,351	$1,796	$15	$1,226
25-100 kW/hr	$3,466	$3,975	$45	$2,629
100-500 kW/hr	$11,975	$10,017	$184	$6,595
500-2500 kW/hr	$44,699	$28,505	$670	$18,999
Over 2500 kW/hr	$101,076	$77,023	$2,621	$51,441
Region (1-hour duration)				
Midwest	$15,355	$9,728	$296	$7,642
Northwest	$2,808	$4,458	$21	$3,064
Southeast	$26,066	$20,729	$527	$13,508
Southwest	$4,094	$3,593	$35	$2,164
West	$19,975	$13,297	$415	$8,802
Time of Day (1-hour duration)				
Night	$7,439	$4,933	$16	$2,831
Morning	$7,711	$6,276	$120	$4,552
Afternoon	$25,244	$19,815	$590	$13,058
Evening	$27,275	$15,073	$94	$9,430

Table 2-3. Reported and Predicted Interruption Costs Across Three Regression Specifications, Residential Customers

Variable	Reported Interruption Costs	Predicted Interruption Costs (Two-part model)	Predicted Interruption Cost (Tobit)	Predicted Interruption Cost (Heckman Two-step model)
Duration				
Voltage Sag	$2.3	$2.4	-$0.6	$18.9
Up to 1 Hour	$4.1	$3.8	-$0.4	$20.8
2 to 4 hours	$7.3	$7.2	$0.4	$26.8
8 to 12 hours	$11.5	$9.4	$1.0	$29.5
Average kW/hr (1-hour duration)				
0-0.5 kW/hr	$3.9	$3.1	-$0.4	$14.1
0.5-1 kW/hr	$3.5	$3.2	-$0.4	$17.3
1-1.75 kW/hr	$4.0	$3.7	-$0.4	$20.7
1.75-2.5 kW/hr	$4.1	$4.1	-$0.4	$23.4
Over 2.5 kW/hr	$5.0	$4.6	-$0.3	$26.5
Region (1-hour duration)				
Northwest	$3.1	$3.6	-$0.5	$23.9
Southeast	$6.2	$4.6	-$0.1	$18.2
Southwest	$1.8	$3.1	-$0.7	$27.5
West	$4.5	$3.6	-$0.3	$15.3
Time of Day (1-hour duration)				
Morning	$5.3	$5.2	$0.0	$19.8
Afternoon	$4.1	$3.5	-$0.3	$14.9
Evening	$3.3	$3.2	-$0.6	$27.6

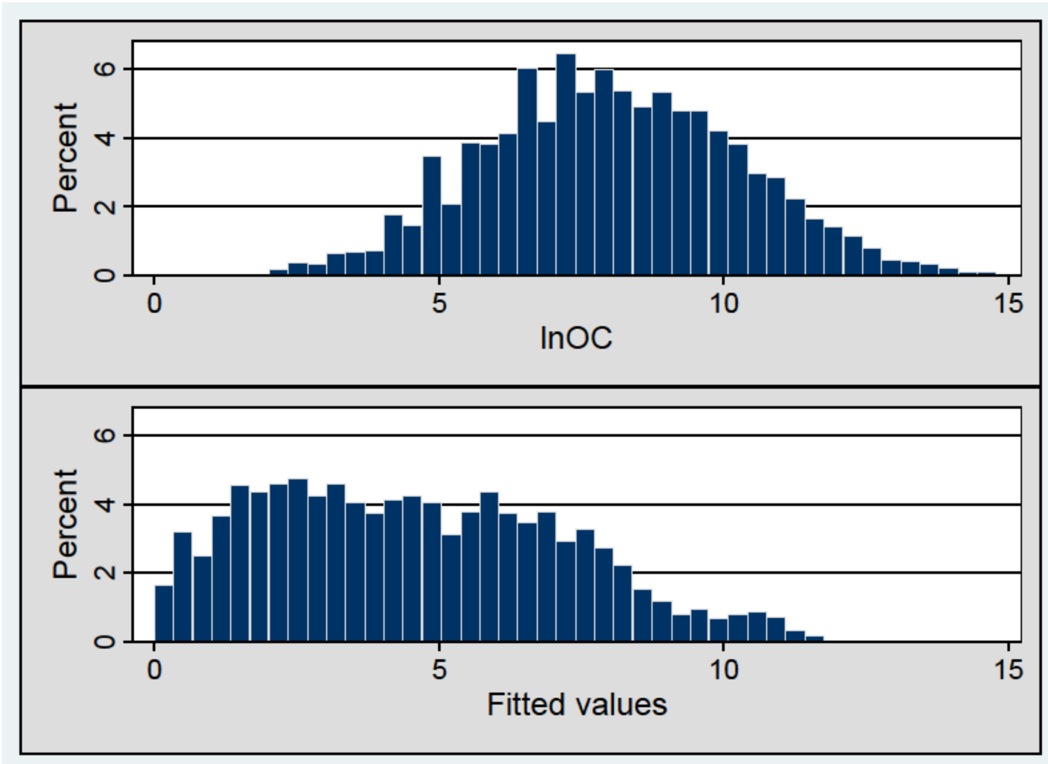


Figure 2-2. Medium and Large Commercial and Industrial Customers Histogram of Reported and Predicted Log Interruption Costs Using Tobit Specification

In particular the Tobit results are of note. See Figure 2-2. They are so far from the true value as to be essentially nonsensical. The graphs above demonstrate clearly why the Tobit produces such dramatic underestimates of interruption costs.

What is conspicuously missing from the top of the figure are the 33.2% of observations which are reported as zero interruption cost. How does the Tobit procedure handle those zeros in the estimation process?

The identical scale of the two histograms makes very clear where the zeros are mapped to in terms of predicted interruption costs. They are assumed to be low (or negative) values, the effect of which is to dramatically bias the predicted interruption costs towards zero in every category. The fault does not lie in the Tobit estimation itself; in fact it performs exactly as intended. The problem is the assumption regarding the nature of the zero values for interruption costs.

The Heckman model also underpredicts interruption costs relative to the reported values, although not as severely as the Tobit model. See Figure 2-3. The charts representing reported and predicted interruption costs for the Heckman model are similar, although not nearly as dramatic as the Tobit results:

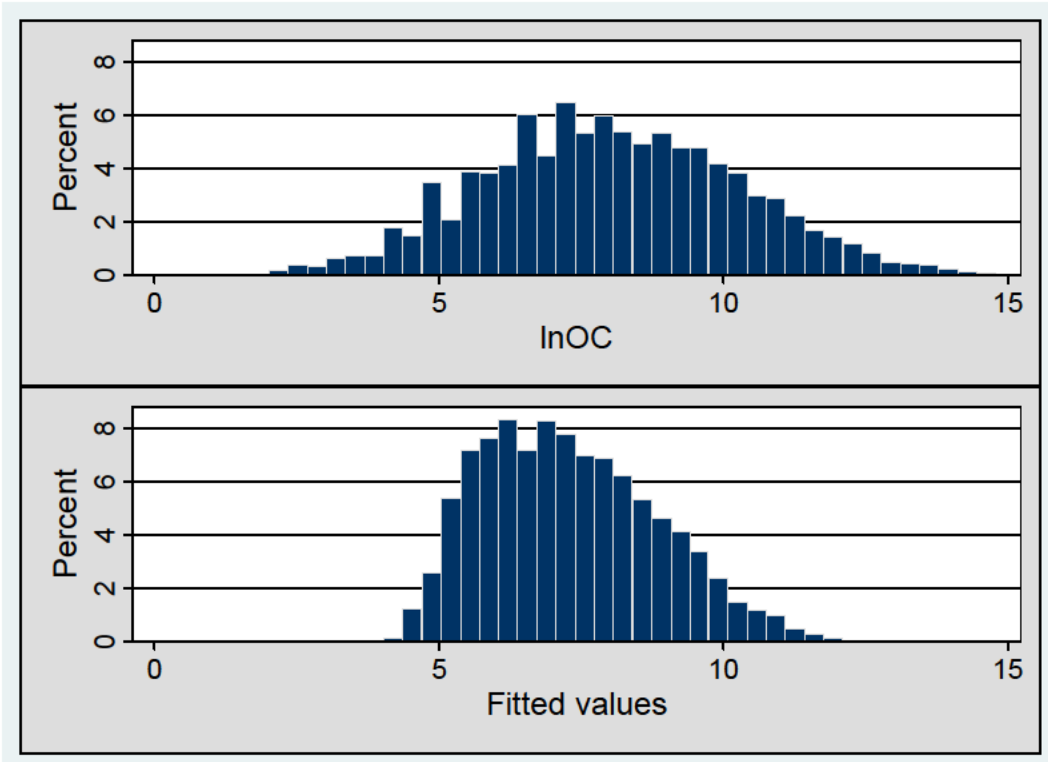


Figure 2-3. Medium and Large Commercial and Industrial Customers Histogram of Reported and Predicted Log Interruption Costs Using Heckman Specification

As with the Tobit case, the Heckman model performs exactly as expected. By assuming that the zero reported interruption costs arise from a self-selected sample and actually represent non-zero values, the Heckman procedure "corrects" the regression coefficients which apply to all observations. For medium and large C&I customers, the correction causes an underprediction of interruption costs. With respect to residential customers, the correction leads to a severe overprediction of willingness to pay for interruptions.

2.6 Implications

The models applied here to the interruption cost data from the various surveys are departures from the previous literature on the modeling of interruption costs. We believe that the use of the two-part model versus the Tobit or other selection model and the GLM versus the standard loglinear model both represent improvements over previous results which significantly increase the statistical accuracy of the predictions from those models and, in turn, should significantly improve the reliability of the customer damage functions derived from them.

3. Medium and Large Commercial and Industrial Customer Results

The medium and large commercial and industrial dataset is built from 13 studies conducted by 10 companies and includes approximately 7,196 respondents. Overall 31,068 total responses were utilized in the analysis. The number of cases varies depending on availability of data since either the study or the scenario details for a particular respondent may contain missing values). The distribution of the available data across various interruption attributes, years, and customer characteristics is described below.

Table 3-1 summarizes the number of records available for analysis by region, season, day of week, and year of study. The results show that the number of responses ranges from 76 to more than 3,600 for various combinations. Overall there is substantial coverage across regions, for winter versus summer seasons, and across year of study. For the medium and large commercial and industrial sector, there is more limited data on weekend interruptions.

Table 3-1. Medium and Large Commercial and Industrial Customers Number of Observations by Region, Company, Season, Day of Week and Year

Region - Company	Season	Day of Week	Year of Survey									Total
			1989	1990	1993	1996	1997	1999	2000	2002	2005	
Midwest-1	Summer	Weekday								2,048		2,048
Midwest-2	Summer	Weekday				1,654						1,654
	Summer	Weekend				298						298
Northwest- 1	Winter	Weekday	1,834									1,834
Northwest- 2	Summer	Weekday						2,335				2,335
	Summer	Weekend						472				472
Southeast- 1	Summer	Weekday					87					87
Southeast- 2	Summer	Weekday			3,649		2,721					6,370
	Winter	Weekday			296		327					623
Southeast- 3	Summer	Weekday		2,106								2,106
Southwest	Summer	Weekday							2,811			2,811
	Summer	Weekend							589			589
	Winter	Weekday							593			593
West-1	Summer	Weekday							1,489			1,489
	Winter	Weekday							293			293
	Winter	Weekend							601			601
West-2	Summer	Weekday	1,624		1,795						2,967	6,386
	Winter	Weekday	403								76	479
		Total:	3,861	2,106	5,740	1,952	3,135	2,807	6,376	2,048	3,043	31,068

While suggesting a reasonable degree of coverage for conducting the meta-analysis, the results in Table 3-1 also point to a key limitation in the data: The results show that there are certain “holes” in the coverage that will limit the ability to use the merged data to sort out the effects for some variables. In particular, the region of the country and the year of the study are highly correlated. In most years only one or two utilities conducted a study, and the studies were done in different parts of the county. As a result, a calculation of the average interruption cost for a given year is heavily influenced by the region and type of scenarios asked in that region. For this reason, the data probably cannot be used effectively to evaluate the changes in interruption costs over time without additional statistical controls for the region (or utility) and scenario characteristics. This problem surfaces for many of the calculations of interruption costs that would be of interest. Simple comparison of average interruption costs for levels of a variable of interest (such as interruption costs for different interruption durations or for different regions) must be interpreted very cautiously outside the context of a multivariate model that can control for other customer or interruption attributes. The underlying group of customers responding to a scenario will vary from scenario to scenario and differences in these underlying groups may be more important in explaining differences in the interruption costs than the levels of the variable of interest (such as duration). For this reason, we remind the reader that the regression analysis presented at the end of this chapter provide the most meaningful information on the value of service. The bivariate tabulations presented in the tables are suggestive, but due to the methodological and data structural issues, may be somewhat misleading. For example, it makes sense to compare the effect of a specific condition on interruption cost only when the same respondents provide information to both permutations. However, frequently one group of respondents provides information about only one kind of scenario, and these results may not be comparable to different respondents. Importantly, only multiple regression or similar analyses take all of these factors into consideration simultaneously and consistently.

3.1 Interruption Cost Descriptive Statistics

Table 3-2 and Table 3-3 show the distribution of interruption costs by interruption duration on a per-event and per-average kW basis, respectively for medium and large commercial and industrial customers. The results in Table 3-2 show interruption costs rising from an average of $7,220 for a voltage sag to $41,459 for an 8-hour interruption. Although the results trend generally upward as would be expected, there are substantial deviations from this trend. For example, the voltage sag has a significantly higher per event cost ($7,220) than a 15-minute interruption (at $2,432). In addition, reported interruption costs for a 30 minute interruption is greater than the cost for a 1 hour interruption and a one hour interruption has a lower average cost than a two hour interruption. Neither of these differences makes sense. They arise because both the 30 minute interruption and the 2 hour interruption were estimated for a relatively small subset of customers that differ substantially from the average customers in the study in terms of their size and type. As discussed above, the table (unlike the regression analysis presented in Section 3.2 below) does not control for all of the other factors within each duration which vary among the scenarios. The effect of duration on interruption costs can only be interpreted in the context of a multivariate model controlling for differences among the studies.

Table 3-2. Medium and Large Commercial and Industrial Customers US 2008$ Interruption Cost per Event by Duration

Duration	N	Mean	Standard Error	Standard Deviation	Percentiles 5%	25%	50%	75%	95%
Voltage sag	6,225	$7,220	751	$59,286	$0	$0	$0	$692	$17,868
15 min	459	$2,432	614	$13,163	$0	$0	$0	$374	$9,969
20 min	403	$8,808	2,252	$45,216	$0	$0	$470	$3,463	$29,360
30 min	908	$35,150	3,816	$114,986	$0	$12	$1,500	$15,897	$171,866
1 hour	13,600	$15,056	737	$85,892	$0	$0	$541	$3,911	$51,349
2 hours	296	$7,298	1,298	$22,330	$0	$0	$831	$2,769	$41,534
4 hours	6,848	$39,870	1,775	$146,908	$0	$352	$3,356	$21,650	$175,884
8 hours	1,753	$41,459	3,861	$161,653	$0	$127	$3,789	$23,488	$164,754
12 hours	576	$28,999	4,231	$101,533	$0	$1,178	$5,279	$18,752	$107,513

Table 3-3. Medium and Large Commercial and Industrial Customers US 2008$ Interruption Cost per Average kW/Hour by Duration

Duration	N	Mean (Ratio)	Standard Error	Standard Deviation	Percentiles of Individual kW/Hour figures 5%	25%	50%	75%	95%
Voltage sag	6,225	$8.1	0.77	$60.9	$0.0	$0.0	$0.0	$5.6	$139.5
15 min	459	$9.3	2.32	$49.7	$0.0	$0.0	$0.0	$6.2	$128.2
20 min	403	$13.6	2.21	$44.4	$0.0	$0.0	$4.7	$19.1	$132.5
30 min	908	$14.0	1.48	$44.5	$0.0	$0.0	$4.2	$21.8	$216.1
1 hour	13,600	$21.5	1.06	$123.1	$0.0	$0.0	$7.7	$46.2	$408.9
2 hours	296	$77.4	14.44	$248.5	$0.0	$0.0	$15.7	$60.5	$435.8
4 hours	6,848	$44.4	2.28	$188.4	$0.0	$2.8	$39.8	$160.8	$1,113.1
8 hours	1,753	$93.3	10.11	$423.1	$0.0	$1.5	$69.9	$316.6	$2,302.3
12 hours	576	$26.5	4.54	$108.9	$0.0	$8.3	$100.6	$304.1	$1,293.8

One of the primary drivers of interruption costs which is not controlled in Table 3-2 is customer size. Interruption cost varies significantly as a function the size of the customer's operation and its dependence on electricity. There are two important proxy measures of customer size that can be used to scale interruption costs to the magnitude of electric demand and usage for typical customers. These are: interruption cost per unserved kW and interruption cost per annual average kWh sold. It is useful to calculate interruption costs scaled to these quantities because in utility planning the magnitude of unserved load or energy is often calculated for alternative design or operating criteria. For example, utilities commonly know the annual sales of energy at various points on the transmission and distribution system by customer type. That is, it is relatively easy to obtain measurement of the annual kWh sold to residential commercial and industrial customers at the feeder, circuit, distribution transformer, and substation and transmission line level. In addition, in some planning applications, degradations or improvements in reliability are often expressed in terms of lost load (kW demand) or unserved energy (unserved annual kWh (properly scaled to interruption duration).

Table 3-3 shows the effect of normalizing the per even interruption costs to an average kW/Hour basis. Some of the oddities present in Table 3-2 are eliminated by this normalization, although there are still inconsistencies. Because the individual figures for interruption costs per average kW/Hour are extremely variable, the mean and standard error figures are based on the total sum of interruption costs divided by annual average kW/Hour.[20] The distribution percentiles are still based on the distribution of the individual values. The costs range from $8.1 per average kW/Hour of demand for a voltage sag to $93.3 per average kW/Hour for an 8-hour interruption (although the figure for a 12-hour interruption is lower than the figure for an 8-hour interruption, it is possible that this difference represents a methodological artifact as only one study used the 12-hour duration).

In Table 3-4 and Table 3-5, comparisons of the average interruption costs for a 1-hour interruption for several key variables—season, day of week, region, and industry—are presented. The data include the mean and standard deviation of interruption costs as well as several percentiles in the distribution. Table 3-4 presents these summary statistics for the raw interruption costs, while
For data on regions, the rank order of the regions is somewhat different when the interruption costs are measured on a per average kW/Hour basis. The Southwest region has the highest costs per average kW/Hour ($37), while the Midwest and Northwest (at slightly less than $20 per average kW/Hour) have the lowest values. Finally, in terms of industry, construction has the highest cost per average kW/Hour at $62.9. The remaining business types range from $7.6 to $43.6 on a per average kW/Hour basis with mining being the lowest.

Some of the interruption cost surveys also included scenarios with advanced warning for a particular interruption (For surveys which did not provide such alternatives, all scenarios are assumed to be interruptions which occur without warning). For medium and large C&I customers there were also questions regarding the presence of backup power generators or power conditioning equipment. However, the only way to make such cost comparisons meaningful is to be certain that one is comparing the same scenarios while varying the characteristics, and do so with essentially the same respondents. In particular, larger customers are likely to have both backup generation and power conditioning, so they might actually report higher interruption costs. The separate effects of those choices as well as advance warning are presented in the regression results below.
presents the same information per average kW/Hour. These values are presented to provide a measure of the typical values and range of values in the underlying data used in the meta-analysis, and provide a check of the validity of the data. However, as noted above, these averages must be compared carefully as the underlying pool of customers included in the calculation changes among each of these categories.

[20] Another possible explanation is that the use of the facility by the customer has changed overtime as indicated by substantial shifts in electricity use over the year. This could be the case of manufacturing facilities or even for restaurants or other small businesses that close for renovations and then reopen.

Table 3-4. Medium and Large Commercial and Industrial Customers 2008 Summary of the Cost per Event of a 1-Hour Outage

Outage Characteristic	N	Mean	Standard Error	Standard Deviation	Percentiles				
					5%	25%	50%	75%	95%
Season									
Winter	1,729	$11,129	1,724	$71,679	$0	$0	$0	$1,558	$34,268
Summer	11,871	$15,628	805	$87,758	$0	$0	$625	$4,230	$53,994
Day									
Weekend	1,359	$2,249	329	$12,146	$0	$0	$125	$979	$9,126
Weekday	12,241	$16,478	816	$90,332	$0	$0	$623	$4,576	$57,819
Region									
Midwest	1,474	$12,294	1,924	$73,871	$0	$0	$587	$3,911	$37,562
Northwest	2,315	$3,552	349	$16,813	$0	$0	$187	$1,250	$14,496
Southeast	4,338	$23,797	1,725	$113,591	$0	$0	$750	$6,749	$89,767
Southwest	1,983	$5,946	1,147	$51,097	$0	$0	$141	$1,432	$14,585
West	3,490	$18,166	1,560	$92,188	$0	$108	$1,082	$6,922	$62,305
Industry									
Agriculture	187	$1,063	290	$3,971	$0	$0	$108	$541	$2,565
Mining	170	$18,501	3,747	$48,858	$0	$245	$1,850	$10,825	$98,287
Construction	129	$3,663	788	$8,945	$0	$0	$301	$4,038	$15,040
Manufacturing	3,620	$41,691	2,576	$155,010	$0	$261	$3,997	$19,750	$174,763
Telco. & Utilities	1,023	$8,837	1,631	$52,166	$0	$0	$208	$1,624	$26,424
Trade & Retail	3,390	$2,818	171	$9,975	$0	$0	$367	$1,624	$12,918
Fin., Ins. & R.E.	585	$5,790	1,526	$36,905	$0	$0	$122	$1,952	$19,087
Services	3,690	$4,810	345	$20,946	$0	$0	$208	$1,869	$19,496
Public Admin.	207	$12,239	3,904	$56,169	$0	$0	$216	$2,549	$46,044

Table 3-5 presents the same information per average kW/Hour. These values are presented to provide a measure of the typical values and range of values in the underlying data used in the meta-analysis, and provide a check of the validity of the data. However, as noted above, these averages must be compared carefully as the underlying pool of customers included in the calculation changes among each of these categories.

Table 3-5. Medium and Large Commercial and Industrial Customers US 2008$ Summary of the Cost per Average kW/Hour of a 1-Hour Interruption

Interruption Characteristic	N	Mean (Ratio)	Standard Error	Standard Deviation	Percentiles of Individual kW/Hour figures				
					5%	25%	50%	75%	95%
Season									
Winter	1,729	$13.8	1.91	$79.5	$0.0	$0.0	$0.0	$20.0	$300.1
Summer	11,871	$22.8	1.21	$131.7	$0.0	$0.0	$9.4	$50.2	$427.2
Day									
Weekend	1,359	$30.6	4.49	$165.4	$0.0	$0.0	$2.9	$35.6	$396.8
Weekday	12,241	$21.4	1.06	$117.7	$0.0	$0.0	$8.2	$47.6	$416.4
Region									
Midwest	1,474	$19.8	2.91	$111.7	$0.0	$0.0	$5.2	$30.4	$181.4
Northwest	2,315	$19.9	2.04	$98.4	$0.0	$0.0	$2.8	$23.4	$176.4
Southeast	4,338	$18.2	1.26	$82.9	$0.0	$0.0	$7.1	$40.6	$311.8
Southwest	1,983	$37.0	6.98	$310.6	$0.0	$0.0	$8.2	$102.0	$880.2
West	3,490	$28.5	2.82	$166.8	$0.0	$0.7	$15.0	$66.2	$594.1
Industry									
Agriculture	187	$43.6	11.59	$158.5	$0.0	$0.0	$3.6	$33.7	$221.3
Mining	170	$7.6	1.23	$16.1	$0.0	$0.4	$6.8	$32.4	$161.9
Construction	129	$62.9	17.03	$193.4	$0.0	$0.0	$12.1	$100.0	$660.1
Manufacturing	3,620	$22.0	1.39	$83.5	$0.0	$0.9	$11.2	$55.9	$520.0
Telco. & Utilities	1,023	$19.0	3.66	$116.9	$0.0	$0.0	$1.4	$25.3	$393.9
Trade & Retail	3,390	$34.2	2.04	$118.5	$0.0	$0.0	$12.9	$49.5	$367.0
Fin., Ins. & R.E.	585	$32.7	9.20	$222.5	$0.0	$0.0	$1.3	$49.2	$615.2
Services	3,690	$18.7	1.33	$81.0	$0.0	$0.0	$3.8	$36.0	$403.6
Public Admin.	207	$14.8	4.45	$64.0	$0.0	$0.0	$1.2	$25.7	$216.5

The data suggest that interruption costs on a per event basis are higher in the summer than the winter ($15,628 versus $11,129); are higher on weekdays than weekends ($16,478 versus $2,249); are higher in the Southeast ($23,797 per event) than in the Northwest ($3,552 per event) or Midwest ($12,294 per event); and are higher for manufacturing ($41,691 per event) and mining ($18,501) than other business and government sectors. Although these patterns are generally similar when examined on a per average kW/Hour basis, there can be substantial differences. The interruption cost per average kW/Hour of demand is $13.8 for winter and $22.8 for summer, consistent with the raw data on interruption costs. Unlike the per-event figures, the day of the week data on an average kW/Hour basis show that interruption costs on a per average kW/Hour are higher on the weekend ($30.6) than during the weekday ($21.4) for medium and large commercial and industrial customers. This is counterintuitive, since we would expect lower average interruption costs during periods when most businesses are closed (weekends) compared to when they are open (weekdays). The problem here is that only five surveys asked about weekend interruptions at all, and the average customer size for those five surveys was 1.2 million annual kWh versus 6.25 million annual kWh for the remaining surveys. As such, any analysis which does not control for size (as in the regression analysis below) can yield misleading figures when simply tabulating costs on a univariate basis.

For data on regions, the rank order of the regions is somewhat different when the interruption costs are measured on a per average kW/Hour basis. The Southwest region has the highest costs per average kW/Hour ($37), while the Midwest and Northwest (at slightly less than $20 per average kW/Hour) have the lowest values. Finally, in terms of industry, construction has the highest cost per average kW/Hour at $62.9. The remaining business types range from $7.6 to $43.6 on a per average kW/Hour basis with mining being the lowest.

Some of the interruption cost surveys also included scenarios with advanced warning for a particular interruption (For surveys which did not provide such alternatives, all scenarios are assumed to be interruptions which occur without warning). For medium and large C&I customers there were also questions regarding the presence of backup power generators or power conditioning equipment. However, the only way to make such cost comparisons meaningful is to be certain that one is comparing the same scenarios while varying the characteristics, and do so with essentially the same respondents. In particular, larger customers are likely to have both backup generation and power conditioning, so they might actually report higher interruption costs. The separate effects of those choices as well as advance warning are presented in the regression results below.

3.2 Customer Damage Function Estimation

The summary of interruption costs for the key characteristics outlined above provides a measure of whether the combination of various studies fit intuitively with expectations of interruption costs for this sector. However, the results may not be particularly useful when attempting to make sense of the values of one particular variable across studies. The average value of interruption costs for any given descriptor variable is a function of the interruption attributes, region, and the customer types that answered that particular scenario. As noted at the beginning of this section, the combination of customer and interruption characteristics can vary substantially depending on the variables being examined. To adequately control for these varying influences, a multivariate regression analysis was conducted to develop a customer damage function. The results of that regression analysis were then used to estimate a general customer damage function expressing commercial and industrial customers' interruption costs as a function of interruption duration, onset time, season, and various customer characteristics such as annual usage, number of employees and other variables.

As discussed above in the methodology section, the usual response distribution for the dependent variable – interruption costs presents certain modeling challenges. In almost all studies, and including the large commercial and industrial customers, a significant number of respondents report "0" (zero) interruption costs for many scenarios. This is particularly true of short duration interruptions, but may be true of even longer ones at certain times of the day or seasons because of backup generation or the ability to shift production without incurring additional costs. To overcome this problem, the analysis reported below uses a two-part model. In the first step, a limited dependent model is used to assess the probability that a particular customer will indeed report a value of zero versus any positive value for a particular interruption scenario, based on a set of independent variables which describe the nature of the interruption as well as customer characteristics. The predicted probabilities from this first stage are retained. In the second step, interruption costs for only those customers who report positive costs are related to a set of independent variables (which may or may not be the same as the independent variables used in the first stage). Predictions are made from this model for all customers, including those who reported zero interruption costs. Finally, the predicted probabilities from the "first part" are multiplied by the estimated interruption costs from the "second part" to generate the final interruption cost predictions.

A second issue with the typical distribution of interruption costs is the presence of a number of extremely large values. As detailed more fully in Section 3 above, all observations meeting the statistical definition of mild outlier (more than 3 times the interquartile range above the 75th or below the 25th percentile were eliminated from the data for both log interruption costs (within industry and duration) and for log of annual kWh usage (within industry). The total number of observations removed by these criteria is 397.[21]

The data on interruption costs are also highly skewed, i.e., there are a small number of relatively high values. The high skew of the underlying data means that the results are not robust to smaller data sets, i.e., the results from one dataset may provide poor predictions for another dataset. A regression analysis such as OLS on the raw values will be extremely inefficient in the statistical sense due to the enormous residual variance, and can also produce negative interruption costs. To overcome this issue, the analysis was conducted under the assumption that the mean of interruption costs is related to the predictor variables through a logarithmic versus a linear link function. The decision to use a lognormal link function was based on several considerations. Using a lognormal transformation gives the underlying distribution of interruption costs a more normal shape with less severe tails (see Figure 3-1 and Figure 3-2).

To observe the magnitude of the impact of the variables in the models on the interruption cost it is necessary to compare the predictions made by the function under varying assumptions. For example, it is possible to observe the effects of duration on interruption cost holding the other variables constant at their sample means. In this way, a prediction is obtained for customer interruption costs under different interruption conditions.

To develop a set of models, several combinations of the variables representing attributes of the interruption (e.g., duration, time of day, advanced warning) and customer characteristics (e.g., number of employees, SIC code, and presence of backup equipment) as well as their interactions were tested. Because not all studies included the same variables, the regression models utilized variables that appeared in all studies

[21] See the discussion on outliers above in Section 3.4.

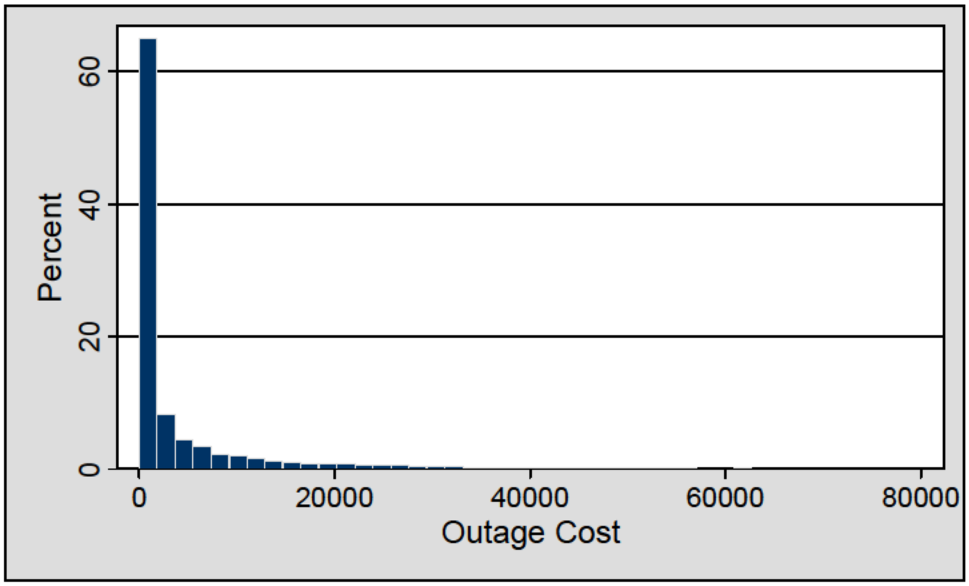


Figure 3-1. Medium and Large Commercial and Industrial Customers Histogram of Interruption Costs (0 to 95th Percentile)

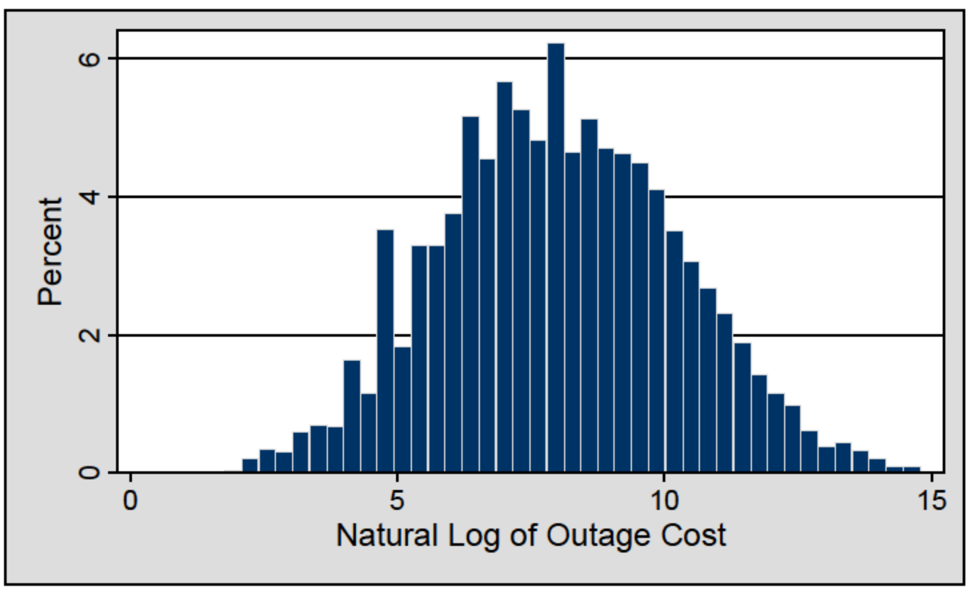


Figure 3-2. : Medium and Large Commercial and Industrial Customers Histogram of Log Interruption Costs, Positive Values Only

Table 3-6 and 3-7 describes initial probit regression model that specifies the relationship between the presence of zero interruption costs and a set of independent variables that includes interruption characteristics, customer characteristics, and industry designation. Although the purpose of this preliminary limited dependent model is only to normalize the predictions from the interruption costs regression in the second part of the two-part model, there are a few interesting results of note:

- The longer the interruption, the more likely that the costs associated with it are positive (the presence of a negative coefficient on the square of duration indicates that this effect diminishes for longer durations).
- Afternoon interruption costs are more likely to incur positive costs than any other time of day.
- Weekday interruptions are more likely to produce positive interruption costs than weekends.
- Summer interruptions are more likely to incur costs than non-summer interruptions.

Table 3-8 describes the GLM regression which relates the level of interruption costs to customer and interruption characteristics as well as industry designation for those variables for which sufficient data from multiple studies were available. A few results of note:

- The longer the interruption, the higher the interruption cost.
- Afternoon and evening interruptions cost more than morning interruptions, weekday interruptions are more costly than weekend interruptions.
- Larger customers (in terms of annual MWh usage) incur larger costs for similar interruptions.
- Construction and manufacturing industries incur larger costs for a similar interruption than other industries.
- Interruption costs in winter and summer are not significantly different.

Table 3-6. Medium and Large Commercial and Industrial Customers Average Values for Regression Inputs

Variable	Average Value
Interruption Characteristics	
Duration (minutes)	122.1
Duration Sq.	14,908.3
Morning	46.0%
Afternoon	40.4%
Evening	3.1%
Weekday	93.7%
Warning Given	8.8%
Summer	85.8%
Customer Characteristics	
Log of Annual MWh	8.9
Backup Gen. or Power Cond.	37.2%
Backup Gen. and Power Cond.	8.4%
Interactions	
Duration X Log of Annual MWh	266.6
Duration Sq. X Log of Annual MWh	32,545.8
Industry	
Mining	1.4%
Construction	0.9%
Manufacturing	28.6%
Telco. & Utilities	7.2%
Trade & Retail	25.0%
Fin., Ins. & R.E.	3.8%
Services	25.2%
Public Admin.	1.8%
Industry Unknown	4.7%

Table 3-7. Medium and Large Commercial and Industrial Customers Regression Output for Probit Estimation

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
Duration	0.007	0.001	0.000
Duration Sq.	-7.01E-06	8.25E-07	0.000
Morning	0.200	0.025	0.000
Afternoon	0.380	0.035	0.000
Evening	-0.020	0.044	0.653
Weekday	0.151	0.028	0.000
Warning Given	0.076	0.027	0.005
Summer	0.461	0.033	0.000
Customer Characteristics			
Log of Annual MWh	0.085	0.008	0.000
Backup Gen. or Power Cond.	0.027	0.028	0.336
Backup Gen. and Power Cond.	0.265	0.050	0.000
Interactions			
Duration X Log of Annual MWh	-1.76E-04	7.54E-05	0.019
Duration Sq. X Log of Annual MWh	1.58E-08	1.18E-07	0.893
Industry			
Mining	0.685	0.161	0.000
Construction	0.376	0.166	0.023
Manufacturing	0.557	0.117	0.000
Telco. & Utilities	0.184	0.123	0.137
Trade & Retail	0.455	0.115	0.000
Fin., Ins. & R.E.	0.230	0.130	0.077
Services	0.164	0.116	0.155
Public Admin.	0.207	0.151	0.170
Industry Unknown	0.150	0.128	0.240
Constant	-1.706	0.129	0.000
Regression Diagnostics			
Observations	31,068		
Log Likelihood	-17,466		
Degrees of Freedom	7,175		
Prob > F	0.000		

Table 3-8. Medium and Large Commercial and Industrial Customers 2008 Regression Output for GLM Estimation

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
Duration	0.009	0.001	0.000
Duration Sq.	-9.01E-06	1.73E-06	0.000
Morning	0.019	0.090	0.838
Afternoon	0.280	0.121	0.021
Evening	0.306	0.140	0.029
Weekday	0.252	0.078	0.001
Warning Given	-0.088	0.060	0.140
Summer	-0.077	0.089	0.386
Customer Characteristics			
Log of Annual MWh	0.451	0.020	0.000
Backup Gen. or Power Cond.	0.080	0.075	0.286
Backup Gen. and Power Cond.	0.127	0.114	0.266
Interactions			
Duration X Log of Annual MWh	-2.09E-04	1.45E-04	0.151
Duration Sq. X Log of Annual MWh	1.73E-07	2.34E-07	0.460
Industry			
Mining	0.430	0.299	0.150
Construction	1.579	0.593	0.008
Manufacturing	1.289	0.273	0.000
Telco. & Utilities	0.815	0.296	0.006
Trade & Retail	0.273	0.267	0.308
Fin., Ins. & R.E.	1.225	0.358	0.001
Services	0.522	0.270	0.053
Public Admin.	0.617	0.346	0.075
Industry Unknown	1.076	0.330	0.001
Constant	4.524	0.298	0.000
Regression Diagnostics			
Observations	20,755		
Log Likelihood	-217,448		
Degrees of Freedom	5,991		
LR Test (Model with Constant Only)	LR $\chi^2(22)$ = 36,378.08 p-value=0.0000		
LR Test (Model with Constant, Duration, and log of annual MWh Only)	LR $\chi^2(22)$ = 5,284.45 p-value=0.0000		

Table 3-9 summarizes the reported versus the predicted values for various important interruption costs drivers from the estimated regression model:

Table 3-9. Medium and Large Commercial and Industrial Customers Summary of Predicted vs. Reported Interruption Cost

Variable	Predicted Interruption Cost	Reported Interruption Cost	Predicted as a % of Reported
Duration			
Voltage Sag	$8,348	$7,220	116%
Up to 1 Hour	$12,573	$15,702	80%
2 to 4 hours	$40,690	$38,521	106%
8 to 12 hours	$45,684	$38,377	119%
Industry (1-hour duration)			
Agriculture	$1,156	$1,063	109%
Mining	$16,824	$24,269	69%
Construction	$7,135	$3,622	197%
Manufacturing	$32,214	$42,185	76%
Telco. & Utilities	$9,032	$9,271	97%
Trade & Retail	$2,547	$2,711	94%
Fin., Ins. & R. E.	$7,615	$5,830	131%
Services	$4,389	$4,813	91%
Public Admin.	$9,937	$13,347	74%
Average kW/hr (1-hour duration)			
0-25 kW/hr	$1,680	$1,801	93%
25-100 kW/hr	$3,992	$4,312	93%
100-500 kW/hr	$10,027	$11,621	86%
500-2500 kW/hr	$28,240	$31,336	90%
Over 2500 kW/hr	$75,274	$106,801	70%
Region (1-hour duration)			
Midwest	$9,791	$11,546	85%
Northwest	$4,789	$3,366	142%
Southeast	$20,693	$25,419	81%
Southwest	$3,891	$8,591	45%
West	$13,971	$18,166	77%
Time of Day (1-hour duration)			
Night	$5,132	$6,976	74%
Morning	$6,349	$8,489	75%
Afternoon	$20,058	$24,090	83%
Evening	$17,295	$24,949	69%

3.3 Key Drivers of Interruption Costs

The customer damage models are the key output from this research. The models can be used to estimate interruption costs for a wide range of interruptions with different attributes (e.g., duration, time of day) and for different types of customers (e.g., large versus small companies). They replace the enormous number of tables that would be required to summarize all the different combinations of characteristics. Using this information is relatively straightforward. To simulate the interruption cost for a particular set of interruption or customer characteristics one multiplies the appropriate value for each variable times the coefficient for that variable. The multiplications are summed across the variables and added to the constant (first entry for each model). Since the variable being predicted—i.e., interruption cost—has been transformed to be the log of the interruption cost, as a final step in the simulation the antilog of the summed value must be taken. The resulting value is the predicted interruption cost for the set of values used for each independent variable.

Figure 3-3, Figure 3-4, and Figure 3-5 below display comparisons of the results of the customer damage functions based on the estimated econometric model described above for various customer characteristics (including industry and size) as well as for varying times of day and seasons. It is evident that the relationship between interruption costs and duration is non-linear – increasing slowly within the first hour, accelerating through the second through the eighth hours, and then beginning to taper off thereafter. All of the predictions are positive at the intercept representing the impact of momentary interruptions.

In Figure 3-3, the customer damage function assumes a summer weekday afternoon interruption for customers with the average value for annual kWh. There appears to be a natural break between “low-cost” interruption industries (Agriculture, Retail, Public Administration, Services, Utilities, and Mining) and “high-cost” interruption industries (Manufacturing, Construction and Finance, Insurance, & Real Estate).

In Figure 3-4, the customer damage function assumes a summer weekday afternoon interruption for a customer with an industry equal to the average industry shares. While there is significant variation in interruption costs according to consumption, the relationship is not at all linear. Indeed, an increase in consumption from 100 kW/Hour to 2500 kW/Hour, an increase of 25-fold, increases interruption costs for a 1-hour interruption by a factor of slightly less than 10.

Figure 3-5 shows the effect of day and season on interruption costs (assuming a customer of average size and an industry equal to the average industry shares). For medium and large C&I customers, there is little seasonal variation, although afternoon interruptions are more costly.

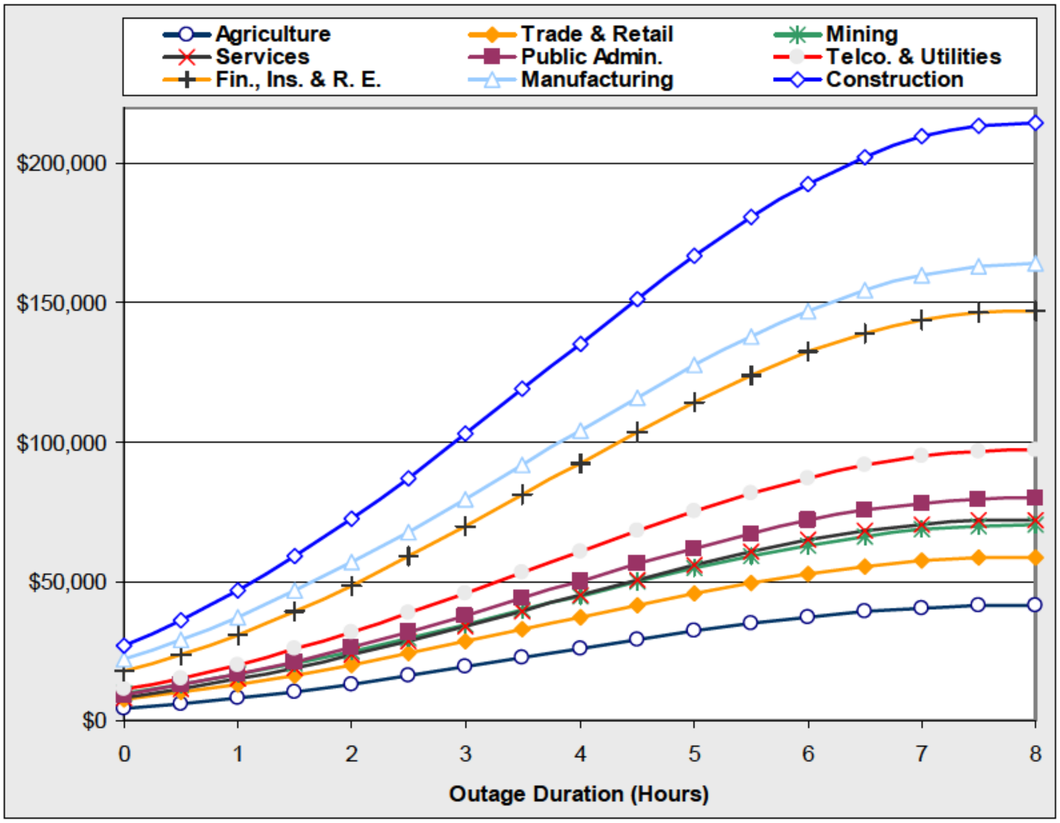


Figure 3-3. Medium and Large Commercial and Industrial Customers US 2008$ Customer Damage Functions by Industry - Summer Weekday Afternoon

The results show that for medium and large commercial and industrial customers, an average customer with 7.1 million annual kWh consumption will experience approximately $17,411 in costs from a 1-hour afternoon interruption in the winter and $20,360 in costs for a summer afternoon 1-hour interruption. These costs increase sharply as duration increases in both the winter and in the summer.

The curvilinear nature of the line suggests that for medium and large commercial and industrial establishments, costs actually moderate with longer interruptions. This makes sense, as focus groups and interview respondents often note that at some point employees are sent home, shifts are eliminated, and the interruptions extend into hours that would be normally non-productive (evening and night time hours). Since none of the studies measure costs beyond 12 hours, it is difficult to extrapolate from this data when and by how much costs rise as an interruption extends into multiple days.

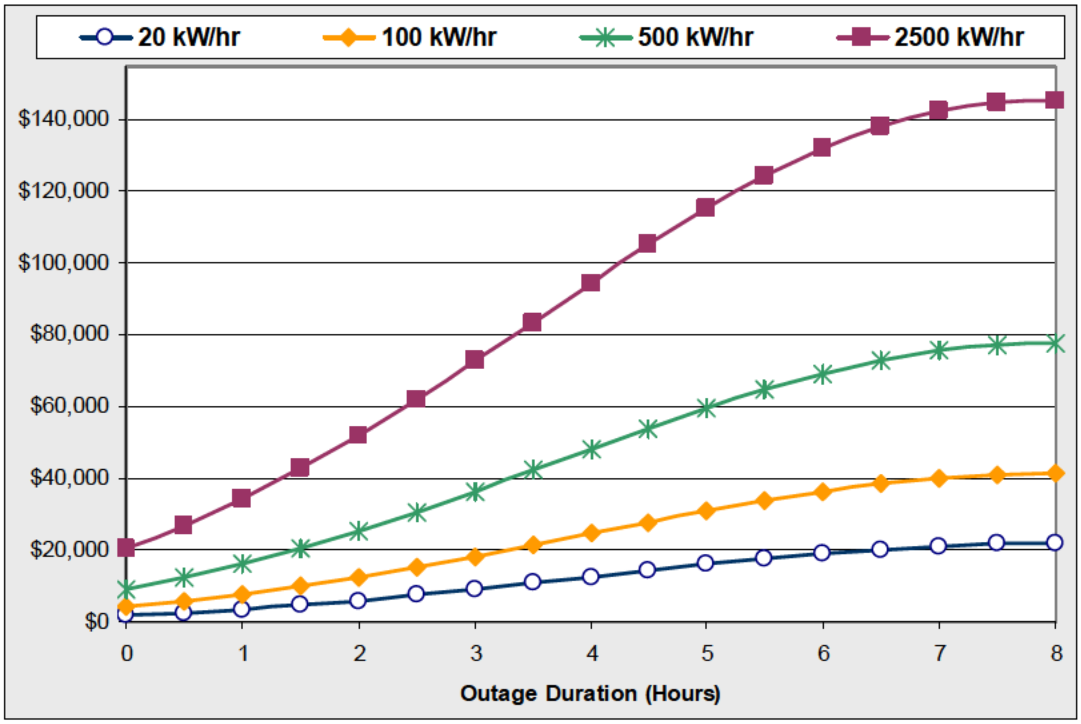


Figure 3-4. Medium and Large Commercial and Industrial Customers US 2008$ Customer Damage Functions by Average kW - Summer Weekday Afternoon

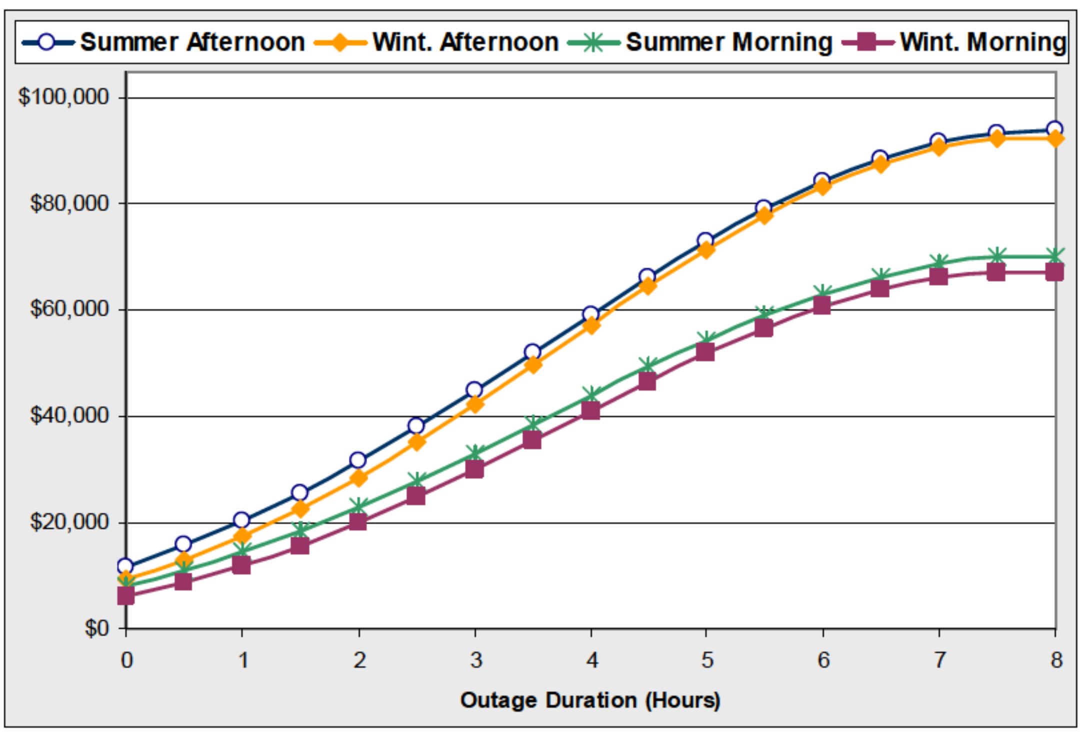


Figure 3-5. Medium and Large Commercial and Industrial Customers US 2008$ Customer Damage Functions by Season and Time of Day

Table 3-10. Medium and Large Commercial and Industrial Customers US 2008$ Expected Interruption Cost

Time of Interruption	Hours per Year	% of Hours per Year	Interruption Duration				
			Momentary	30 minutes	1 hour	4 hours	8 hours
Summer Weekday Morning	521	6%	$8,133	$11,035	$14,488	$43,954	$70,190
Summer Weekday Afternoon	435	5%	$11,756	$15,709	$20,360	$59,188	$93,890
Summer Weekday Evening	435	5%	$9,276	$12,844	$17,162	$55,278	$89,145
Summer Weekday Night	695	8%	$6,936	$9,586	$12,788	$40,954	$65,982
Summer Weekend Morning	209	2%	$5,696	$7,835	$10,410	$32,879	$52,850
Summer Weekend Afternoon	174	2%	$8,363	$11,318	$14,828	$44,656	$71,228
Summer Weekend Evening	174	2%	$6,364	$8,945	$12,110	$40,841	$66,384
Summer Weekend Night	278	3%	$4,767	$6,688	$9,038	$30,294	$49,188
Winter Weekday Morning	1,043	12%	$6,120	$8,683	$11,851	$41,152	$67,234
Winter Weekday Afternoon	869	10%	$9,306	$12,963	$17,411	$57,097	$92,361
Winter Weekday Evening	869	10%	$6,533	$9,492	$13,231	$49,608	$82,177
Winter Weekday Night	1,390	16%	$4,915	$7,126	$9,913	$36,902	$61,050
Winter Weekend Morning	417	5%	$4,097	$5,908	$8,180	$29,921	$49,341
Winter Weekend Afternoon	348	4%	$6,347	$8,977	$12,220	$42,025	$68,543
Winter Weekend Evening	348	4%	$4,271	$6,314	$8,936	$35,468	$59,378
Winter Weekend Night	556	6%	$3,220	$4,750	$6,709	$26,426	$44,177
Anytime	***8,760***	***100%***	***$6,558***	***$9,217***	***$12,487***	***$42,506***	***$69,284***

3.4 Implications

From the above examples it should be apparent that it is possible to use the customer damage functions from the above models to estimate customer interruption costs under a wide variety of conditions. However, it is not appropriate to use these functions to estimate interruption costs for individual customers. The regression functions used above can be used to predict the mean of customer interruption costs for populations of customers with different characteristics under different conditions. There is substantial unexplained variation among customers in the interruption costs they experience resulting from factors that are not accounted for in the above equations (e.g., process design differences, resistance of equipment to electric disturbances, etc.) that will not generally be known without an in-depth interview. The existence of these unknowns implies that the prediction for any individual customer from the above functions may be significantly in error. Inferences about the nature of specific elements of a population based solely upon aggregate statistics collected for the group to which those individuals belong is commonly known as the ecological fallacy. This fallacy assumes that individual members of a group have the *average* characteristics of the group at large. These customer damage functions should only be applied to reasonably large populations of customers to ensure that random but significant differences among customers do not produce estimates that deviate dramatically from the predictions made by the above equations.

4. Small Commercial and Industrial Results

The small commercial and industrial dataset is built from 12 studies conducted by 9 companies and includes approximately 4,636 respondents. Overall, there were approximately 20,673 total responses available for the analysis. The distribution of the available data across various interruption attributes, years, and customer characteristics is described first. A summary of the multivariate analysis is presented second.

In terms of coverage, Table 4-1 summarizes the number of records available for analysis by region, season, day of week, and year of study. Overall there were 20,673 responses to various scenario combinations across the studies (excluding outliers). The results show that there are from 48 to more than 3,500 responses depending on the scenario and region combination. There are a substantial number of cases available for the analysis of summer and winter scenarios occurring on both weekdays and weekends. The data also vary reasonably across regions although, as with the medium and large C&I results in Section 4, there is no coverage for the Northeast. Most of the studies were completed in the past 10 years, but two studies date back to the late 1980's and early 1990's. Overall, the data in Table 4-1 suggest sufficient coverage to develop models of interruption costs for a wide cross-section of the country and across a range of scenarios.

Table 4-1. Small Commercial and Industrial Customers Number of Observations by Region, Company, Season, Day of Week and Year

Region - Company	Season	Day of Week	Year of Survey									Total
			1989	1990	1993	1996	1997	1999	2000	2002	2005	
Midwest-1	Summer	Weekday								1,119		1,119
Midwest-2	Summer	Weekday				155						155
	Summer	Weekend				48						48
Northwest- 1	Winter	Weekday	375									375
Northwest- 2	Summer	Weekday						3,552				3,552
	Summer	Weekend						731				731
Southeast- 2	Summer	Weekday			1,374		2,785					4,159
	Winter	Weekday			188							188
Southeast- 3	Summer	Weekday		766								766
Southwest	Summer	Weekday							1,346			1,346
	Summer	Weekend							450			450
	Winter	Weekday							449			449
West-1	Summer	Weekday							2,046			2,046
	Winter	Weekday							415			415
	Winter	Weekend							821			821
West-2	Summer	Weekday			831						2,966	3,797
	Winter	Weekday									256	256
		Total:	375	766	2,393	203	2,785	4,283	5,527	1,119	3,222	20,673

While the data in Table 4-1 show fairly broad coverage across both geography and interruption type, they also indicate the need for caution in interpreting the data for certain combinations of characteristics, just as was true with the medium and large C&I. For example, all of the 1989 data are winter weekday scenarios from one region (the Northwest), while all of the 1990 data are summer weekdays from the Southeast. Comparing the average interruption costs for the years 1989 and 1990 without some effort to control for the effects of the differences in region and type of scenario would be misleading.

4.1 Interruption Cost Descriptive Statistics

The next few tables provide a summary of the observed interruption costs for a few key variables but, again, caution must be used in interpreting the results because of coverage issues.

Table 4-2 shows the distribution of interruption costs per event by interruption duration. The results show interruption costs rising from an average of $273 for a voltage sag to $4,079 for an 8-hour interruption. The results trend generally upward as would be expected, although the figure for a 30 minute interruption is higher than would be expected and the figure for a 12-hour interruption is less than the figure for an 8-hour interruption (It is possible that the latter result represents a methodological artifact as only one study used the 12-hour duration). However, as discussed above, the table (unlike the regression analysis presented in Section 4.2 below) cannot control for all of the other factors which vary among the scenarios included within each duration. The effect of duration on interruption costs can only be examined in the context of a multivariate model controlling for differences among the studies.

Table 4-3 shows interruption costs converted to a cost per average kW/Hour. Because the individual figures for interruption costs per average kW/Hour are extremely variable (due in part to customers with extremely low kW usage and thus extremely high average kW/Hour figures), the mean and standard error figures are based on the total sum of interruption costs divided by annual average kW/Hour. The distribution percentiles are still based on the distribution of the individual values. Again, the figures are generally increasing, but as discussed above, only a multiple regression analysis can sort out these effects simultaneously to discern the true relationship between interruption duration and costs.

Table 4-2. Small Commercial and Industrial Customers Interruption Cost per Event by Duration

Duration	N	Mean	Standard Error	Standard Deviation	Percentiles				
					5%	25%	50%	75%	95%
Voltage sag	3,419	$273	24.4	$1,430	$0	$0	$0	$21	$1,246
15 min	92	$256	88.7	$850	$0	$0	$0	$0	$1,480
20 min	215	$392	92.1	$1,351	$0	$0	$59	$235	$1,174
30 min	256	$775	139.2	$2,228	$0	$0	$7	$300	$5,174
1 hour	8,911	$723	26.6	$2,511	$0	$0	$32	$423	$3,250
2 hours	188	$2,718	1,093.6	$14,995	$0	$0	$0	$498	$4,153
4 hours	5,519	$2,508	123.0	$9,139	$0	$0	$392	$1,664	$10,430
8 hours	1,393	$4,079	312.3	$11,656	$0	$54	$812	$3,247	$16,237
12 hours	680	$2,951	223.2	$5,821	$0	$375	$1,194	$3,125	$12,502

Table 4-3. Small Commercial and Industrial Customers US 2008$ Interruption Cost per Average kW/Hour by Duration

Duration	N	Mean (Ratio)	Standard Error	Standard Deviation	Percentiles of Individual kW/Hour figures				
					5%	25%	50%	75%	95%
Voltage sag	3,419	$120.1	10.8	$633.2	$0.0	$0.0	$0.0	$9.8	$661.5
15 min	92	$85.0	29.4	$281.7	$0.0	$0.0	$0.0	$0.0	$442.8
20 min	215	$187.5	45.6	$669.2	$0.0	$0.0	$31.9	$159.6	$1,591.8
30 min	256	$318.7	58.1	$930.1	$0.0	$0.0	$2.8	$112.0	$2,239.3
1 hour	8,911	$324.8	12.1	$1,144.6	$0.0	$0.0	$15.9	$231.2	$1,943.6
2 hours	188	$934.7	378.5	$5,189.4	$0.0	$0.0	$0.0	$231.7	$1,940.6
4 hours	5,519	$1,185.4	59.1	$4,390.0	$0.0	$0.0	$217.5	$976.4	$7,605.6
8 hours	1,393	$2,145.2	169.2	$6,313.6	$0.0	$31.2	$582.2	$2,241.4	$14,197.2
12 hours	680	$1,313.0	98.5	$2,568.9	$0.0	$189.6	$653.8	$1,715.3	$6,735.8

Table 3-4 provides a summary of the average interruption cost for 4 other interruption attributes or customer characteristics including season, weekday/weekend, region, and SIC code. The results are shown only for scenarios where the duration is 1 hour. The data suggest that interruption costs on a per event basis are higher in the summer than in the winter ($737 versus $543); are higher on weekdays than weekends ($765 versus $459); are higher in the Southwest than in other regions of the country; and are higher for Mining and Construction versus other industries.

Table 4-4. Small Commercial and Industrial Customers US 2008$ Summary of the Cost of a 1-Hour Interruption

Interruption Characteristic	N	Mean	Standard Error	Standard Deviation	Percentiles				
					5%	25%	50%	75%	95%
Season									
Winter	638	$543	72.3	$1,826	$0	$0	$0	$245	$3,059
Summer	8,273	$737	28.1	$2,556	$0	$0	$49	$433	$3,289
Day									
Weekend	1,229	$459	57.2	$2,006	$0	$0	$0	$188	$1,835
Weekday	7,682	$765	29.4	$2,581	$0	$0	$54	$480	$3,461
Region									
Midwest	366	$732	110.1	$2,107	$0	$0	$115	$587	$2,936
Northwest	2,352	$341	21.8	$1,058	$0	$0	$0	$250	$1,500
Southeast	2,584	$799	53.6	$2,723	$0	$0	$0	$380	$3,847
Southwest	1,346	$967	87.3	$3,202	$0	$0	$61	$612	$4,307
West	2,263	$886	60.1	$2,860	$0	$0	$138	$554	$3,792
Industry									
Agriculture	599	$352	60.5	$1,480	$0	$0	$0	$108	$1,624
Mining	33	$1,545	526.3	$3,024	$0	$0	$108	$1,304	$8,565
Construction	373	$1,301	248.3	$4,795	$0	$0	$73	$692	$4,607
Manufacturing	750	$913	99.5	$2,724	$0	$0	$43	$625	$4,846
Telco. & Utilities	474	$810	113.6	$2,473	$0	$0	$31	$489	$4,846
Trade & Retail	2,154	$627	37.7	$1,748	$0	$0	$95	$465	$3,059
Fin., Ins. & R.E.	642	$975	121.8	$3,086	$0	$0	$0	$440	$5,412
Services	3,233	$531	28.0	$1,590	$0	$0	$12	$375	$2,447
Public Admin.	99	$310	114.0	$1,135	$0	$0	$0	$192	$1,285

The mean and standard error of interruption costs per average kW/Hour in Table 4-5 below are also based on the total sum of interruption costs divided by annual average kW/H (the distribution percentiles are still based on the distribution of the individual values). Like the per-event figures, the data on a per average kW/Hour basis indicate that summer interruptions ($331) cost more than winter interruptions ($247). Weekday interruptions ($341) cost more than weekend interruptions ($220), illustrating lower average interruption costs during periods when most (retail) businesses are closed (weekends) compared to when they are open (weekdays).

Table 4-5. Small Commercial and Industrial Customers US 2008$ Summary of the Cost per Average kW/Hour of a 1-Hour Interruption

Interruption Characteristic	N	Mean (Ratio)	Standard Error	Standard Deviation	Percentiles of Individual kW/Hour figures				
					5%	25%	50%	75%	95%
Season									
Winter	638	$247.0	33.2	$838.0	$0.0	$0.0	$0.0	$129.0	$1,354.8
Summer	8,273	$330.8	12.8	$1,164.6	$0.0	$0.0	$20.9	$243.4	$1,999.7
Day									
Weekend	1,229	$219.9	27.6	$966.6	$0.0	$0.0	$0.0	$106.1	$992.3
Weekday	7,682	$340.5	13.3	$1,166.7	$0.0	$0.0	$22.4	$267.5	$2,095.5
Region									
Midwest	366	$352.7	55.1	$1,054.9	$0.0	$0.0	$55.9	$371.3	$2,685.4
Northwest	2,352	$147.7	9.5	$459.0	$0.0	$0.0	$0.0	$117.7	$940.8
Southeast	2,584	$287.6	19.5	$990.8	$0.0	$0.0	$0.0	$141.8	$1,534.6
Southwest	1,346	$522.8	47.2	$1,731.1	$0.0	$0.0	$33.1	$330.8	$2,328.5
West	2,263	$505.2	35.1	$1,671.5	$0.0	$0.0	$104.2	$441.9	$3,080.8
Industry									
Agriculture	599	$241.7	42.3	$1,035.5	$0.0	$0.0	$0.0	$89.5	$2,701.6
Mining	33	$926.9	335.7	$1,928.3	$0.0	$0.0	$137.0	$905.9	$9,058.6
Construction	373	$618.4	120.0	$2,317.3	$0.0	$0.0	$39.7	$496.1	$3,307.5
Manufacturing	750	$382.0	41.7	$1,141.9	$0.0	$0.0	$24.0	$310.9	$2,508.9
Telco. & Utilities	474	$358.5	51.0	$1,110.2	$0.0	$0.0	$14.0	$212.7	$2,397.2
Trade & Retail	2,154	$260.8	16.0	$743.7	$0.0	$0.0	$40.3	$225.6	$1,488.4
Fin., Ins. & R.E.	642	$457.8	58.1	$1,471.4	$0.0	$0.0	$0.0	$249.4	$2,550.5
Services	3,233	$235.1	12.5	$713.5	$0.0	$0.0	$5.9	$209.8	$1,464.7
Public Admin.	99	$166.1	61.0	$607.4	$0.0	$0.0	$0.0	$106.2	$1,249.4

4.2 Customer Damage Function Estimation

For the small C&I database, a similar set of procedures and analyses were conducted as those applied to the medium and large C&I database. A two-part model consisting of an initial Probit model to determine the probability of positive interruption costs was combined with a GLM model which relates average interruption costs to a set of independent variables via a logarithmic link function with Gamma distributed errors. The same truncation procedures described in Section 2 and implemented on the medium and large C&I database in Section 3 were also employed here. All observations meeting the statistical definition of mild outlier (more than 3 times the interquartile range above the 75th or below the 25th percentile were eliminated from the data for both log interruption costs (within industry and duration) and for log of annual kWh usage (within industry). The total number of observations removed by these criteria is 1,057.[22] The distributions of both the raw interruption costs and the natural log of interruption costs for the small C&I customer database are shown in Figure 4-1 and Figure 4-2.

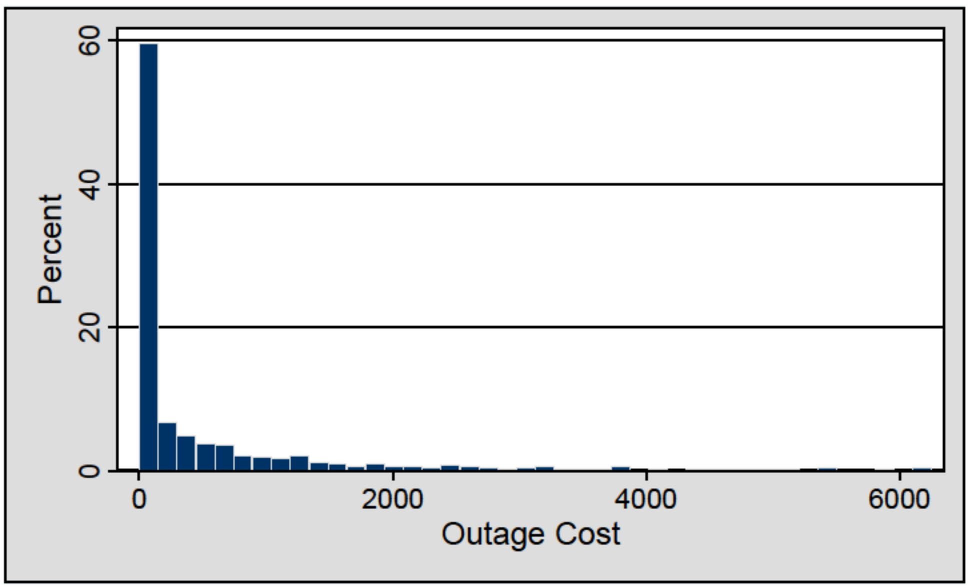


Figure 4-1. Small Commercial and Industrial Customers Histogram of Interruption Costs (0 to 95th Percentile)

[22] See the discussion on outliers above in Section 3.4.

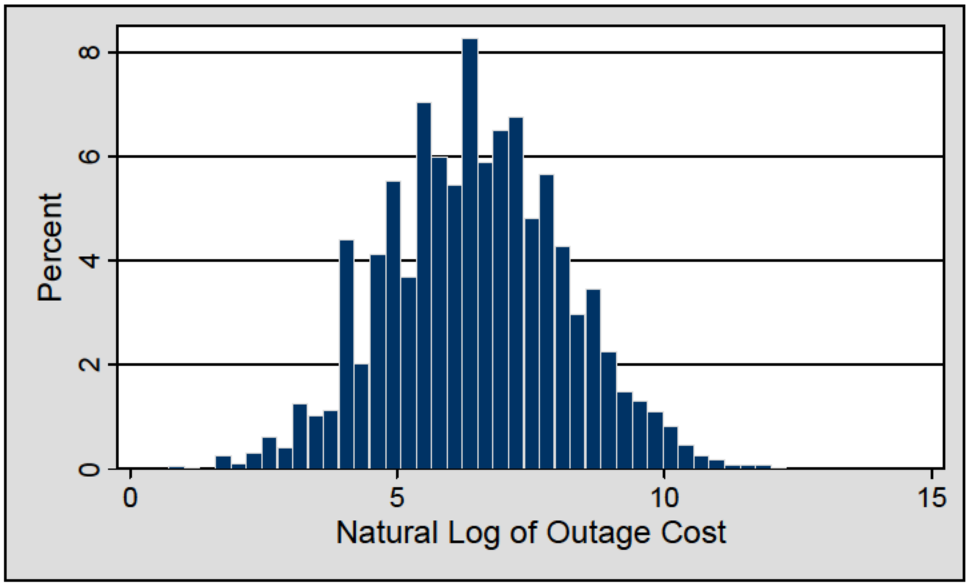


Figure 4-2. Small Commercial and Industrial Customers Histogram of Log Interruption Costs, Positive Values Only

Table 4-6 and 4-7 describe the initial probit regression model that specifies the relationship between the presence of zero interruption costs and a set of independent variables that includes interruption characteristics, customer characteristics, and industry designation. Although the purpose of this preliminary limited dependent model is only to normalize the predictions from the interruption costs regression in the second part of the two-part model, there are a few interesting results of note:

- The longer the interruption, the more likely that the costs associated with it are positive (the presence of a negative coefficient on the square of duration indicates that this effect diminishes for longer durations).
- Afternoon interruption costs are significantly more likely to incur positive costs than any other time of day, weekday interruptions are more likely to produce positive interruption costs than weekends, and summer interruptions are more likely to incur costs than non-summer interruptions.
- Customers with higher usage are more likely to have positive interruption costs.

Table 4-6. Small Commercial and Industrial Customers Average Values for Regression Inputs

Variable	Average Value
Interruption Characteristics	
Duration (minutes)	147.7
Duration Sq.	21,815.0
Morning	50.8%
Afternoon	30.7%
Evening	2.5%
Weekday	90.1%
Warning Given	9.1%
Summer	87.9%
Customer Characteristics	
Log of Annual MWh	3.0
Backup Gen. or Power Cond.	26.2%
Backup Gen. and Power Cond.	3.4%
Interactions	
Duration X Log of Annual MWh	436.5
Duration Sq. X Log of Annual MWh	64,476.9
Industry	
Mining	0.4%
Construction	4.9%
Manufacturing	9.5%
Telco. & Utilities	4.8%
Trade & Retail	26.9%
Fin., Ins. & R.E.	6.2%
Services	33.0%
Public Admin.	1.0%
Industry Unknown	6.3%

Table 4-7. Small Commercial and Industrial Customers Regression Output for Probit Estimation

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
Duration	0.003	0.001	0.000
Duration Sq.	-2.71E-06	9.08E-07	0.003
Morning	0.549	0.028	0.000
Afternoon	0.746	0.041	0.000
Evening	0.076	0.063	0.226
Weekday	0.231	0.029	0.000
Warning Given	-0.004	0.032	0.903
Summer	0.252	0.040	0.000
Customer Characteristics			
Log of Annual MWh	-0.066	0.027	0.014
Backup Gen. or Power Cond.	0.063	0.033	0.055
Backup Gen. and Power Cond.	0.330	0.080	0.000
Interactions			
Duration X Log of Annual MWh	1.02E-03	2.14E-04	0.000
Duration Sq. X Log of Annual MWh	-9.82E-07	3.23E-07	0.002
Industry			
Mining	0.639	0.204	0.002
Construction	0.710	0.090	0.000
Manufacturing	0.648	0.078	0.000
Telco. & Utilities	0.546	0.096	0.000
Trade & Retail	0.680	0.071	0.000
Fin., Ins. & R.E.	0.525	0.088	0.000
Services	0.507	0.069	0.000
Public Admin.	0.206	0.179	0.249
Industry Unknown	0.383	0.087	0.000
Constant	-1.714	0.103	0.000
Regression Diagnostics			
Observations	20,673		
Log Likelihood	-12,547		
Degrees of Freedom	4,618		
Prob > F	0.000		

Table 4-8 describes the GLM regression which relates the level of interruption costs to customer and interruption characteristics as well as industry designation for those variables for which sufficient data from multiple studies were available. A few results of note:

- The longer the interruption, the higher the interruption cost (the presence of a negative coefficient on the square of duration indicates that this effect diminishes for longer durations).
- Weekday interruptions are more costly than weekend interruptions, but summer interruptions cost less than non-summer interruptions.
- Larger customers (in terms of annual MWh usage) incur larger costs for similar interruptions.
- The construction and mining industries incur larger costs for a similar interruption than other industries.
- Time of day does not impact the magnitude of interruption costs.

Table 4-8. Small Commercial and Industrial Customers Regression Output for GLM Estimation

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
Duration	0.010	0.002	0.000
Duration Sq.	-1.26E-05	2.17E-06	0.000
Morning	-0.087	0.128	0.494
Afternoon	-0.036	0.142	0.797
Evening	-0.084	0.177	0.633
Weekday	0.284	0.086	0.001
Warning Given	-0.148	0.071	0.038
Summer	-0.541	0.158	0.001
Customer Characteristics			
Log of Annual MWh	0.168	0.072	0.019
Backup Gen. or Power Cond.	0.240	0.073	0.001
Backup Gen. and Power Cond.	0.455	0.165	0.006
Interactions			
Duration X Log of Annual MWh	-1.14E-03	5.43E-04	0.036
Duration Sq. X Log of Annual MWh	2.08E-06	7.43E-07	0.005
Industry			
Mining	0.505	0.444	0.255
Construction	0.567	0.239	0.018
Manufacturing	0.069	0.187	0.713
Telco. & Utilities	0.111	0.227	0.624
Trade & Retail	-0.328	0.174	0.060
Fin., Ins. & R.E.	0.152	0.211	0.471
Services	-0.414	0.171	0.015
Public Admin.	-0.485	0.378	0.200
Industry Unknown	0.244	0.216	0.259
Constant	6.755	0.262	0.000
Regression Diagnostics			
Observations	11,286		
Log Likelihood	-97,537		
Degrees of Freedom	3,616		
LR Test (Model with Constant Only)	LR $\chi^2(22)$ = 5,275.37 p-value=0.0000		
LR Test (Model with Constant, Duration, and log of annual MWh Only)	LR $\chi^2(22)$ = 2,912.43 p-value=0.0000		

Table 4-9. Small Commercial and Industrial Customers Summary of Predicted vs. Reported Interruption Cost

Variable	Predicted Interruption Cost	Reported Interruption Cost	Predicted as a % of Reported
Duration			
Voltage Sag	$374	$273	137%
Up to 1 Hour	$660	$712	93%
2 to 4 hours	$2,465	$2,515	98%
8 to 12 hours	$3,992	$3,709	108%
Industry (1-hour duration)			
Agriculture	$503	$352	143%
Mining	$1,358	$1,545	88%
Construction	$1,447	$1,285	113%
Manufacturing	$901	$954	94%
Telco. & Utilities	$864	$799	108%
Trade & Retail	$586	$597	98%
Fin., Ins. & R. E.	$867	$977	89%
Services	$477	$526	91%
Public Admin.	$287	$368	78%
Average kW/hr (1-hour duration)			
0-1 kW/hr	$597	$616	97%
1-2 kW/hr	$624	$771	81%
2-3 kW/hr	$688	$728	95%
3-4.5 kW/hr	$738	$698	106%
4.5-6 kW/hr	$746	$610	122%
Region (1-hour duration)			
Midwest	$497	$606	82%
Northwest	$503	$338	149%
Southeast	$765	$797	96%
Southwest	$544	$967	56%
West	$810	$886	91%
Time of Day (1-hour duration)			
Night	$489	$223	219%
Morning	$621	$660	94%
Afternoon	$800	$1,046	76%
Evening	$576	$168	343%

4.3 Key Drivers of Interruption Costs

Figures 4-3 - 4-6 display a comparison of the results of the customer damage function based on the estimated econometric model over the durations found in the sample dataset for several key drivers, including industry, time of day/season, and customer size. The results show that the relationship between damage and duration is non-linear for small customers just as it was for medium and large customers, albeit at much lower average values. Costs increase slowly within the first hour; accelerate through the second through the eighth hours; and, again, decline thereafter. All of the predictions are positive at the intercept representing the cost of momentary interruptions.

The results indicate that interruption costs for construction are significantly higher than those of any other business activity in the small customer class. The costs are roughly 50% more than those experienced by the next highest sector, mining. Costs for construction and mining are significantly higher than those of other businesses because they depend heavily on electricity to directly support production. Costs for other business types are relatively close to those of retail trade – though the differences among them are statistically significant.

Interruption costs for winter interruptions are significantly higher than those experienced in summer; and interruption costs during the night and on weekends are significantly lower as expected. The results show that an average small-medium customer in terms of number of employees and consumption will have approximately $818 in costs for a 1-hour summer afternoon interruption and $1,164 for a 1-hour winter afternoon interruption.

Figure 4-4 shows that the size of customer's load has an impact on interruption costs, but the relationship is nonlinear and small in magnitude. Increasing average kW/Hour consumption by a factor of 20 from 0.25 to 5.0 results in only a small increase in customer interruption cost, except at longer durations.

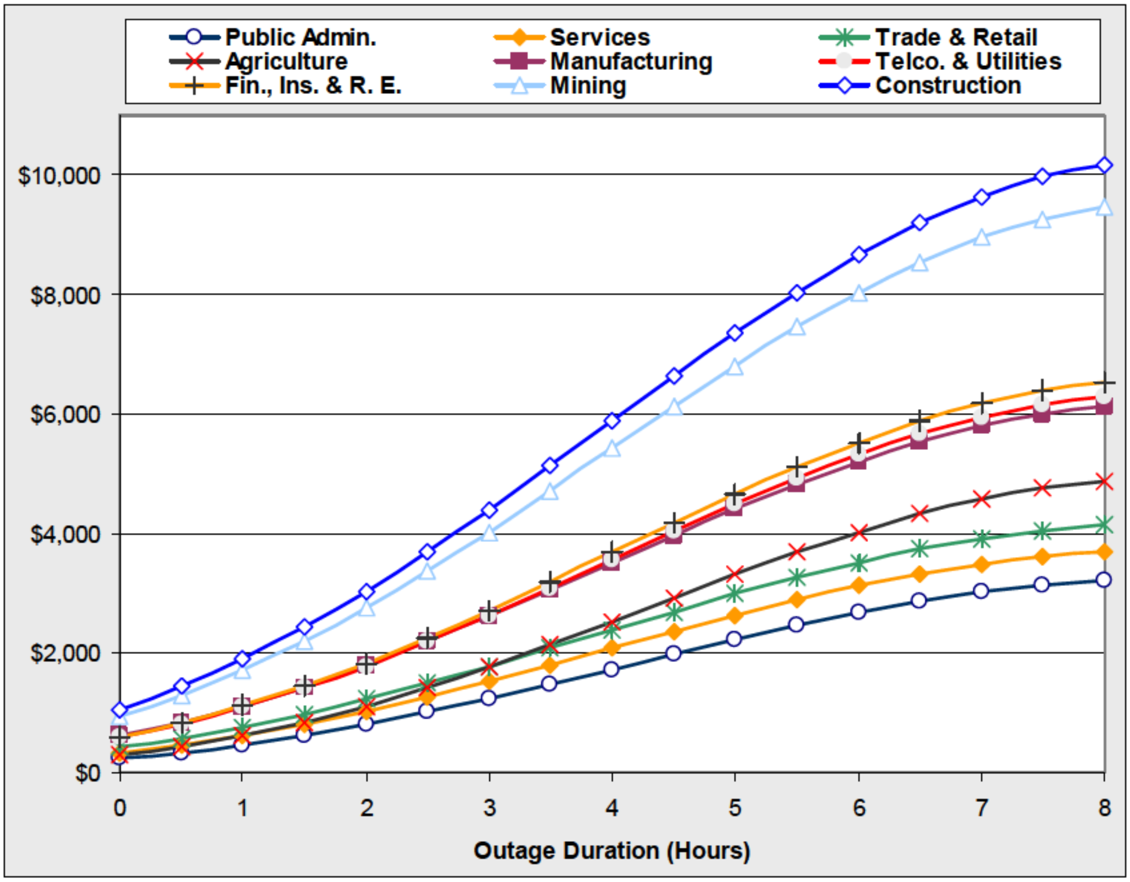


Figure 4-3. Small Commercial and Industrial Customers US 2008$ Customer Damage Functions by Industry- Summer Weekday Afternoon

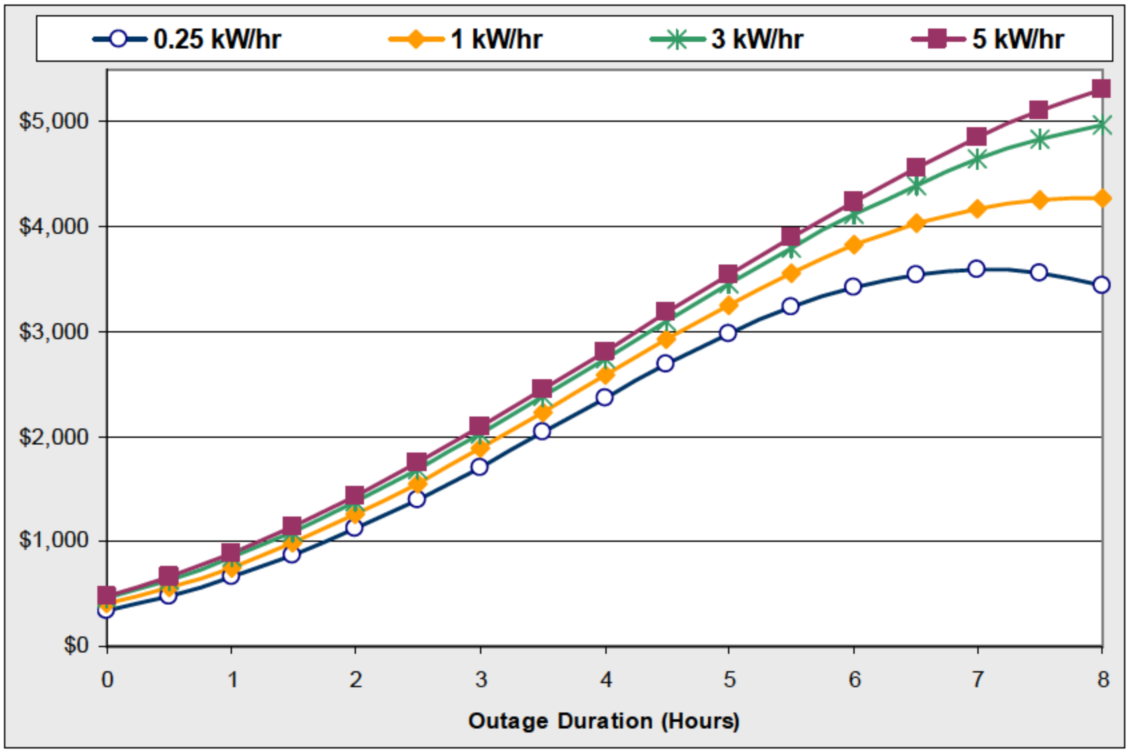


Figure 4-4. Small Commercial and Industrial Customers US 2008$ Customer Damage Functions by Average kW - Summer Weekday Afternoon

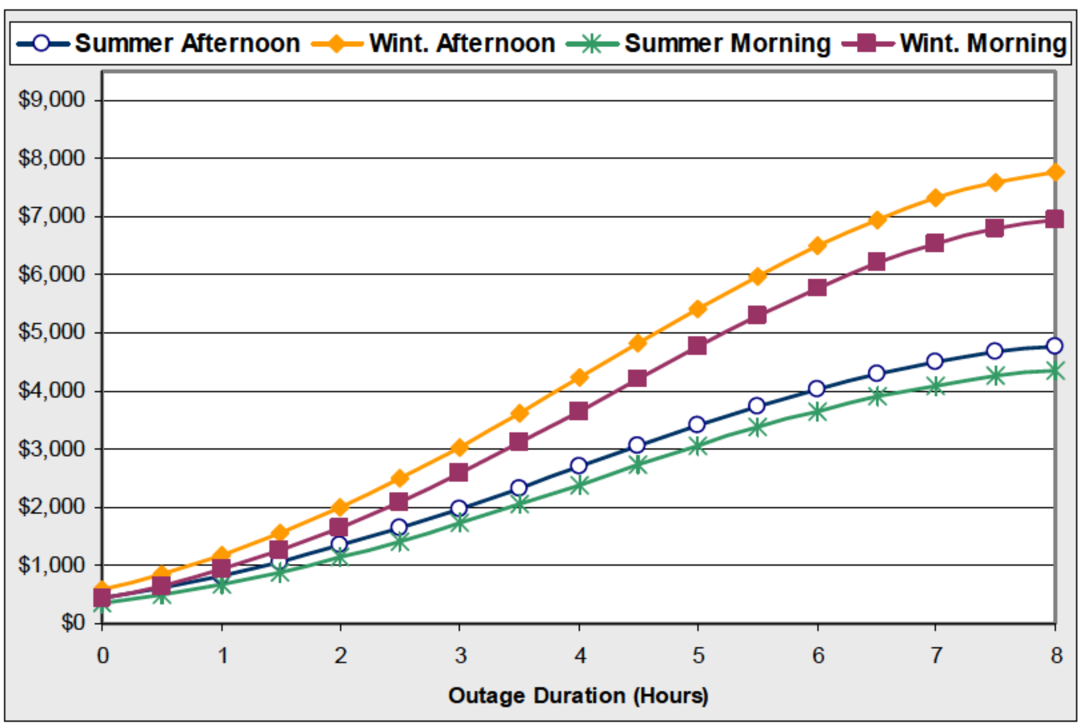


Figure 4-5. Small Commercial and Industrial Customers US 2008$ Customer Damage Functions by Season and Time of Day

Table 4-10. Small Commercial and Industrial Customers US 2008$ Expected Interruption Cost

Time of Interruption	Hours per Year	% of Hours per Year	Interruption Duration				
			Momentary	30 minutes	1 hour	4 hours	8 hours
Summer Weekday Morning	521	6%	$346	$492	$673	$2,389	$4,348
Summer Weekday Afternoon	435	5%	$439	$610	$818	$2,696	$4,768
Summer Weekday Evening	435	5%	$199	$299	$431	$1,881	$3,734
Summer Weekday Night	695	8%	$195	$296	$430	$1,946	$3,927
Summer Weekend Morning	209	2%	$203	$296	$414	$1,620	$3,067
Summer Weekend Afternoon	174	2%	$265	$378	$519	$1,866	$3,414
Summer Weekend Evening	174	2%	$107	$166	$246	$1,202	$2,512
Summer Weekend Night	278	3%	$103	$162	$242	$1,230	$2,618
Winter Weekday Morning	1,043	12%	$451	$660	$928	$3,659	$6,953
Winter Weekday Afternoon	869	10%	$592	$846	$1,164	$4,223	$7,753
Winter Weekday Evening	869	10%	$237	$368	$546	$2,699	$5,670
Winter Weekday Night	1,390	16%	$228	$358	$537	$2,760	$5,904
Winter Weekend Morning	417	5%	$253	$381	$549	$2,408	$4,791
Winter Weekend Afternoon	348	4%	$343	$504	$711	$2,846	$5,443
Winter Weekend Evening	348	4%	$122	$195	$298	$1,662	$3,697
Winter Weekend Night	556	6%	$116	$187	$289	$1,679	$3,811
Anytime	***8,760***	***100%***	***$293***	***$435***	***$619***	***$2,623***	***$5,195***

5. Residential Results

The residential database differs from the two commercial and industrial databases. The most important difference is that most residential studies of interruption costs or value of service do not focus on direct worth or cost estimates; rather they utilize willingness to pay or willingness to accept measures. Developing these measures generally involves describing a scenario to a residential customer and then asking them what they would be willing to pay to avoid this specific interruption or what they would be willing to accept as compensation (usually described as a credit on their bill) in order to put up with the interruption. The primary reason for using these alternatives to direct cost is the assumption that much of the "cost" of an interruption for residential customers is associated with the hassle, inconvenience, and personal disruption of the interruption, rather than direct out-of-pocket expenses, like buying candles or flashlight batteries. In this situation, customers may be able to more accurately represent the value of reliability by expressing their willingness to pay to avoid an interruption (or their willingness to accept some type of credit to accept an interruption) rather than calculate an out of pocket cost or savings.

In theory, from an economic perspective, willingness to pay (WTP) and willingness to accept (WTA or Credit) measures should produce the same value for a given interruption.[23] In practice, it is difficult to construct questions that produce identical results. Customers tend to place paying the utility in a different frame of reference than accepting a credit from the utility. Typically, willingness to accept measures produce a higher estimated value than willingness to pay measures. There are various practical and theoretical reasons offered for this finding. As a practical matter for this meta-analysis, all of the studies used a WTP framework and only a few also tested a WTA framework. Consequently the analysis focuses only on the WTP results.

In addition to the differences in measuring interruption costs, the residential sector is also a much more homogenous population with respect to interruption costs. Where commercial and industrial customer studies find interruption costs from 0 to hundreds of millions of dollars, the typical residential study shows that interruption costs vary over a much smaller range depending on the scenario. This effectively reduces the variation in the interruption cost measurement making it somewhat more difficult to find powerful explanatory variables. Households themselves are also more homogenous than business customers in terms of the end uses, dependence on electricity for critical operations, and consumption. This is not to say that reliability is not important to residential customers, rather to note that the range of variation in interruption costs and in customer characteristics is much narrower in the residential sector.

The residential database was built from 8 studies conducted by 6 companies, with a total of 7,546 respondents. There were approximately 26,026 individual responses to scenarios that form the basis of the merged dataset, subject to availability as a result of missing data and removal of outliers. Table 5-1 below shows the distribution of responses available for analysis by region, season, day of the week, and year:

[23] Although, technically WTP measures could be constrained by income. This analysis makes no attempts to reconcile any differences between WTA and WTP.

Table 5-1. Residential Customers Number of Cases by Region, Company, Season, Day of Week and Year

Region - Company	Season	Day of Week	Year of Survey 1989	1993	1997	1999	2000	2005	Total
Northwest- 1	Summer	Weekday	718						718
	Winter	Weekday	1,392						1,392
Northwest- 2	Winter	Weekday				3,554			3,554
	Summer	Weekday				718			718
Southeast- 2	Summer	Weekday		2,792	3,101				5,893
	Summer	Weekend			489				489
	Winter	Weekday		335					335
Southwest	Summer	Weekday					2,461		2,461
	Summer	Weekend					372		372
	Winter	Weekday					760		760
West-1	Summer	Weekday					1,946		1,946
	Winter	Weekday					797		797
	Winter	Weekend					372		372
West-2	Summer	Weekday		1,601				3,531	5,132
	Winter	Weekday		384				703	1,087
		Total:	2,110	5,112	3,590	4,272	6,708	4,234	26,026

5.1 Interruption Cost Descriptive Statistics

As with the commercial and industrial dataset, it is useful to see the underlying average costs, even though they are embedded in the data for customers who responded to the various scenarios. Table 5-2 shows that residential consumers generally report increasing WTP as the length of the interruption increases. However, the data are inconsistent and the standard deviations are generally larger than the average. The inconsistency suggests that the interruption costs reported by customers tend to vary widely across the studies and the average interruption costs for any given duration are subject to a great deal of influence from the studies used for that scenario.

The two most robust estimates for duration are the 1-hour and 4-hour as these two scenario durations were used in multiple studies across multiple regions. The average WTP per event for a 1-hour interruption is $4.2 and the average for a 4-hour interruption is $7.1, suggesting only a modest impact of duration on residential customer's willingness to pay to avoid an interruption.

Table 5-2. Residential Customers Interruption Cost by Duration

Duration	N	Mean	Standard Error	Standard Deviation	Percentiles				
					5%	25%	50%	75%	95%
Voltage sag	4,456	$2.2	0.093	$6.2	$0.0	$0.0	$0.0	$1.3	$12.8
30 min	1,453	$1.1	0.126	$4.8	$0.0	$0.0	$0.0	$0.0	$6.1
1 hour	10,518	$4.2	0.088	$9.0	$0.0	$0.0	$0.1	$4.3	$24.5
2 hours	335	$3.8	0.306	$5.6	$0.0	$0.0	$1.4	$6.9	$13.8
4 hours	7,495	$7.1	0.140	$12.1	$0.0	$0.0	$2.6	$7.8	$30.6
8 hours	1,769	$10.1	0.347	$14.6	$0.0	$0.0	$5.4	$12.5	$46.7

Table 5-3. Interruption Cost per Average kW/Hour by Duration

Duration	N	Mean (Ratio)	Standard Error	Standard Deviation	Percentiles of Individual kW/Hour figures				
					5%	25%	50%	75%	95%
Voltage sag	4,456	$1.4	0.062	$4.1	$0.0	$0.0	$0.0	$1.1	$10.6
30 min	1,453	$0.6	0.069	$2.6	$0.0	$0.0	$0.0	$0.0	$3.5
1 hour	10,518	$2.6	0.056	$5.8	$0.0	$0.0	$0.1	$3.4	$18.0
2 hours	335	$2.3	0.189	$3.5	$0.0	$0.0	$0.9	$3.4	$11.7
4 hours	7,495	$5.3	0.112	$9.7	$0.0	$0.0	$2.2	$8.6	$30.4
8 hours	1,769	$6.7	0.247	$10.4	$0.0	$0.0	$3.7	$11.7	$37.8

The WTP figures for several other key variables are shown in Table 5-4 for the raw costs and in Table 5-5 for the average kW/Hour costs. All figures are for scenarios with 1-hour duration, but they include a range of other attributes like winter versus summer and time of day. Overall, the results suggest that interruption costs per event for residential customers are:

- Higher in the summer than in the winter;
- Significantly higher on weekends than on weekdays (reversing the trend for commercial and industrial customers.

While these patterns are generally consistent with results from individual studies of interruption costs, caution must be used in interpreting the point estimates as different groups of customers responded to different combinations of scenario attributes. The customer damage functions presented below are the only reliable way to make generalizations about how interruption costs vary according to the various drivers.

Table 5-4. Residential Customers US 2008$ Summary of the Cost of a 1-Hour Interruption

Interruption Characteristic	N	Mean	Standard Error	Standard Deviation	Percentiles 5%	25%	50%	75%	95%
Season									
Winter	2,524	$2.9	0.170	$8.5	$0.0	$0.0	$0.0	$0.6	$25.0
Summer	7,994	$4.7	0.102	$9.1	$0.0	$0.0	$0.7	$6.4	$24.5
Day									
Weekend	489	$8.6	0.498	$11.0	$0.0	$1.3	$6.4	$12.8	$32.1
Weekday	10,029	$4.0	0.088	$8.8	$0.0	$0.0	$0.0	$3.8	$20.8
Region									
Northwest	3,566	$3.2	0.143	$8.5	$0.0	$0.0	$0.0	$1.3	$25.0
Southeast	3,233	$6.6	0.172	$9.8	$0.0	$0.1	$2.8	$6.9	$25.6
Southwest	1,078	$1.8	0.213	$7.0	$0.0	$0.0	$0.0	$0.0	$12.2
West	2,641	$3.7	0.169	$8.7	$0.0	$0.0	$0.5	$3.7	$16.2

Table 5-5. Residential Customers US 2008$ Summary of the Cost per kW/Hour of a 1-Hour Interruption

Interruption Characteristic	N	Mean (Ratio)	Standard Error	Standard Deviation	Percentiles of Individual kW/Hour figures 5%	25%	50%	75%	95%
Season									
Winter	2,524	$1.5	0.089	$4.4	$0.0	$0.0	$0.0	$0.2	$13.9
Summer	7,994	$3.1	0.070	$6.2	$0.0	$0.0	$0.6	$4.3	$19.2
Day									
Weekend	489	$5.3	0.326	$7.2	$0.0	$0.7	$3.9	$8.4	$28.6
Weekday	10,029	$2.5	0.057	$5.7	$0.0	$0.0	$0.0	$3.0	$17.4
Region									
Northwest	3,566	$1.6	0.073	$4.4	$0.0	$0.0	$0.0	$0.6	$13.9
Southeast	3,233	$4.2	0.113	$6.4	$0.0	$0.1	$2.2	$6.5	$22.8
Southwest	1,078	$1.0	0.117	$3.8	$0.0	$0.0	$0.0	$0.0	$7.5
West	2,641	$3.6	0.165	$8.5	$0.0	$0.0	$0.5	$4.0	$19.8

5.2 Customer Damage Function Estimation

To account for the influences of different interruption and customer characteristics, a multivariate analysis of the residential data was conducted. A two-part model consisting of an initial Probit model to determine the probability of positive interruption costs was combined with a GLM model which relates average interruption costs to a set of independent variables via a logarithmic link function with Gamma distributed errors. The same truncation procedures described in Section 2 and implemented on the C&I databases in Sections 3 and 5 were also employed here. The total number of observations eliminated is 742.[24]

[24] This includes 21 anomalous observations on Household Size which were eliminated by inspection, rather than the procedures described in Section 3.4.

The residential data presents different challenges than the C&I data. Although the residential data are less variable and contain fewer outliers, the percent of customers giving a "0" response can be as high as 60 to 80 percent for short duration interruptions. Use of the two-part model allows for the estimation of unbiased parameters to measure the relative effects of the interruption attributes and customer characteristics given the high number of 0 responses. The distributions of both the raw interruption costs and the natural log of interruption costs for the small C&I customer database are shown in Figure 5-1 and Figure 5-2.

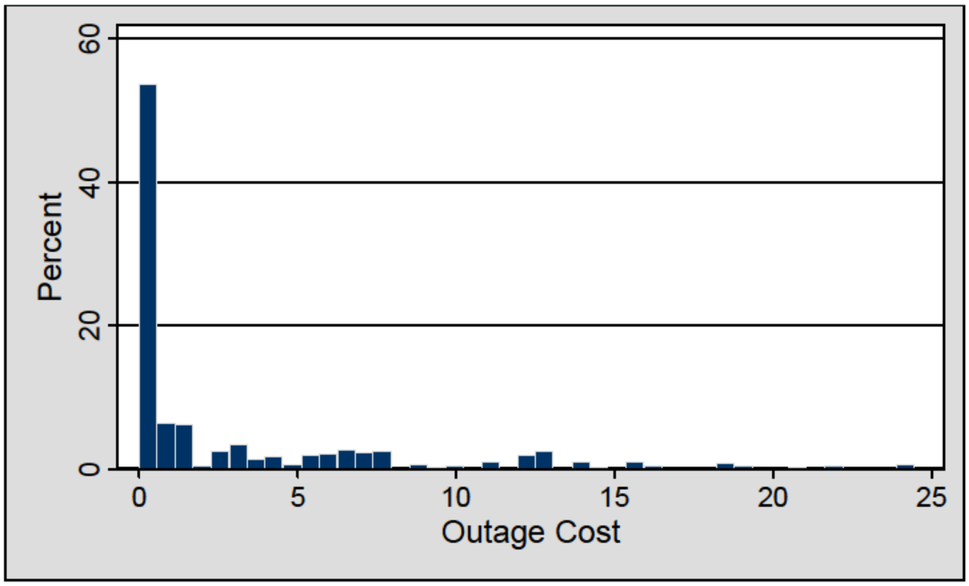


Figure 5-1. Residential Customers Histogram of Interruption Costs (0 to 95th Percentile)

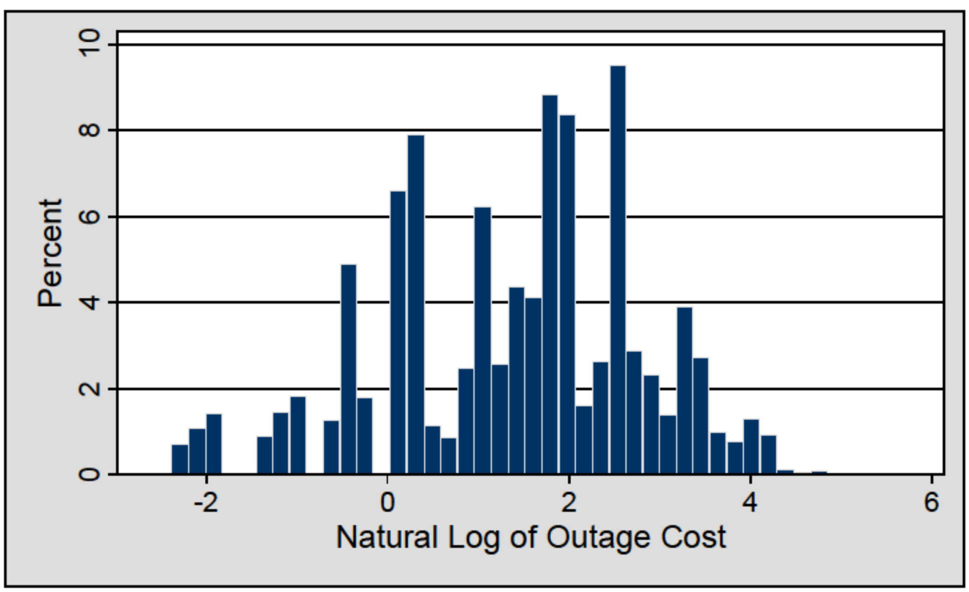


Figure 5-2. Residential Customers Histogram of Log Interruption Costs, Positive Values Only

In creating the customer damage functions, the residential analysis focuses on the WTP estimates of interruption costs instead of the WTA because there is more data across the studies in which a WTP framework was used.

The same basic treatment of the dependent variable used in the commercial and industrial datasets is also used for the residential data. In the first step a probit model was run on a dummy variable equal to zero for those observations with zero WTP and 1 for positive WTP. The predicted probabilities from this first step were retained. In the second step a GLM model using a log link function was used to relate the mean of interruption costs to the variables representing interruption scenarios and customer characteristics using a log link function and assuming the gamma family of error distribution.

Although the purpose of the preliminary probit model is only to normalize the predictions from the interruption costs regression in the second part of the two-part model, there are a few interesting results of note in Table 5-6 below.

Table 5-6: Residential Customers Average Values for Regression Inputs

Variable	Average Value
Interruption Characteristics	
Duration	129.2
Duration Sq.	16,694.9
Afternoon	44.2%
Evening	35.9%
Weekday	95.3%
Summer	68.1%
Customer Characteristics	
Log of Annual MWh	2.6
Household Income	$67,327.0
Backup Gen.	6.5%
Medical Equipment	5.1%
Interruption in Last 12 Months	71.3%
Attached Housing	5.0%
Apartment/Condo	10.3%
Mobile Home	3.9%
Manufactured Housing	2.1%
Unknown Housing	2.3%
Residents 0-6 Years Old	0.2
Residents 7-18 Years Old	0.5
Residents 19-24 Years Old	0.2
Residents 25-49 Years Old	0.9
Residents 50-64 Years Old	0.5
Residents 65+ Years Old	0.4

- The longer the interruption, the more likely that the WTP to avoid it is positive (the presence of a negative coefficient on the square of duration indicates that this effect diminishes for longer durations).
- Customers are more likely to pay a positive amount to avoid a morning interruption versus any other time of day, a weekend interruption versus a weekday interruption (although the effect is not statistically significant), and a summer interruption versus a non-summer interruption.

Table 5-7. Residential Customers Average Values for Regression Inputs

Variable	Average Value
Interruption Characteristics	
Duration	129.2
Duration Sq.	16,694.9
Afternoon	44.2%
Evening	35.9%
Weekday	95.3%
Summer	68.1%
Customer Characteristics	
Log of Annual MWh	2.6
Household Income	$67,327.0
Backup Gen.	6.5%
Medical Equipment	5.1%
Interruption in Last 12 Months	71.3%
Attached Housing	5.0%
Apartment/Condo	10.3%
Mobile Home	3.9%
Manufactured Housing	2.1%
Unknown Housing	2.3%
Residents 0-6 Years Old	0.2
Residents 7-18 Years Old	0.5
Residents 19-24 Years Old	0.2
Residents 25-49 Years Old	0.9
Residents 50-64 Years Old	0.5
Residents 65+ Years Old	0.4

Table 5-8. Residential Customers Regression Output for Probit Estimation

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
Duration	4.34E-03	1.71E-04	0.000
Duration Sq.	-5.52E-06	3.50E-07	0.000
Afternoon	-0.154	0.030	0.000
Evening	-0.624	0.024	0.000
Weekday	-0.009	0.030	0.764
Summer	0.521	0.022	0.000
Customer Characteristics			
Log of Annual MWh	-0.013	0.022	0.547
Household Income	1.75E-06	4.27E-07	0.000
Backup Gen.	-0.212	0.059	0.000
Medical Equipment	0.120	0.066	0.071
Interruption in Last 12 Months	0.107	0.031	0.000
Attached Housing	0.221	0.065	0.001
Apartment/Condo	0.007	0.047	0.879
Mobile Home	0.008	0.070	0.910
Manufactured Housing	0.343	0.094	0.000
Unknown Housing	-0.003	0.089	0.978
Residents 0-6 Years Old	0.027	0.025	0.289
Residents 7-18 Years Old	0.011	0.016	0.473
Residents 19-24 Years Old	0.057	0.028	0.043
Residents 25-49 Years Old	0.027	0.022	0.212
Residents 50-64 Years Old	0.013	0.024	0.584
Residents 65+ Years Old	-0.052	0.027	0.056
Constant	-0.532	0.080	0.000
Regression Diagnostics			
Observations	26,026		
Log Likelihood	-16,296		
Degrees of Freedom	7,538		
Prob > F	0.000		

Table 5-9 shows the GLM model developed from the residential data. This model used the maximum available data across the studies since most of the studies included household income, kWh annual usage, and region along with the interruption attribute variables. A few results of note:

- The longer the interruption, the higher the WTP to avoid it (the presence of a negative coefficient on the square of duration indicates that this effect diminishes for longer durations).
- Customers have a higher WTP to avoid evening interruptions.

- Customers have a higher WTP to avoid weekend interruptions versus weekday interruptions, but the WTP for summer interruptions is not significantly different from non-summer interruptions.
- Larger customers (in terms of annual MWh usage) incur larger costs for similar interruptions.

Table 5-9. Residential Customers Regression Output for GLM Estimation

Variable	Coefficient	Standard Error	P-Value
Interruption Characteristics			
Duration	3.29E-03	2.48E-04	0.000
Duration Sq.	-2.86E-06	4.50E-07	0.000
Afternoon	-0.189	0.043	0.000
Evening	0.128	0.029	0.000
Weekday	-0.157	0.036	0.000
Summer	-0.016	0.031	0.618
Customer Characteristics			
Log of Annual MWh	0.201	0.032	0.000
Household Income	2.42E-06	5.93E-07	0.000
Backup Gen.	0.267	0.093	0.004
Medical Equipment	0.144	0.101	0.155
Interruption in Last 12 Months	0.008	0.044	0.854
Attached Housing	0.114	0.090	0.207
Apartment/Condo	0.081	0.063	0.197
Mobile Home	0.078	0.102	0.446
Manufactured Housing	0.157	0.117	0.183
Unknown Housing	0.328	0.143	0.022
Residents 0-6 Years Old	0.039	0.032	0.230
Residents 7-18 Years Old	0.051	0.022	0.020
Residents 19-24 Years Old	0.022	0.036	0.549
Residents 25-49 Years Old	-0.042	0.030	0.168
Residents 50-64 Years Old	-0.036	0.032	0.271
Residents 65+ Years Old	0.022	0.036	0.527
Constant	1.305	0.112	0.000
Regression Diagnostics			
Observations	14,023		
Log Likelihood	-44,164		
Degrees of Freedom	4,657		
LR Test (Model with Constant Only)	LR $\chi^2(22)$ = 1,773.84 p-value=0.0000		
LR Test (Model with Constant, Duration, and log of annual MWh Only)	LR $\chi^2(22)$ = 556.20 p-value=0.0000		

Table 5-10 presents the average of the reported and predicted WTP figures for several categories. The model appears to provide an excellent overall fit to the data.

Table 5-10. Residential Customers US 2008$ Summary of Predicted vs. Reported Interruption Cost

Variable	Predicted Interruption Cost	Reported Interruption Cost	Predicted as a % of Reported
Duration			
Voltage Sag	$2.4	$2.2	109%
Up to 1 Hour	$3.7	$3.9	95%
2 to 4 Hours	$7.1	$6.9	103%
8 Hours	$9.7	$10.1	96%
Average kW/hr (1-hour duration)			
0-0.5 kW/hr	$2.9	$3.5	83%
0.5-1 kW/hr	$3.2	$3.3	97%
1-1.75 kW/hr	$3.7	$4.0	93%
1.75-2.5 kW/hr	$4.0	$4.1	98%
> 2.5 kW/hr	$4.6	$4.3	107%
Region (1-hour duration)			
Northwest	$3.5	$3.2	109%
Southeast	$4.6	$6.6	70%
Southwest	$3.0	$1.4	214%
West	$3.6	$3.7	97%
Time of Day (1-hour duration)			
Morning	$5.0	$5.7	88%
Afternoon	$3.6	$3.6	100%
Evening	$3.1	$3.0	103%

5.3 Key Drivers of Interruption Costs

Figure 5-3, Figure 5-4, and Figure 5-5 below show the predicted interruption costs across various durations for a summer afternoon interruption. Figure 5-3 shows a simulation of interruption costs for households with low versus high annual consumption, where low consumption was defined as less than 0.25 kW/Hour on average and high was defined as greater than 4 kW/Hour on average. The simulation shows the effect of household energy consumption on predicted interruption costs. The difference between a low consumption household and a high consumption household ranges from $2.80 to $4.70 for a 1-hour interruption to $7.50 to $13.00 for an 8-hour interruption.

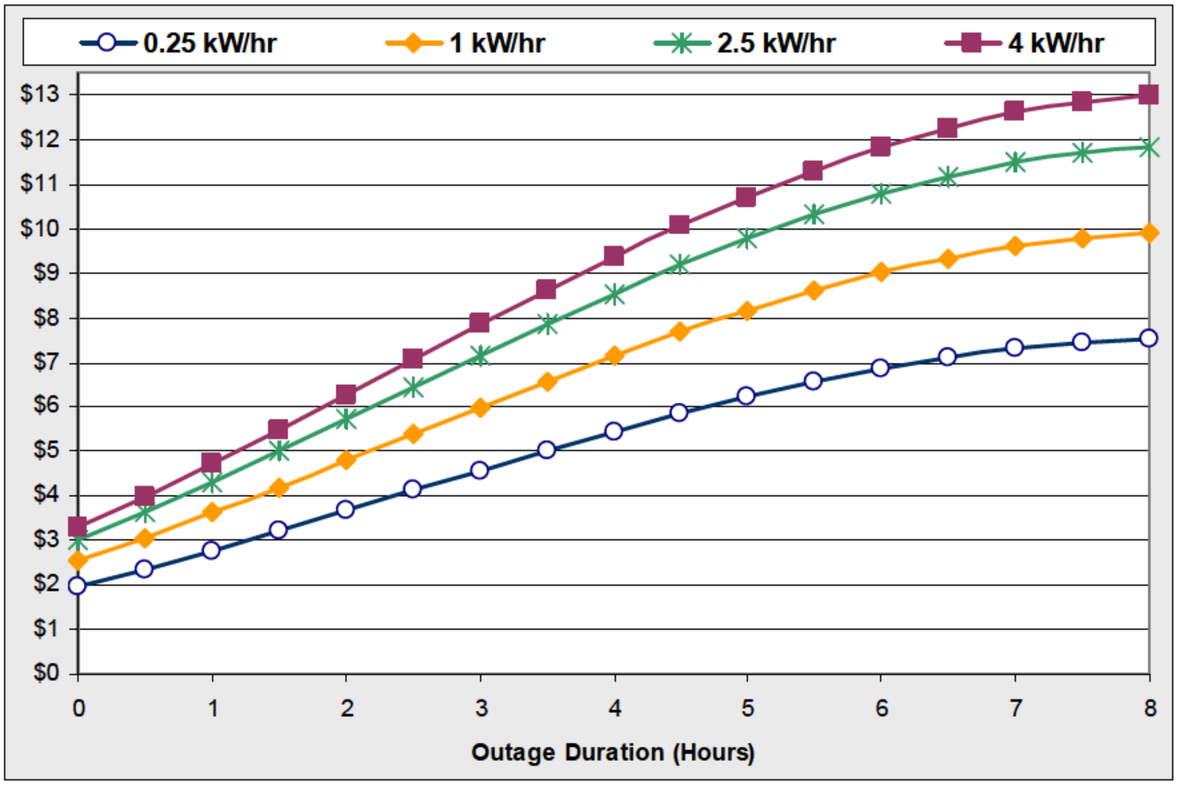


Figure 5-3. Residential Customers US 2008$ Customer Damage Functions by Average kW - Summer Weekday Afternoon

Figure 5-4 shows a simulation of interruption costs for households with low versus high annual income, where low consumption was defined as less than $25,000 on average and high was defined as greater than $100,000 on average. The simulation shows the effect of annual income on predicted interruption costs. The difference between a low income household and a high income household ranges from $3.40 to $4.40 for a 1-hour interruption to $9.40 to $11.90 for an 8-hour interruption.

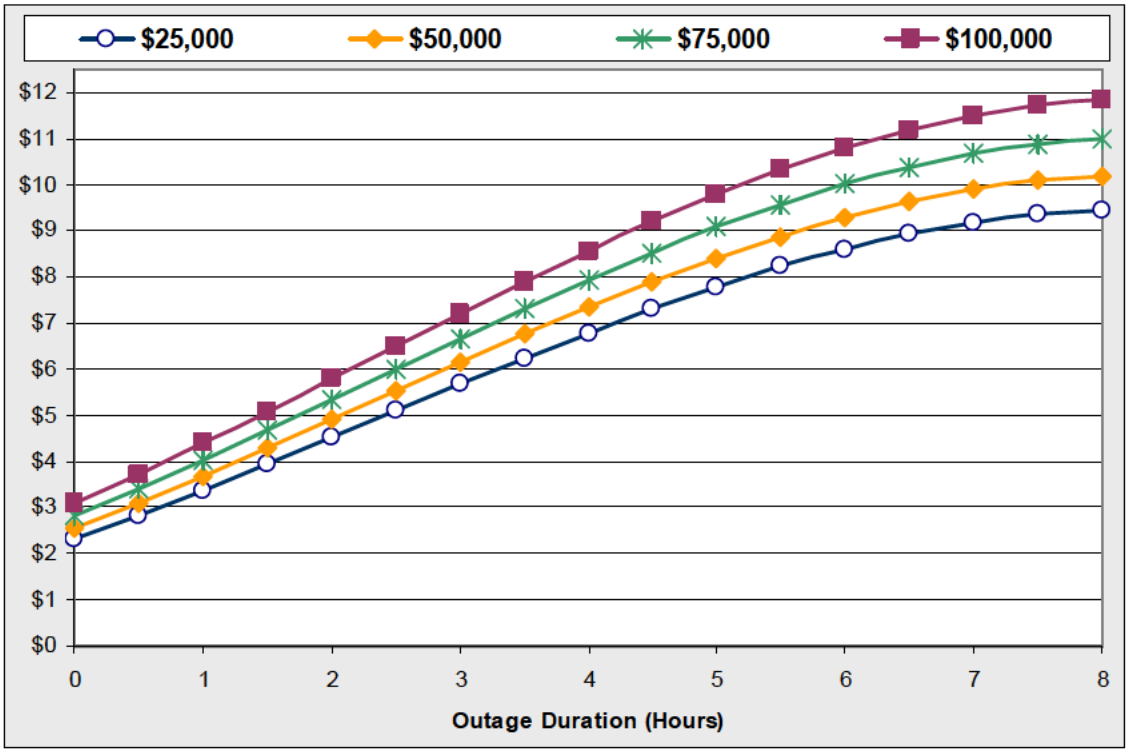


Figure 5-4. Residential Customers US 2008$ Customer Damage Functions by Household Income - Summer Weekday Afternoon

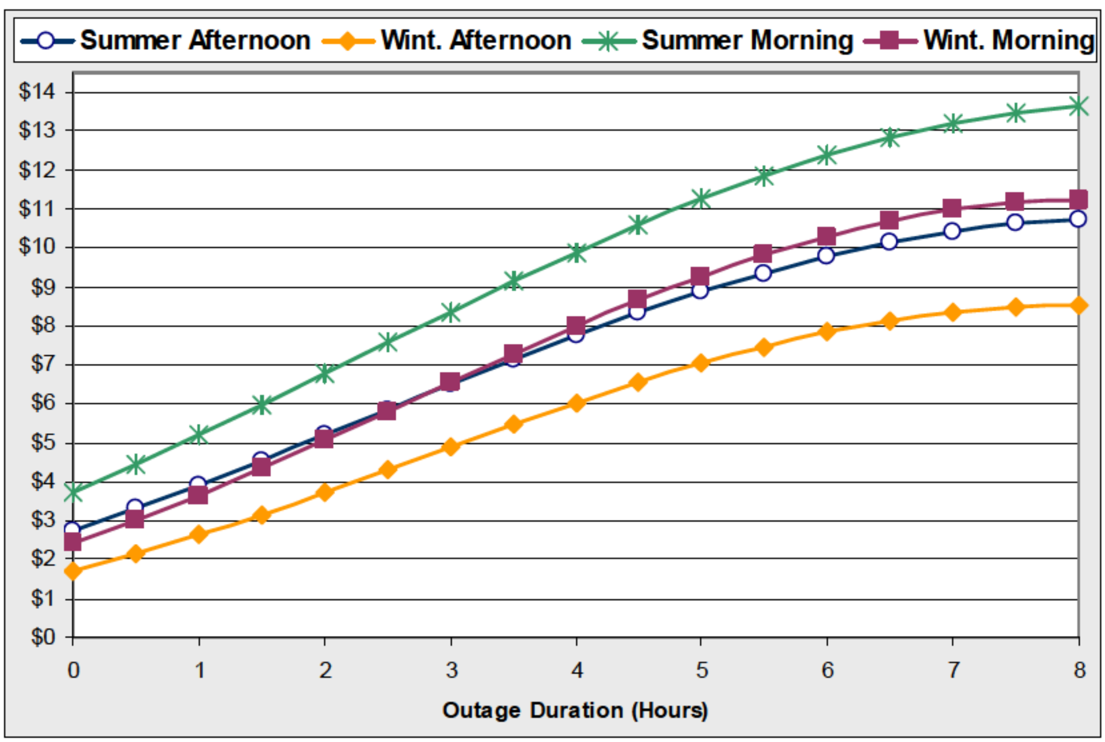


Figure 5-5. Residential Customers US 2008$ Customer Damage Functions by Season and Time of Day

Table 5-11. Residential Customers US 2008$ Summary of Predicted vs. Reported Interruption Cost

Time of Interruption	Hours per Year	% of Hours per Year	Interruption Duration				
			Momentary	30 minutes	1 hour	4 hours	8 hours
Summer Weekday Morning	521	6%	$3.7	$4.4	$5.2	$9.9	$13.6
Summer Weekday Afternoon	435	5%	$2.7	$3.3	$3.9	$7.8	$10.7
Summer Weekday Evening	435	5%	$2.4	$3.0	$3.7	$8.4	$11.9
Summer Weekday Night	695	8%	$2.4	$3.0	$3.7	$8.4	$11.9
Summer Weekend Morning	209	2%	$4.4	$5.2	$6.1	$11.6	$16.0
Summer Weekend Afternoon	174	2%	$3.2	$3.9	$4.6	$9.1	$12.6
Summer Weekend Evening	174	2%	$2.9	$3.6	$4.4	$9.9	$14.0
Summer Weekend Night	278	3%	$2.9	$3.6	$4.4	$9.9	$14.0
Winter Weekday Morning	1,043	12%	$2.4	$3.0	$3.7	$8.0	$11.2
Winter Weekday Afternoon	869	10%	$1.7	$2.1	$2.6	$6.0	$8.5
Winter Weekday Evening	869	10%	$1.3	$1.7	$2.1	$5.7	$8.2
Winter Weekday Night	1,390	16%	$1.3	$1.7	$2.1	$5.7	$8.2
Winter Weekend Morning	417	5%	$2.9	$3.6	$4.3	$9.4	$13.2
Winter Weekend Afternoon	348	4%	$2.0	$2.5	$3.1	$7.1	$10.0
Winter Weekend Evening	348	4%	$1.5	$2.0	$2.5	$6.7	$9.7
Winter Weekend Night	556	6%	$1.5	$2.0	$2.5	$6.7	$9.7
Anytime	***8,760***	***100%***	***$2.1***	***$2.7***	***$3.3***	***$7.4***	***$10.6***

5.4 Implications

The results from combining the data across the residential studies for this meta-analysis are encouraging but require further work to clarify the value of service reliability in this sector. The most encouraging aspect is that it appears that data from several studies can be reasonably combined to test the effects of various interruption attributes and customer characteristics across a broader geography and range of interruption scenarios than is possible in individual studies. The combined results, particularly when controlled in a multivariate analysis, are fairly consistent in the prediction of interruption cost values across various durations, and the results are plausible. Overall, the models show average 1-hour summer afternoon interruption costs for residential customers in the $2 to $5 range, an estimate that is not substantially different than other efforts to estimate this cost, yet it is based on combining data across several studies with slightly different methodologies and from different parts of the country. Further, the estimates along the duration curve and the variation across types of characteristics are generally sensible given what is known about interruption costs.

6. Intertemporal Analysis

Several of the studies utilized in this meta-analysis are in fact repeat studies conducted by the same utility (although the respondents were randomly chosen for each survey). The question naturally arises as to whether it is possible to estimate the effect of time on interruption costs, (i.e., are interruption costs generally increasing over time)?

6.1 Methodology

The methodology for the Intertemporal analysis is identical to that for the static analyses except for the addition of a dummy variable representing year differences in interruption costs from the base year (the earliest year the study was conducted) in the GLM equation relating mean interruption costs to the structural variables.

6.2 Results

There were a total of six cases involving a total of twelve studies which lent themselves to the intertemporal analysis. The results of those six comparisons are presented below (the results of the first step probit analyses as well as all other coefficients from the second step GLM analyses have been suppressed for brevity.

Table 6-1. Impact of Year Across Six Intertemporal Models

Company and Survey Year Tested	Coefficient	Standard Error	P-Value
West-2 (Year = 2005)			
Medium and Large C&I (base year = 1989)	-0.017	0.172	0.923
Small C&I (base year = 1993)	-0.219	0.186	0.239
Residential (base year = 1993)	-0.046	0.115	0.686
Southeast-2 (Year = 1997)			
Medium and Large C&I (base year = 1993)	0.295	0.243	0.226
Small C&I (base year = 1993)	-1.501	0.219	0.000
Residential (base year = 1993)	0.482	0.063	0.000

6.3 Implications

The most striking feature of this analysis is the degree to which, in an overall sense, reported costs have remained stable in the 10-15 year period since from the first study to the most recent. In four of the six cases, the p-value shown indicates the likelihood that any differences observed between the average interruption costs in each period would be expected as part of normal sampling variation rather than providing evidence of different interruption costs. Of the two cases where there is statistical significance, one produces a negative result, which would seem counterintuitive. These results do not offer strong evidence that the observed differences between costs in the two periods is due to a true change in value over time, or terribly reliable guidance regarding the magnitude of the difference.

7. Recommendations for Further Research

7.1 Interruption Cost Database Improvements

Several significant improvements should be made to the interruption cost meta-database. These improvements include the collection of additional interruption cost data on key geographical locations where information is currently not available and development of an easy to use interruption cost calculator that does not require extensive knowledge of econometric techniques to calculate customer interruption cost estimates.

Additional Interruption Cost Surveying Should be Undertaken for Key Geographical Areas of the US

The current interruption cost meta-database contains significant numbers of observations of interruption costs for customers located in the West, Southwest, Southeast, Northwest and Lower Mid-West. Significantly absent are interruption cost estimates for customers in the Northern tier of the Mid-West (i.e., Chicago metro and Minneapolis) and the Northeast corridor (e.g., New York metro, Boston metro and Baltimore-Washington corridor). There are reasons to suspect that interruption costs in these regions may be significantly different from those for other regions of the nation. This problem could be solved by carrying out customer interruption cost studies for a small number of key utilities located in these regions using the sampling and measurement protocols that were used in the other studies in the meta-database. This information is needed to round out the full database on the US and to ensure that interruption cost estimates can be made available to planners in those regions.

An Easy to Use Interruption Cost Calculator Should be Developed Using the Customer Damage Functions from the Meta-Database

An important factor limiting the expanded use of value-based electricity reliability planning is the somewhat arcane nature of the topic. Customers, not to mention grid planners, and policy makers, typically have only a nebulous appreciation for the economic value of reliable electric service, and thus are unable to properly account for it during resource planning processes. On a going forward basis as the demand for electricity capacity at all levels of electric systems expands to meet load growth resulting from the electrification of transportation and increasing penetration of renewable resources, the need for careful analysis of the benefits of capacity expansion, undervaluation of capacity investments may cause real problems.

The interruption cost estimation procedures outlined in this report are valid and reasonable. However, in their present form they are difficult for most intended users to apply. In order to address this issue, a simple, useful, and user-friendly tool that will enable customers to quickly estimate the economic value of reliable electric service should be developed. In order to help make value-based reliability planning a more common practice, the tool should be publicly available and posted online along with reasonable documentation.

The interruption cost calculator should be a windows application that requests some basic information from users about the interruption scenario from customers in order to produce customized estimates of interruption costs. These input variables would correspond to the planning level and the principle variables in the customer damage functions that have already been developed. Examples of key inputs include: the share of residential, small C&I, and medium/large C&I customers; the duration and onset time of the interruptions, and environmental attributes such as the season, average temperature, and humidity. The output would focus on the interruption costs for the region, utility, circuit, etc. that the user seeks to model. In other words, the estimate would combine the residential and commercial interruption costs to reflect those in the area being modeled, and provide a break down of share of interruption costs borne by different customer types.

In order to present the most robust, user-friendly tool to consumers, it should incorporate a number of toggles and options features in the calculator, enabling users to quickly and easily load default input factors and customize those inputs to suit their needs. Prior to releasing this tool to the general public, it must undergo extensively pressure-testing to make sure it produces reasonable results and that users cannot easily cause it to produce erroneous calculations. It should also be beta-tested it with planners and other industry users to work out all possible bugs or kinks and ensure a smooth roll-out.

The Interruption Cost Calculator Should Explicitly Model Statistical Uncertainty

In many planning applications it is not only important to know the expected or average value of lost load but the uncertainty associated with those impacts. Uncertainty can arise from two sources: uncertainty associated with the regression parameters of the statistical model and uncertainty associated with the key drivers or inputs into the customer damage function. Any eventual interruption cost calculator should take account of both sources of uncertainty and produce the full probability distribution of the value of lost load. With such a tool in place, it would be possible to make such statements as "based on the known uncertainties in the estimates of interruption costs, customer population sizes and reliability history, there is a 95% chance that the value of lost load for the system of interest is greater than X" (e.g., X is $50 Billion).

This could be accomplished by expanding the interruption cost calculator to work with Crystal Ball or @Risk, Monte Carlo simulation software packages that works as add-ins to MS Excel. The underlying calculator would also require some additional work on the input options in order to allow them to be modeled stochastically at the user's discretion.

With the development of the enhanced interruption cost calculator, it would be relatively straightforward to develop a Monte Carlo simulation-based model for estimating the value of lost load for the US, for a region, for a transmission line and even for a distribution circuit. This aspect of the calculator would also have to undergo significant bench and beta-testing to ensure that it was working properly and that users were not able to drive it to produce results that were nonsensical.

7.2 Interruption Cost Application Demonstration Projects

An important impediment to the application of value based reliability planning is the absence of publically available templates and widely accepted examples of the application of economic analysis in the context of utility transmission and distribution planning. Some utility planners and engineers may question whether the overlay of economic considerations will yield decisions about reliability investments that are truly optimal. An important next step in encouraging the use of value based planning by regulators and utilities is the assembly of carefully conducted demonstrations or case studies. There are many policy decisions where interruption costs can be used to assess whether the benefits of increasing reliability (the avoided interruption costs) outweigh the costs of investments. These include:

1. Evaluation of the economic benefits of specific Smart Grid applications on specific systems;
2. Assessing the economic costs and benefits of adding distributed generation (fuel cells, wind and solar) to grid connections;
3. Evaluating the reasonableness of routine grid reinforcement investments designed to preserve reliability at its present levels;
4. Selecting optimal resource adequacy levels for generation; and
5. Evaluating the economic benefits of Demand Response programs.

Some work has been undertaken in virtually all of these applications. However, most of this work has been done by utilities during internal efforts to plan for system reinforcement in preparing requests for funds to undertake system reinforcement or in the context of other regulatory proceedings and virtually none of it has been published.

There is a critical need to assemble concrete examples of the above kinds of analyses and to develop reasonable analysis techniques that both regulators and utility planners can understand. In most cases, this search will reveal that critical flaws existed either in the interruption cost assumptions used in the analysis or in the ways in which these cost assumptions were integrated with decision making. Therefore, it is also highly desirable that a set of ideal demonstrations be built – taking account of what has already been learned, but incorporating the best available techniques for incorporating information about interruption costs into the above described types of planning decisions.

7.3 Basic Research in Interruption Cost Estimation

Use of Common Reliability Indicators with Customer Interruption Cost Information Needs Development and Test

For many years now utilities have been tracking the reliability of their transmission and distribution systems using aggregate level performance indicators such as the System Average Interruption Frequency Index (SAIFI), the System Average Interruption Duration Index (SAIDI) and the Momentary Average Interruption Frequency Index (MAIFI). These average performance indicators provide very crude information about the impacts of unreliability on customers. Take, for example, the measurement of SAIFI. It represents the average frequency of interruption for all customers on the system components for which it is being reported (system, area, substation, line, etc.). It is the number of customer interruptions divided by the number of customers on the system. Unfortunately, this research shows that not only does the frequency of interruptions matter from the point of view of interruption cost, but so does duration – as well as the types of customers being interrupted. It is not possible to calculate the interruption cost for the system component by multiplying the interruption cost per event of duration (SAIDI) (properly weighted for the composition of customers by type on the system) times the average frequency of interruptions (SAIFI). This is so because underlying SAIDI is some set (frequency) of events of varying duration. A simplifying assumption that can be made is that the average duration is made up of n = (SAIFI) interruptions. In essence, this scales the SAIDI to the average frequency of interruptions. The problem with this approach is that it ignores the real distribution of unreliability with respect to time. Moreover, because the relationship between interruption cost and duration is positive and non-linear, this approach contains the potential to significantly underestimate the real interruption costs being experienced on the system component.

The use of these system average indicators is well established and will not likely change to accommodate the calculation of more realistic reliability impacts. Instead what is needed is careful research to discover and document the biases (if any) that may be introduced in making different kinds of simplifying assumptions designed to estimate interruption costs for system components (under different conditions) from information about the impacts of these conditions on commonly used reliability indicators.

Partial Interruption Costs Are Not Well Understood

Virtually all interruption cost studies to date have developed interruption costs for full interruptions. While this information is vary useful for valuing reliability improvements obtainable from system reliability reinforcements, they are of limited use for evaluating the costs and benefits of demand response. Demand response typically involves partial, rather than full interruptions. Most demand response programs do not involve full interruptions. Instead, customers reduce their demand partially in response to control or price signals coming from the system operators. The value of demand response to the system is the cost of the full interruption that might have been experienced by all parties on the system absent the demand response. The costs experienced by demand response participants are not the cost of a full interruption, but instead are the value of the part of the load they curtail at the time of the demand response request. For purposes of evaluating the cost effectiveness of demand response programs, it is not appropriate to consider the value of the partial interruption to be zero – although in some cases it undoubtedly is. The question is: what is the value of the partial interruption for customers participating in these programs if it is not zero.

The current meta-database (focused on the value of full interruptions) cannot address this issue. To do so, additional research should be undertaken to measure the cost of partial interruptions for loads of different types. There is a solid literature on utility customer response to curtailable and interruptible programs and to time varying rates. With the increasing penetration of advanced metering equipment, evidence of customer response to pricing and load control methodologies is becoming increasingly available. A careful review of the literature and results of ongoing customer studies designed to estimate the value of partial interruptions to customers should be undertaken to supplement the existing information in the meta database on full interruption costs.

Less Costly Methods for Measuring Customer Interruption Cost are Needed

A major barrier to widespread use of customer interruption cost information in regulation and utility planning is the cost of collecting reliable information on customer interruption costs. The meta-data base and customer damage functions described in this paper will make reasonable "placeholder" estimates of customer interruption costs widely available and should go a long way toward solving this problem.

However, in the ideal case, a more refined and less expensive approach should be developed for estimating customer interruption costs. The current generation of customer interruption cost surveys was built on state of the art survey techniques that were available in the 1980s. Given the experience with these methods and the changes in survey technology that have evolved over the past 10 years it should be possible to develop a new, more accurate and much less expensive process for measuring customer interruption costs. In particular, the following improvements should be investigated:

1. It is likely that large commercial and industrial customer interruption cost can be measured using a combination of internet and telephone interviewing – reducing the costs of the current on-site approach to interruption cost measurement for this class of customer by two-thirds. This approach should be tested.
2. It may also be possible to measure large and medium customer interruption costs using a webinar format in which a large number of respondents are guided through a standard survey instrument by a single super-interviewer who answers questions from the audience as the form is completed on line. Again, this would significantly reduce costs and should be tested.
3. Medium and small commercial and industrial customers can be measured using the internet after an appropriate respondent at each target organization has been identified by telephone.

All of these approaches (and maybe others) should result in much lower data collection cost. The question is: will the resulting data be comparable to what is obtained using conventional survey measurement techniques?

Experiments should be undertaken to test and perfect alternative interruption cost data collection methodologies that yield both valid and reliable information. These tests will be difficult to carry out. The inherent variation in interruption costs measurements and the current costs of some of the measurement techniques are high. The challenge will be to design experimental tests of the reliability of measurements that are sufficiently powerful to detect meaningful differences arising from the survey designs.

The Impact of Changing Interruption Frequency is Not Well Understood

All of the surveys used in the meta-analysis measured the economic cost a single interruption in the context of the customer's current level of service. That is, they ask the customer to describe the costs they would experience in the event of a single interruption. It is not described as an additional interruption. Indeed the survey forms do not allow measurement of the impact of increasing frequency on interruption cost. It is unknown how the costs of interruption would change if the frequency of interruptions were increased or decreased.

While it is reasonable to assume that interruption costs will increase or decrease monotonically with frequency, this assumption should be investigated.

8. Summary and Conclusions

This paper describes research designed to merge the results from 28 previously confidential interruption cost surveys into several large, integrated data sets (for different customer types) that can be used to estimate electricity customer interruption costs for the US. The principal benefit of this work is the development of reliable estimates of customer interruption costs for populations of industrial, commercial, and residential customers in the US derived from a rich database of responses to customer interruption cost surveys. The interruption costs reported in this paper illustrate the usefulness of the customer damage functions that have been estimated using the meta-database assembled for this research.

Although customer damage functions reported in this paper represent a significant improvement over past information about customer interruption costs, there are limitations to how the data from this meta-analysis should be used. First, certain very important variables in the data are confounded among the studies we examined. In particular, region of the country and year of the study are correlated in such a way that it is impossible to separate the effects of these two variables on customer interruption costs. Thus, for example, it is unclear whether the higher interruption cost values for the southwest are purely the result of the hot summer climate in that region or whether those costs are higher in part because of the particular economic and market conditions that prevailed during the year when the study for that region was done.

There is also some correlation between regions and scenario characteristics. The sponsors of the interruption-cost studies were generally interested in measuring interruption costs for conditions that were important for planning for their specific systems. As a result, interruption conditions described in the surveys for a given region tended to focus on periods of time when interruptions were more “problematic” for that region (e.g., summer peak or months when thunderstorms are common). Unfortunately, the time periods when the chance of interruptions is greatest are not identical for all sponsors of the studies we relied upon, so interruption scenario characteristics tended to be different in different regions. Fortunately, most of the studies we examined included a summer afternoon interruption, so we could compare that condition among studies.

A further limitation of our research is that the surveys that formed the basis of the studies we examined were limited to certain parts of the country. No data were available from the northeast/mid-Atlantic region, and limited data were available for cities along the Great Lakes. The absence of interruption cost information for the northeast/mid-Atlantic region is particularly troublesome because of the unique population density and economic intensity of that region. It is unknown whether, when weather and customer compositions are controlled, the average interruption costs from this region are different than those in other parts of the country.

This paper has removed an important barrier to the widespread use of value based reliability planning in regulation and utility system planning – the availability of reasonable estimates of customer interruption costs. There are others. Additional work that needs to be done includes:

1. Additional interruption cost surveying should be carried out in regions where information on customer interruption costs is currently unavailable (i.e., the Northeast Corridor and the Northern Tier of the Mid-West)

2. An easy to use interruption cost calculator should be developed driven by the customer damage functions described in this paper.
3. Additional work should be carried out to develop the ability to model uncertainty in interruption cost estimates
4. Robust examples of the use of customer interruption costs to assess the benefits arising from different kinds of reliability reinforcements and regulatory decisions should be developed and published
5. Additional basic research is needed to develop reasonable ways of using customer interruption cost information with currently used indicators of reliability performance (e.g., SAIFI and SAIDI); estimate partial interruption cost; and develop modern and less expensive techniques for estimating customer interruption costs.

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Appendix A. Data Transformation

Creating the meta-datasets involved a multi-step process. First, the datasets, codebooks and survey instruments had to be obtained from the companies if Population Research Systems did not have them already available. Second, datasets had to be standardized and merged. This Appendix describes these processes.

A.1 Acquiring the Datasets

Companies that had conducted VOS studies were contacted by phone by the Project Director. Typically they asked for documentation, so they were emailed a letter and a document explaining the genesis and purpose of the study. When requested, Non-Disclosure Agreements were signed assuring that customer-specific information would not be made available, an assurance that was actually part of the study design. Because PRS had conducted several of the studies, the data and other materials for those studies were in-house. In other cases we received data files from the utility, or from the consulting firm that conducted the study. In one instance, the data were on 5-¼" floppy disks but fortunately they were still readable.

A.2 Construction of The Database

Altogether, we received 28 different datasets from surveys fielded by 10 different utility companies between 1989 and 2005. Some of the utilities surveyed all three customer types – medium and large commercial and industrial C&I, small C&I, and residential – while others did not. In some cases there was only one dataset for commercial and industrial customers, and these were sorted into medium-large or small according to electricity usage. Table A- 1. Inventory of Datasets lists the utility company, survey year, and types of data for each of these 28 datasets.

Table A- 1. Inventory of Datasets

<table>
<tr><th>Utility Company</th><th>Survey Year</th><th>Medium and Large C&I</th><th>Small C&I</th><th>Residential</th></tr>
<tr><td>Southeast-1</td><td>1997</td><td colspan="2">X</td><td></td></tr>
<tr><td rowspan="2">Southeast-2</td><td>1993</td><td>X</td><td>X</td><td>X</td></tr>
<tr><td>1997</td><td>X</td><td>X</td><td>X</td></tr>
<tr><td>Southeast-3</td><td>1990</td><td>X</td><td>X</td><td></td></tr>
<tr><td>Midwest-1</td><td>2002</td><td colspan="2">X</td><td></td></tr>
<tr><td>Midwest-2</td><td>1996</td><td>X</td><td>X</td><td></td></tr>
<tr><td>West-1</td><td>2000</td><td>X</td><td>X</td><td>X</td></tr>
<tr><td rowspan="3">West-2</td><td>1989</td><td>X</td><td></td><td></td></tr>
<tr><td>1993</td><td></td><td>X</td><td>X</td></tr>
<tr><td>2005</td><td>X</td><td>X</td><td>X</td></tr>
<tr><td>Southwest</td><td>2000</td><td>X</td><td>X</td><td>X</td></tr>
<tr><td>Northwest-1</td><td>1989</td><td colspan="2">X</td><td>X</td></tr>
<tr><td>Northwest-2</td><td>1999</td><td colspan="2">X</td><td>X</td></tr>
</table>

Note: The Midwest-1 company classified the target populations as industrial and commercial rather than medium and large C&I and small C&I, as did the other surveys. This distinction did not pose a problem during the standardization process since the companies could be re-apportioned according to annual kWh. Once received, the next tasks were to read the datasets, identify the variables required for the analysis, standardize these variables, merge the datasets, and then standardize the dollar amounts into 2008 dollars. The variables required for the C&I data and Residential data are in Table A- 2 and Table A- 3:

Table A- 2. Variables for Commercial & Industrial Meta-Sets

Interruption Specific	Respondent-Specific
Season	Number of interruptions
Hour of day	Back-up generator
Day of week	Annual usage
Duration	SIC Code
Warning given	Number of employees
Interruption cost per event	
Year of survey	
Geographic region	

Table A- 3. Variables for Residential Meta-Sets

Interruption Specific	Respondent-Specific
Year of survey	Housing type and ownership
Season	Sick bed/medical & med. equipment.
Hour of day	Home business
Day of week	HH Income
Duration	Number of interruptions
Warning given	Back-up generator
Geographic region	Annual kWh
Willingness to pay	
Willingness to accept	

The small C&I and medium and large C&I data required the same variables, so in order to create the small C&I dataset and the medium and large C&I dataset, all of the available C&I datasets were merged together into a single C&I dataset. The C&I dataset was then parsed into two portions: small C&I and medium and large C&I, based on annual kWh.

A common cutoff point for separating small C&I from medium and large C&I is at 50,000 annual kWh; customers falling below 50,000 annual kWh are considered small C&I, while those above 50,000 annual kWh fall into the category medium and large C&I. The resulting medium and large C&I dataset has 30,966 observations and the small C&I dataset has 21,365 observations.

As explained in the note at the bottom of Table A- 1, the Midwest-1 company's customer base was divided into industrial and commercial customer types, rather than using small C&I and medium and large C&I. To conform to the customer types defined in the other datasets, we apply the same decision rule, based on annual kWh, to their industrial and commercial customers, effectively reassigning them as small C&I or medium and large C&I.

The combined residential dataset is a straightforward merge of the eight individual residential datasets. The resulting residential dataset has 26,738 observations.

A.3 Missing Data and Treatment Of Outliers

There are two relevant dependent variables in the all three of the datasets: (1) total interruption cost, and (2) total interruption cost per average kW (calculated by dividing annual kWh by 8760 – the number of hours in a year). For the purposes of analysis, there is a different sample size for each dependent variable, based on the number of observations with missing values on the particular dependent variable.

The analysis samples are constructed from the original survey datasets as follows: First, all observations meeting the statistical definition of mild outlier (more than 3 times the interquartile range above the 75^{th} or below the 25^{th} percentile were eliminated from the data for both log interruption costs (within industry and duration) and for log of annual kWh usage (within industry) were removed from the analysis.[25] Second, those observations with missing values on the relevant dependent variable are eliminated.

For all C&I data combined, there are 60,537 cases, but only 53,406 have data for average kW. About 2.8% of cases are excluded owing to outliers and missing data, leaving 51,741 cases available for calculating total cost.

For the residential dataset, there are 36,168 cases, but only 26,789 have data for average kW, household income and household size. About 2.7% of cases are excluded owing to outliers and missing data, leaving 26,026 cases available for calculating total cost.

A.4 Calculation of Total Interruption Costs – C&I

The calculation of total interruption cost varies according to the format of each survey. Some surveys, in addition to asking about total interruption costs, ask for detailed estimates of component costs, including lost production/sales, damage to equipment or materials, extra overhead, addition labor and overtime costs, and other costs associated with an interruption. Other surveys only request a total estimated cost for each interruption scenario.[26]

[25] See the discussion on outliers above in Section 3.4.
[26] This analysis assumes that reported costs are the same whether the question asks for specific cost components or total costs. The issue of whether the format of such question might tend to bias the results in one direction or another is left to future research.

In cases where both total costs and component costs are available, our estimate of total interruption cost is based on the sum of the component costs. However, if the sum of component costs does not match the estimate of total cost provided by the customer, we use the estimate of total cost in our analysis instead of the sum of component costs.

Furthermore, many surveys include multiple scenarios to gather information about interruptions under different conditions. Interruption scenarios may vary by the time of day, day of the week, season, duration of the interruption, and whether or not there is advanced warning of the interruption. Within our datasets, each scenario is a separate observation. Therefore, each customer may have multiple records within a given dataset, up to a maximum of 6 records for the Northwest-2 C&I data. In other words, the scenario became a case to which the individual data were appended.

A.5 Calculation Of Willingness to Pay – Residential

The residential surveys do not ask customers for estimates of interruption costs because household respondents are unable to accurately gauge the costs unlike business customers. Rather, residential customers are generally asked two questions: (1) how much would you be willing to pay for electric service to avoid the power interruption in the case of this interruption (willingness to pay or WTP)? and (2) how much would you accept as a credit for a particular interruption scenario (willingness to accept or WTA)?

These questions can be posed in many ways. Some surveys allow customers to select WTP and WTA amounts from a list of possible choices. Others permit customers to enter any amount into a blank field. Many surveys use a combination of methods. For example, the West-1 residential survey asks customers the following questions to determine WTP and WTA.

> Suppose an electric service was available to handle all of your electrical needs during this **Y** hour interruption. With this service, you would not have to make any adjustments to the interruption since your electricity would not go off.
>
> Would you pay **$X** for this electric service to avoid this **Y** hour interruption? (CIRCLE ONE NUMBER)
> 1 No
> 2 Yes
> -8 Don't Know
> -9 Refused/Missing
>
> Would you pay **2 * $X** for this electric service to avoid this **Y** hour interruption? (CIRCLE
> ONE NUMBER)
> 1 No
> 2 Yes
> -8 Don't Know
> -9 Refused/Missing

Would you pay ½ * **$X** for this electric service to avoid this **Y** hour interruption?
(CIRCLE
ONE NUMBER)
1 No
2 Yes
-8 Don't Know
-9 Refused/Missing

What is the **maximum** you would pay for this electric service to avoid this **Y** hour interruption?
$_______
-8 Don't Know
-9 Refused/Missing

Our WTP and WTA amounts are calculated as the maximum amount provided by the customer. In the case of a categorical response, each category was converted to a numeric value prior to applying the maximization rule.

A.6 Explanatory Variables

In order to consolidate our 28 datasets into a single dataset for each customer type, we needed to enforce conformity of measures across datasets. Year of survey simply ranges from 1989 to 2005. The region of the U.S. is recoded as: West, Southwest, Northwest, Midwest, and Southeast. Regional assignments are based on the location of the utility company. We do not have any information from the Northeast.

Most interruption scenarios include the duration of the interruption, season of the year, day of the week, hour of the day, and whether or not advance warning of the interruption is provided. There are 12 different durations, ranging from a voltage sag to a 12-hour interruption. It is coded as a continuous variable Season has been coded as a dichotomous variable for winter or summer (no spring or fall scenarios). Day of the week is sometimes specified, although most surveys only distinguish between a weekday and a weekend, so it is coded as a dichotomous variable. Hour of the day has been collapsed into four categories: night (11pm-1am) morning (6am-11am), afternoon (12pm-4pm), evening (5pm-8pm). Interruption scenarios do not cover all hours of the day. Advance warning of an interruption is dichotomized into a Yes/No indicator.

SIC is a 4-digit coded used to categorize companies into industries. The first digit represents the broadest industry classification and each subsequent digit provides a more granular description of the company's activities. We have coded SICs into a relatively broad 9-category indicator of industry classification, using the first two digits of each company's SIC codes.

Our categories are: manufacturing; agriculture; mining; construction; retail and trade; finance, insurance, and real estate; services; telecommunications and utilities; and public administration. Each category and its corresponding range of SIC codes is listed in Table A- 4.

Table A- 4. Categorization of SIC Codes

SIC Range	Industry Category
01xx-09xx	Agriculture, Forestry, & Fishing
10xx-14xx	Mining
15xx-17xx	Construction
20xx-39xx	Manufacturing
40xx-49xx	Transportation, Communication, & Utilities
50xx-59xx	Wholesale & Retail Trade
60xx-67xx	Finance, Insurance, & Real Estate
70xx-89xx	Services
91xx-97xx	Public Administration

A.7 Dollar Standardization

Interruption cost numbers in the small C&I and medium and large C&I datasets, as well as WTP and WTA figures in the residential dataset, are standardized to 2008 dollars using the GDP deflator from the U.S. Bureau of Economic Analysis (http://www.bea.gov/national). The base year for the deflator is 2008 (2008=100). In 1989, the earliest year in the survey, the GDP deflator is 64.2. For each survey year, we calculated a deflation factor using the formula:

$$\text{Deflation factor} = 1 \,/\, \text{GDP deflator}$$

The final step is to standardize our dollar denominated figures – interruption cost, WTP, WTA, household income – to 2008 dollars. This is done by multiplying each dollar amount by the deflation factor corresponding to the year of the survey.

Appendix B. Survey Methodology

With the publication of the *Interruption Cost Estimation Guidebook*, survey protocols for gathering these data were developed and generally followed by the various firms conducting VOS studies. The methodology varies somewhat for each customer group, and each will be summarized in this appendix.

B.1 Survey-Based Method of Cost Estimation

The studies used to create the meta-database in this project employed a survey-based methodology to gather information about the value of reliable service. The results allow for the development of estimates of interruption costs. There are two forms of estimates – direct cost (or worth) and imputed cost estimation. Direct cost is more typically used for non-residential customers, whereas the imputed cost is used for residential customers because many of the costs to residential customers are of an intangible nature, whereas the costs to businesses typically are quantifiable.

B.1.1 Direct Cost Estimation

With the direct measurement approach, the survey describes hypothetical interruption "scenarios" that have different characteristics. Each interruption scenario describes a specific combination of characteristics making up one interruption event. Characteristics that are varied include:

- The season in which it occurs (summer and winter).
- The day of the week (weekend versus a weekday).
- Start time.
- Duration.
- Complete or partial loss of service (voltage sag or black-out).
- Voluntary or mandatory.
- Amount of advance warning, if any.

Respondents will usually receive several scenarios. However, because the utility often wants to explore more scenarios that respondents can reasonably expect to have time or patience to answer, there are typically several versions with a questionnaire, each having three to five scenarios. An example of such a scenario is:

> At 1:00 PM on a summer weekday, the electric power serving your business stops without warning. You don't know how long this power interruption will last when it occurs. After one hour your power comes back on.

Then the C&I customers are asked to estimate the costs, damages, and if relevant, savings accrued from each interruption. They are given a worksheet to fill out which looks something like this:

For this interruption, estimate costs from:	
Damage to equipment:	$________
Damage to materials:	$________
Wages paid without production:	$________
Other costs:	$________
Lost sales (or production):	$________
Percentage of sales to be recouped: % x Sales lost	$________
Total sales lost:	$________
Less:	
Wages saved:	$________
Energy costs saved:	$________
Other savings:	$________
Total Costs:	**$________**

B.1.2 Cost Estimation Through Imputation

Willingness to pay and willingness to accept credit (WTP and WTA) approaches instead ask the customer what they would pay to avoid the interruption occurrence, or how much the customer would have to be compensated to be indifferent to the interruption. As with the direct cost approach, the survey describes hypothetical interruption "scenarios" that have different characteristics. The imputed approaches are especially useful in situations where intangible costs are present that are difficult to estimate using the direct worth approach, which is typically the case for residential customers. Because not all surveys used the WTA measure, the meta-analysis employed mainly WTP. A full discussion of the advantages and disadvantages of the direct worth and imputed methods can be found in Chapter 3 of the *Interruption Cost Estimation Guidebook*.

The example below is from a mail survey.

Case #1: On a summer weekday, a power interruption occurs at 3:00 PM without any warning. You do not know how long the power interruption will last, but after 1 hour your household's electricity is fully restored.

Willingness to Accept Credit Imputation:

Suppose your Utility could provide you with a credit on your bill each time your home experienced this interruption, whether or not you were home. What would be the least amount that you would consider a fair payment for each time this interruption occurred in your home? (Circle or enter a number)

$0	$.10	$.25	$.50	$1	$2	$3	$4	$5	$6	$8
$10	$12	$15	$20	$25	$30	$40	$50	Other: $_____		

Willingness to Pay Imputation:

Suppose a back-up service was available to handle all of your household's electrical needs during this power interruption. You would be billed by the supplier only for when and for how long the back-up service provided you with electricity. If you were charged a fee for this service only when you decided to use it (by using an on-off switch in your home), what is the most you would be willing to pay for this service each time you used it to avoid this power interruption? (Circle or enter number)

$0	$.10	$.25	$.50	$1	$2	$3	$4	$5	$6	$8
$10	$12	$15	$20	$25	$30	$40	$50	Other: $_____		

An alternate version of a WTP question when fielded by telephone is:

> Suppose an electrical service was available to you during the power interruption. With this service, you would not have to make any adjustments to the interruption since your electricity would not go off.
>
> Would you pay $10.00 for this service to avoid the interruption? (YES or NO)
> [IF YES]: Would you pay $20.00 for this service?
> [IF NO]: Would you pay $5.00 for this service?

In general, however, it is ideal to conduct this kind of research using mailed survey instruments, although it's possible a combined mixed mode mail-Internet methodology may now be reasonable.

B.1.3 Survey Design

As is typical, the survey is conducted based on actual usage, hence groups into medium and large C&I or small. In reality, the survey instruments may be designed to ask questions that are relevant to different companies given their primary mode of business. Manufacturing companies are asked about production and materiel costs, damages and savings resulting from interruptions to their resources, equipment, and labor. Retail and commercial organizations are asked about the impact of power loss on sales and inventory. A few studies have included other subgroups, such as agricultural customers, hospitals, and service organizations. In the meta-database, we exclude these latter categories due to an inadequate number of cases.

B.2 Data Collection Methodology

B.2.1 Non-Residential Customers

Survey instruments for interruption cost studies are complex and difficult to answer. For very large organizations, it is best to have a mid-level to senior-level analyst or consultant conducting the interview on-site. This interview takes approximately 2 to 4 hours, and can include input from more than one departmental manager. Sometimes several persons will be interviewed together, and other times sequentially. Answers required for the survey are not likely to be known "off the top of one's head" nor would they be reliable if given as such. Therefore, the process is a "phone-mail-interview" technique, where the research organization is given the initial list of company and contacts, the correct respondent(s) is identified in an initial phone call, and an onsite interview is then scheduled. The respondent is then mailed or faxed the survey instrument with instructions, so that this information will be available at the time of the on-site interview. The presence of the interviewer ensures that the respondent has a clear understanding of how to interpret the survey requirements.

A less expensive variation of this procedure is “phone-mail-phone” where instead of conducting the interview on-site, the interview is conducted over the phone. This methodology may be appropriate for the small/medium organizations. Finally, there have been low budget projects where the account contact was sent the survey by mail and then returned it. With follow-up, such as reminder postcards and other best practices in mail surveys, this method may have a reasonably high response rate but the data quality tend to be compromised.

B.2.2 Residential Customers

There is much less of a respondent recruit issue for residential customers. This survey is usually conducted by mail, using best practices for mail surveys to garner a high response rate. Residential surveys can also be conducted by telephone. There are certain implications about questionnaire design (such as the way WTP questions can be asked) for each methodology. Insert text here

Appendix C. Recommendations for Questionnaire Design

One of the benefits of conducting this meta-analysis is revisiting the questionnaire design and the data analysis made possible by these survey instruments. Reviewers of an earlier version of this document also noted that improvements to methodology could be made. Therefore, should a utility, Public Utilities Commission, a federal agency or other organization choose to conduct a VOS study, it is worthwhile to consider the lessons learned along the way. Certainly, studies conducted by utilities need to address that utility's specific operating environment and customer mix. Nevertheless, there are some practices that could not only provide the utility with better data, but also allow for future meta-analyses and contributions to a wider industry understanding of the value customers place on reliability. These practices are summarized in this Appendix.

C.1 Macro- Versus Micro-Views

The customer groups presented in this research include households, businesses, and manufacturers. While some utilities branch out to a more diverse set of businesses, manufacturers or producers, such as agricultural or healthcare organizations, no study include the broad impacts of an interruption on societal or government costs. Some of those costs would understandably be more difficult to quantify, but others can be captured in dollars. For example, governments lose sales tax revenue, and may need to expend emergency dollars for police or other security measures. A government office does not lose sales revenue, but it does lose productivity in the form of staff that gets paid regardless, or fees for government licenses and services that go uncollected. Future studies are advised to branch out to these non-business interruption costs.

C.2 The Impact of Back-Up Systems

After extensively analyzing the different survey instruments, it is becoming obvious that the meaning and implications of having a back-up generation system are not consistently captured in the survey methodology. In these questionnaires, respondents are asked at one point in the survey whether they have a back-up generator or system, and then only later answer the scenario-specific questions. Two problems are inherent in the question about back-up systems. First, the precise kind of back-up system is not necessarily clarified, for example, is it just for lighting, or is it for full operations? Second, the presence of the generator and the tally of interruption costs are separated, so it is not clear if the respondent is adequately taking the backup generation capability or costs into consideration.

C.3 Advance Warning

In the studies employed in this meta-analysis, scenarios with advance warning are not necessarily paired with the identical scenario (and company-respondent) without advance warning, so the aggregate analysis yield highly problematic or counter-intuitive results. The implication of this methodological problem is that it will be difficult to compare the costs of transmission to generation interruptions.

C.4 Facilitating Regional Comparisons

Being able to compare the results of one study to another are important for an individual utility as well as for cross-service territory insights. There are several techniques in survey design or database design that would facilitate this kind of analysis. These are:

- Noting regional climates in a standardized nomenclature.
- Including standard interruption scenarios, such as, by including one-hour summer afternoon weekday for C&I, and one-hour winter morning weekend for residential customers.
- Standardization of costs and savings calculations in the commercial and industrial surveys, and scales for asking willingness to pay and willingness to accept credit questions for the residential surveys.
- Noting whether the location is urban, suburban or rural.

Many organizations and industries have standardized protocols (such as quality) in order to have a better understanding of benchmarks, trending and best practices. Standards to VOS studies would go a long way in ensuring comparability across time and territory.

C.5 Commercial and Industrial Classification Codes

More help needs to be provided to respondents in answering this question, such as a brief summary next to a check-box for the code so at the very least, they can get the correct top-level classification. Yet even using a precise industrial classification code has its limitations. A retail company that gets the bulk of its business on weekdays from 9am to 5pm from customers in the store is going to have a different reaction to an interruption than an establishment that does 75% of its business in the evenings, or during Friday to Sunday (e.g., movie theatres). A professional services firm that relies on electronics and telecommunications equipment comes to a standstill, while another has activities that can be accomplished without power. While some instruments do note the regular business hours, the information about the kind of business needs to be standardized for ease of analysis and cross-comparison.

C.6 Residential Costs and Presence At Home

In some cases, household respondents are asked to input their WTP or WTA for interruptions regardless of whether they were home. Yet a debate around the meaning of costs for residents hinges on whether they are home, and how much of the cost of an interruption is due to cessation of household activity, and how much is due to impact on household appliances and electronics. Indicating whether the respondent is normally at home during the time of the interruption scenario would add clarification.

I/A

Duke Energy Progress (DEP)
DSDR / CVR Evaluation

Program Description

Distribution System Demand Response (DSDR) is an operational mode of Volt Var Optimization (VVO) that supports peak shaving and emergency MW (demand) reduction. Duke Energy Progress (DEP) implemented DSDR in 2014. The DSDR mode of operation is implemented by the software within a centralized Distribution Management System (DMS). The DMS obtains telemetered data via 2-way communications from substation devices, distribution line voltage regulators, distribution line capacitor banks, medium voltage sensors, and low voltage sensors. The DMS software performs a power load flow analysis based on near real-time measurement inputs. Afterwards, it sends out commands to the voltage regulators and capacitor banks to optimize the voltage for DSDR. Currently, DSDR can provide peak shaving voltage reduction of approximately 3.6% across the distribution network in DEP. The DMS in DEP is capable of optimized modes (i.e.- DSDR) or non-optimized (i.e. – emergency) modes. The emergency modes are designed for a speedy, temporary response during bulk power emergencies with voltage reduction capability of up to 5.0%. Initially, the DEP DSDR targeted approximately 310 MW of peak demand reduction capability to defer construction of a new Combustion Turbine (CT) plant. The North Carolina Utility Commission classified DSDR as an Energy Efficiency program with rider recovery. The goal was exceeded and DEP achieved 322 MW of load reduction.

The initial implementation of DSDR not only included a Distribution Management System (DMS), but also a significant amount of circuit conditioning (such as installing voltage regulating devices and capacitors, balancing load on distribution circuits, and reconductoring some distribution lines to larger wire sizes). These forms of circuit conditioning help reduce line losses, which improve grid efficiency, reduce reactive power on the grid, and enable a higher voltage reduction to achieve maximum peak shaving. Additional devices, such as medium voltage sensors and low voltage sensors, were deployed to provide additional telemetry on the system. The substation and distribution line devices needed for DSDR were deployed in the optimal locations and equipped with 2-way communications ability.

The purpose of this evaluation is to conduct a cost/benefit analysis of moving DEP from the current DSDR (peak shaving) operational strategy to a Conservation Voltage Reduction (CVR) operational strategy. Conservation Voltage Reduction (CVR) is an operational mode of VVO that supports voltage reduction and energy conservation. The CVR functionality would target an estimated 2% voltage reduction for the majority of the hours in the year. This voltage reduction is estimated to result in an approximate 1.4% load reduction on average for enabled circuits. The substation, distribution, telecommunications, and IT infrastructure are already in place because DSDR already exists in DEP. As such, it is expected that few new devices will be installed. The current DEP DMS will transition to the enterprise DMS platform in the future. The software within the future enterprise DMS platform will have the ability to operate in various modes, including the current DSDR mode and CVR mode. This evaluation assumes the future version of the DMS platform will have already been deployed with the software capability to operate in DSDR or CVR mode, and that comprehensive testing will have already been performed on the required changes to the DMS system. Because the 2-way communications and control infrastructure are already in place in DEP, the settings on the substation and distribution devices can be programmed to enable these devices to properly operate when the DMS is in CVR mode or DSDR mode. Changing the predominant operational strategy in DEP from DSDR to CVR would affect the amount of maximum peak shaving capability. If the DMS is operating in CVR mode, transitioning to DSDR mode when load has already been reduced will <u>not</u> provide the peak shaving benefit realized today. The net result is that the amount of peak shaving would be reduced, and therefore will require relief from the current DSDR peak shaving obligation. This evaluation shows the incremental cost/benefits of transitioning to CVR operational mode. However, the lost benefits (including the initial deferral of peaking units), due to the reduction of peak shaving capability have yet to be calculated. To make an informed decision, further analysis will be required to accurately quantify the impacts on DSDR. When the DMS upgrade is complete, Duke Energy will be able to conduct additional testing and a more thorough analysis of the peak shaving capability impact.

NOTE:
The value of lost benefits due to the reduction in peak shaving capability are <u>not</u> included in this Cost/Benefit analysis, as further testing will be required.

Conservation Voltage Reduction (CVR) Operational Mode <u>Incremental</u> Cost Details

Incremental Capital								
COSTS ($1,000)	**NPV**	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Total Deployment**	**Years 5-26**	**Total 26 Year**
TRANSMISSION	**366**	98	100	102	104	**404**	**0**	**404**
TELECOM	**0**	0	0	0	0	**0**	**0**	**0**
IT	**3,794**	1,008	1,033	1,059	1,085	**4,185**	**0**	**4,185**
DISTRIBUTION	**3,285**	879	896	914	933	**3,622**	**0**	**3,622**
PM / AFUDC	**935**	248	258	260	265	**1,031**	**0**	**1,031**
Total Incremental Capital	**8,380**	**$2,233**	**$2,287**	**$2,335**	**$2,387**	**$9,242**	**$0**	**$9,242**
Incremental O&M								
TRANSMISSION	**4**	1	1	1	1	**4**	**0**	**4**
TELECOM	**0**	0	0	0	0	**0**	**0**	**0**
IT	**38**	10	10	11	11	**42**	**0**	**42**
DISTRIBUTION	**33**	9	9	9	9	**36**	**0**	**36**
PM / AFUDC	**0**	0	0	0	0	**0**	**0**	**0**
Total Incremental O&M	**74**	**$20**	**$20**	**$21**	**$21**	**$82**	**$0**	**$82**
Total Incremental Cost	**8,454**	**$2,253**	**$2,307**	**$2,356**	**$2,408**	**$9,324**	**$0**	**$9,324**

NOTE:
The value of lost benefits due to the reduction in peak shaving capability are *<u>not</u>* *included in this Cost/Benefit analysis, as further testing will be required.*

Conservation Voltage Reduction (CVR) Operational Mode Incremental Benefit Details (with CO2 Benefit)

A negative ( ) value in the Benefits tables represents avoided costs or savings.

BENEFITS ($1,000) : (With CO2 Benefit)

BENEFITS ($1,000)	NPV	Year 1	Year 2	Year 3	Year 4	Total Deployment	Years 5-26	Total 26 Year
Operational Benefits								
Improved VAR Mgt	**0**	0	0	0	0	**0**	**0**	**0**
Fixed O&M	**0**	0	0	0	0	**0**	**0**	**0**
Variable O&M	**(10,756)**	0	0	0	(307)	**(307)**	**(563,546)**	**(563,853)**
Reagent Cost	**(64)**	0	0	0	(3)	**(3)**	**(164)**	**(167)**
Start Cost	**(5,799)**	0	0	0	19	**19**	**(14,944)**	**(14,925)**
SUBTOTAL:	**(16,620)**							
Customer Benefits								
Fuel	**(192,539)**	0	0	0	(2,980)	**(2,980)**	**(521,364)**	**(524,344)**
SUBTOTAL:	**(192,539)**							
Operational Benefits and Customer Benefits								
SUBTOTAL:	**(209,159)**							
Environmental Benefits								
SO2	**(3)**	0	0	0	(0)	**(0)**	**(6)**	**(6)**
Nox	**(178)**	0	0	0	(7)	**(7)**	**(405)**	**(411)**
CO2	**(57,011)**	0	0	0	0	**0**	**(183,928)**	**(183,928)**
SUBTOTAL:	**(57,192)**							
TOTAL (All Benefits)	**(266,351)**	**0**	**0**	**0**	**(3,277)**	**(3,277)**	**(1,284,357)**	**(1,287,634)**

TOTAL COSTS

COSTS ($1,000)	NPV	Year 1	Year 2	Year 3	Year 4	Total Deployment	Years 6-26	Total 26 Year
TOTAL CAPITAL	$8,380	$2,233	$2,287	$2,335	$2,387	**$9,242**	**$0**	**$9,242**
TOTAL O&M	$74	$20	$20	$21	$21	**$82**	**$0**	**$82**
TOTAL:	**$8,454**	**$2,253**	**$2,307**	**$2,356**	**$2,408**	**$9,324**	**$0**	**$9,324**

Key Financials:

Duke Energy Progress
Docket No E-2, SUB 1219
PS DR 54-14

Key Financials	
Investment Period:	26 Years
Net Present Value (NPV):	$257,897 M
Benefit / Cost Ratio (26 Year NPV):	31.5

NOTE:
The value of lost benefits due to the reduction in peak shaving capability are not included in this Cost/Benefit analysis, as further testing will be required.

Conservation Voltage Reduction (CVR) Operational Mode Incremental Benefit Details (without CO2 Benefit)

A negative ( ) value in the Benefits tables represents avoided costs or savings.

BENEFITS ($1,000) : (Without CO2 Benefit)								
BENEFITS ($1,000)	NPV	Year 1	Year 2	Year 3	Year 4	Total Deployment	Years 5-26	Total 26 Year
Operational Benefits								
Improved VAR Mgt	0	0	0	0	0	0	0	0
Fixed O&M	0	0	0	0	0	0	0	0
Variable O&M	(10,781)	0	0	0	(235)	(235)	(26,725)	(26,961)
Reagent Cost	(23)	0	0	0	0	0	(84)	(84)
Start Cost	(10,850)	0	0	0	(478)	(478)	(33,155)	(33,633)
SUBTOTAL:	(21,655)							
Customer Benefits								
Fuel	(204,332)	0	0	0	(4,621)	(4,621)	(563,865)	(568,486)
SUBTOTAL:	(204,332)							
Operational Benefits and Customer Benefits								
SUBTOTAL:	(225,986)							
Environmental Benefits								
SO2	(5)	0	0	0	(0)	(0)	(10)	(10)
Nox	(174)	0	0	0	(8)	(8)	(454)	(462)
CO2	0	0	0	0	0	0	0	0
SUBTOTAL:	(179)							
TOTAL (All Benefits)	(226,165)	0	0	0	(5,342)	(5,342)	(624,293)	(629,635)

TOTAL COSTS

COSTS ($1,000)	NPV	Year 1	Year 2	Year 3	Year 4	Total Deployment	Years 6-26	Total 26 Year
TOTAL CAPITAL	$8,380	$2,233	$2,287	$2,335	$2,387	$9,242	$0	$9,242
TOTAL O&M	$74	$20	$20	$21	$21	$82	$0	$82
TOTAL:	$8,454	$2,253	$2,307	$2,356	$2,408	$9,324	$0	$9,324

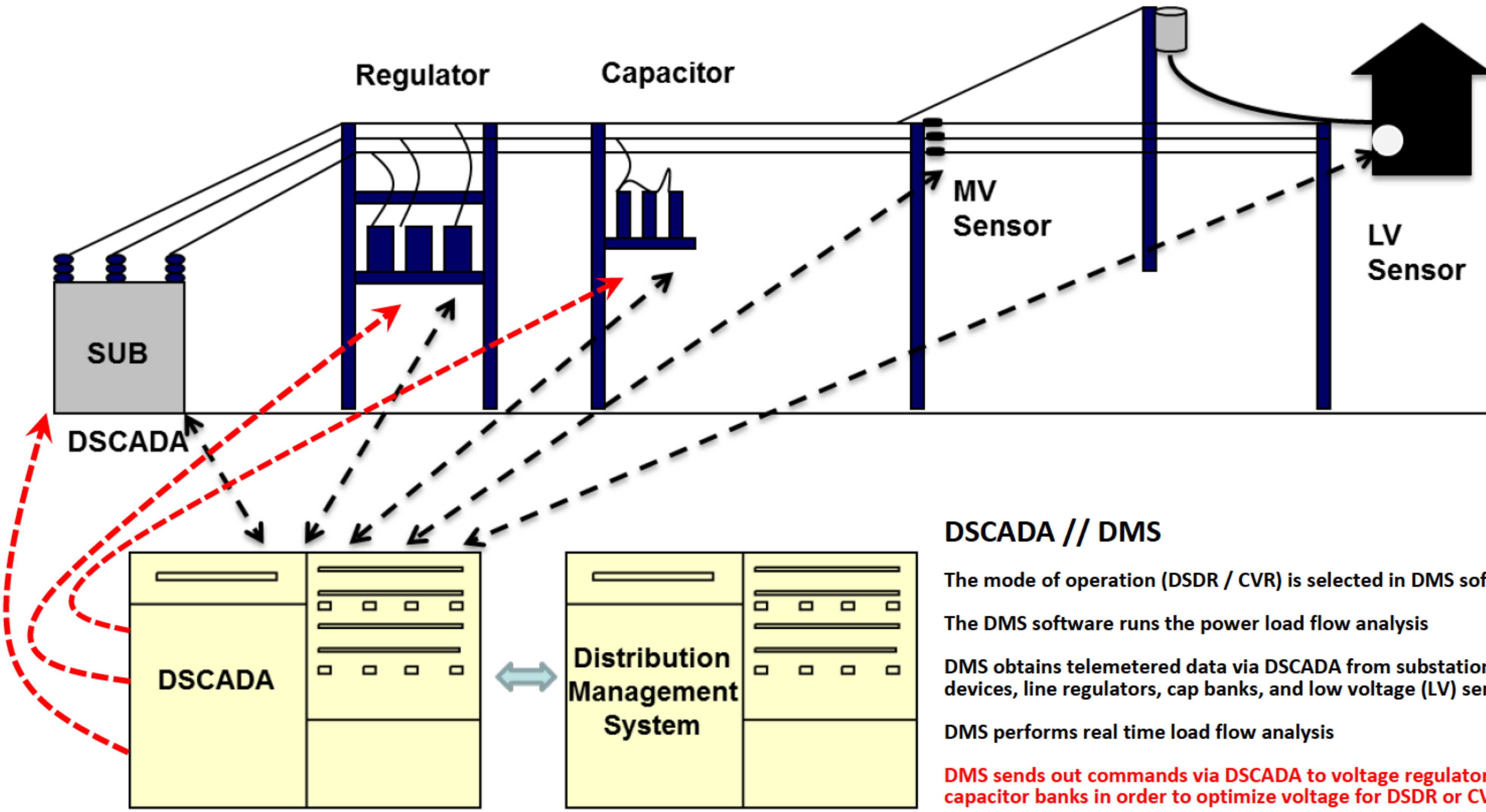
Key Financials:

Key Financials	
Investment Period:	26 Years
Net Present Value (NPV):	$217,711
Benefit / Cost Ratio (26 Year NPV):	26.8

/ Var Optimization Terminology

VVO	*Volt/VAR Optimization*	Management of Voltage levels and Reactive Power at optimal levels to operate the grid more efficiently
IVVC	*Integrated Volt/VAR Control*	Full coordination and configuration of intelligent field devices and a management/control system (e.g., DMS, DSCADA) that uses grid data to achieve efficient grid operation while maintaining distribution voltages within acceptable operating limits
DSDR	*Distribution System Demand Response*	Operational mode of VVO that supports peak shaving and emergency MW *(demand)* reduction (alternative to building peaking plant generation)
CVR	*Conservation Voltage Reduction*	Operational mode of VVO that supports 24/7 voltage reduction and energy conservation (alternative to building base load generation)
DMS	*Distribution Management System*	Primary information system used to monitor, analyze, and control the distribution grid efficiently and reliably

DEP DSDR / CVR Illustrative Overview



DSCADA // DMS

The mode of operation (DSDR / CVR) is selected in DMS software

The DMS software runs the power load flow analysis

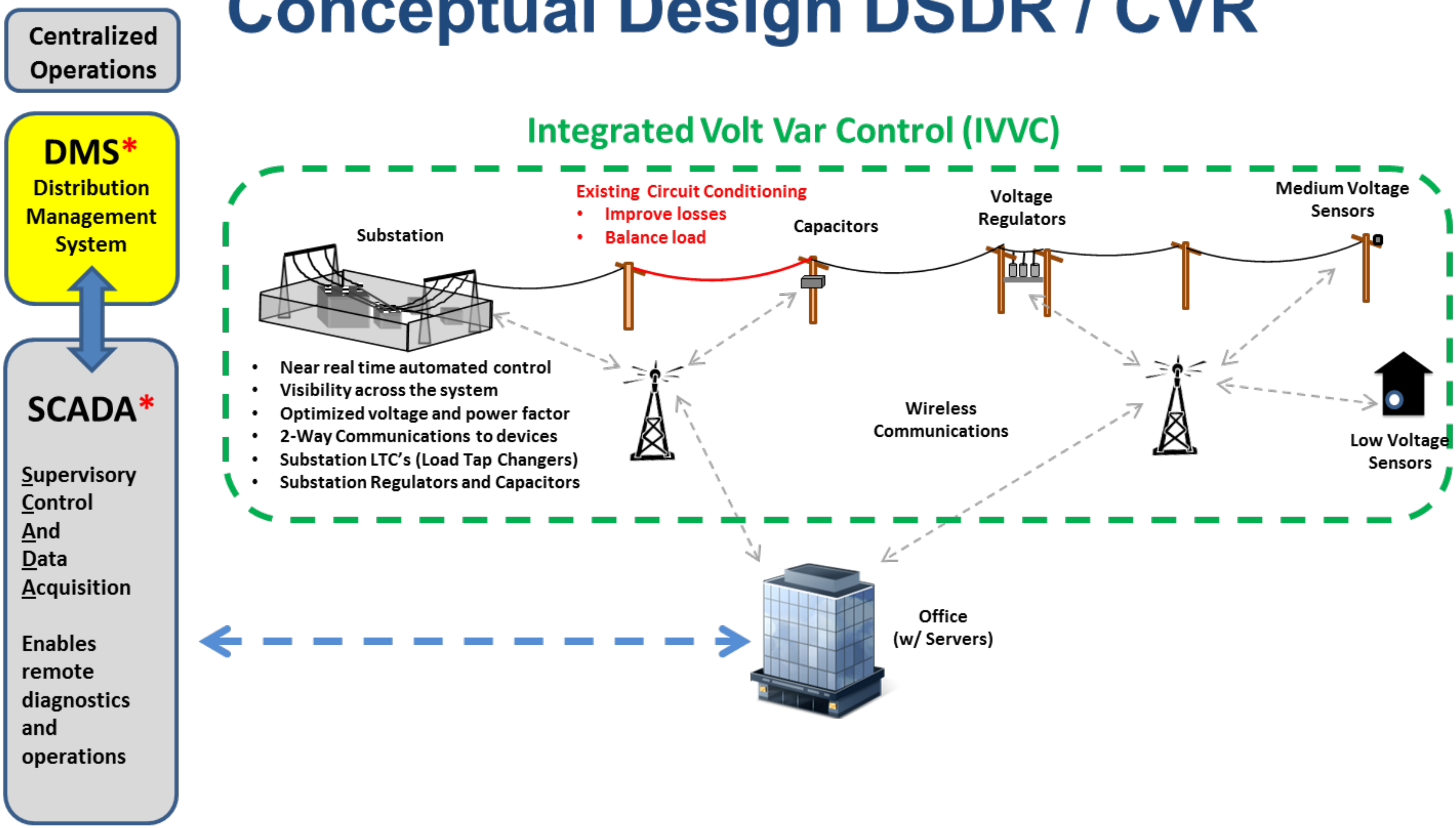
DMS obtains telemetered data via DSCADA from substation devices, line regulators, cap banks, and low voltage (LV) sensors

DMS performs real time load flow analysis

DMS sends out commands via DSCADA to voltage regulators and capacitor banks in order to optimize voltage for DSDR or CVR

Duke Energy Progress
Docket No E-2, SUB 1219
PS DR 54-14

DEP "High-Level" Conceptual Design DSDR / CVR



- DMS & SCADA already exists.
- The DMS Software will be enabled to operate in either DSDR or CVR mode.

I/A

Duke Energy Progress
Response to
NC Public Staff Data Request
Data Request No. NCPS 132

Docket No. E-2, Sub 1219

Date of Request: **February 28, 2020**
Date of Response: **March 9, 2020**

☐ **CONFIDENTIAL**

☒ **NOT CONFIDENTIAL**

Confidential Responses are provided pursuant to Confidentiality Agreement

The attached response to NC Public Staff Data Request No. 132-7, was provided to me by the following individual(s): Karen Ann Ralph, Lead Planning & Regulatory Support Specialist, and was provided to NC Public Staff under my supervision.

Camal. O. Robinson
Senior Counsel
Duke Energy Progress

Request:

7. Has DEP considered a small-scale roll out of the DSDR Conversion in order to quantify the amount of lost peak reduction capabilities? Please explain the Company's position on a small-scale roll out.

a. If the Company does not believe that a small scale roll out is appropriate, please explain why not, and further explain how the Company would respond if it found, after completing the DSDR Conversion, that the cost of lost peak reduction capabilities was greater than the benefit of energy saved operating in CVR mode.

Response:

The Company intends to test CVR functionality and its affect (if any) on DSDR peak shaving fuctionality. The Company has to implement the changes in the DMS in order to perform the testing with CVR and peak shaving functionality. The Company does intend to test small-scale CVR prior to testing it system wide. Some of this testing could include on/off testing on groupings of circuits as well as system wide tests.

I/A

Public Staff
Thomas Exhibit 9

Duke Energy Progress
Response to
NC Public Staff Data Request
Data Request No. NCPS 126

Docket No. E-2, Sub 1219

Date of Request: **February 26, 2020**
Date of Response: **March 9, 2020**

☐ **CONFIDENTIAL**

☒ **NOT CONFIDENTIAL**

Confidential Responses are provided pursuant to Confidentiality Agreement

The attached response to NC Public Staff Data Request No. 126-5, was provided to me by the following individual(s): Karen Ann Ralph, Lead Planning & Regulatory Support Specialist, and was provided to NC Public Staff under my supervision.

Camal. O. Robinson
Senior Counsel
Duke Energy Progress

North Carolina Public Staff
Data Request No. 126
DEP Docket No. E-2, Sub 1219
Item No. 126-5
Page 1 of 2

Request:

5. The responses and supplemental responses to DR 79-1 included four transmission projects characterized as "GIP – System Intelligence", summarized in the table below. Please respond to the following questions.

Project ID	Project Description	Total Capitalized	Estimate	In-Service Date	Over Budget?
150305B01	BNP U1 - Upgrade Relay Protection f	1,003,113	385,411	03-2018	160%
140908A01	Camden 230kV - Replace Relay Protec	1,570,041	1,528,647	06-2018	3%
150211D01	Morehead Wildwood 230kV - Repl DFR,	1,026,529	857,026	04-2019	20%
150121A01	Blewett H.E Plt - Install Wave Trap	2,052,099	249,115	01-2020	724%
	TOTAL	**5,651,783**	**3,020,199**		**87%**

a. Please describe how each of these projects meets the definitions of the Transmission System Intelligence program, as described in Oliver Exhibit 10, page 41.
b. Please explain the cost overruns, compared to the estimate, for each project that is more than 10% over budget. This explanation should include a narrative and supporting documentation (including any change orders) sufficient to demonstrate that the $5.6 million spent on these four projects is reasonable and prudent.
c. Oliver Exhibit 10 lists a total capital spend of $86.4 million over the next three years on Transmission System Intelligence (approximately $23.7 M of which is allocated to DEP). Please confirm that these four projects fall under Transmission System Intelligence. If not, please provide the GIP program under which they do fall.
d. Based on the cost overruns on these projects, does DEP believe the 3-year capital budget for the Transmission System Intelligence program proposed in GIP is understated? If not, please explain why not.

Response:

Refer to the file "DEP PS DR 126-5 System Intelligence Projects.xlsx" for the below items

DEP PS DR 126-5
System Intelligence

a. See column E
b. See column I, D, and C
c. Yes, these four projects fall under Transmission System Intelligence
d. The project cost estimate that was pulled into DR 79-1 is based on the initial project

scoping. Project templates are used to estimate costs based on the work identified. When the projects go through formal Development, the designers and engineers determine the exact scope of what is needed to accomplish the requested work, and also look at what additional work is prudent to include based on other requested projects in the queue and established reliability program initiatives. The intent is to efficiently bundle work to deliver the overall lowest cost for replacing the required equipment.

DEP does not believe the 3 year capital budget for the Transmission System Intelligence program to be overstated. The annual spend in the Exhibit 10 tables represent an estimated annual cashflow comprised of active projects being executed during that year that contribute to the total deferral targets. The actual spend for a given year in a particular area such as System Intelligence may be more than that stated year's estimate due to the overall composition of the Grid Modernizing work being executed in that year. DEP is working to make sure that the overall 3 Year spend target is maintained but it may vary due to changing project plans.

Individual project spending at completion versus its authorized spend is not captured in these tables. These are annual cashflow estimates based on a portfolio of projects and their estimated cash flow for that year.

I/A

Duke Energy Progress
Docket No. E-2 Sub 1219
DR # PS DR 126-5

Project	Project Name	Project Description (from Project Authorization Plan)	Business Case Summary (from PAP)	System Intelligence Basis (from Exhibit 10, P. 41)	Total Capitalized	Authorized Total Project Funding	Estimate	Explanation
F140908A	Camden 230kV - Replace Relay Protection	The scope of this project is to replace line relay protection panels for the Lugoff (SCPSA) and Camden Jct. 230kV lines as well as replace carrier set associated with Lugoff (SCPSA) 230kV Line. Additionally the Asset Performance sponsored project to replace the DFR will be included in the project.	Santee Cooper has requested DEP to upgrade the line panel relays at the Camden end of the Camden - Lugoff line for better coordination as they finish there multi-year line panel upgrades on their system. DEP will also take this opportunity to upgrade the DFR and Camden Jct. 230kV line panel as well.	Replacement of electromechanical relays with digital relays that provide real time system parameters fault locations and event records for system analysis. Replacement of a digital fault recorder to facilitate identification of circuit fault locations and enable rapid response to system outages and disturbances.	$ 1 570 041	$ 1 457 404	$ 1 528 647	Under 10% delta no explanation needed
F150121A	Blewett H.E. Plt - Install Wave Trap	The scope of the project is to install Zone 2 power line carrier such that there is redundant coverage with instantaneous tripping for 100% of the Blewett Plant-Rockingham 115kV Line.	The basis for this project is that no carrier currently exists on this line and redundant carrier is needed. DEP is designing and installing instantaneous protection to the relaying scheme through carrier protection to harden the system.	This is a resiliency project that enables remote monitoring and visibility of the Transmission system and improves the ability to quickly isolate faults on the system to minimize customer impacts.	$ 2 052 099	$ 3 216 514	$ 249 115	The preliminary project estimate was not updated in the financial tracking system used for the DR 79-1 "Estimate" field after detailed Project Development was completed. The main cost change driver was the need for a transit cable system consisting of an elevated bridge with three cable tray systems serving both transmission the plant and telecommunications. This was the best engineering solution for this location where a standard cable tray was not an option due to the geological survey results that indicated that the slope was not stable enough to support any structure. Modifications and additions to the plant building are imited by the historical preservation rules governing the plant building. As shown the total capitalized spend is less than the authorized total project funding.
F150211D	Morehead Wildwood 230kV - Replace DFR	The scope of this project is to replace the Havelock North 115 kV SLY transmission line relay protection replace the station SR 5000 series RTU and replace the TR1630 Digital Fault Recorder (DFR).	System Reliability Program driving replacement of EM and SS relays. System Reliability Program to replace SR8000 series RTU's- A failed RTU could result in a loss of remote breaker control a loss of indication and a loss of metering to the ECC. Without proper indication system operators may not know the full state of the transmission system. In addition system operators may not be able to remotely manipulate transmission breakers to restore or isolate portions of the transmission system which may extend grid SAIDI and CMI. System Reliability Program to replace the legacy fault recorder used in DEP the Rochester Instrument Systems (RIS) TR-1630. These fault recorders were installed from the mid-1980's to mid-1990's. Some locations have dual DFRs installed to obtain more analog channel coverage with this older design. The product is no longer supported by Ametek and is not reliable. At present the only spare parts that are available are parts salvaged from fault recorders removed from service. These have experienced increased failure rates.	Replacement of electromechanical relays with digital relays that provide real time system parameters fault locations and event records for system analysis. Replacement of a digital fault recorder to facilitate identification of circuit fault locations and enable rapid response to system outages and disturbances. Replacement of a remote terminal unit to facilitate SCADA communication and control.	$ 1 026 529	$ 719 562	$ 857 026	The original estimate only included Protection & Control engineering and construction costs and did not include needed Substation design and construction work or Telecom work. Total Capitalized was 20% over the estimate due to these factors.
F150305B	BNP U1 - Updgrade Relay Protection	The scope of this project is to upgrade the electromechanical transmission line protection for the Delco East 230kV line (U1) and the Castle Hayne East 230kV (U1) during the spring 2018 BNP 1 refuel outage. Install new microprocessor relay protection panel in the new control building. Move Delco East 230kV and Castle Hayne East 230kV lines digital fault recorder inputs to the DFR in the new switchyard control building.	System Reliability program for EM and SS relays. Transmission Line protection for a l 8 of the lines at Brunswick Nuclear Plant are targeted to be moved from the old switchyard control building to the in service new control building. These moves/upgrades will occur as opportunities are created for each line. The work should also be coordinated with each of the unit refuel outages.	Replacement of electromechanical relays with digital relays that provide real time system parameters fault locations and event records for system analysis.	$ 1 003 113	$ 2 333 794	$ 385 411	The preliminary project estimate was not updated in the financial tracking system used for the DR 79-1 "Estimate" field after detailed Project Development was completed. Preliminary estimate did not consider the Nuclear Plant Engineering Change (EC) review cost as well as extra construction costs due to nuclear plant refue ing outage time constraints to complete the work. As shown the total capitalized spend is less than the authorized total project funding and no overrun

Exhibit JRW-1

Duke Energy Progress, LLC
Recommended Cost of Capital

Panel A - Primary Cost of Capital Recommendation

Capital Source	Capitalization Ratios*	Cost Rate	Weighted Cost Rate
Long-Term Debt	50.0%	4.11%	2.06%
Common Equity	50.0%	9.00%	4.50%
Total Capitalization	100.0%		6.56%

* Capital Structure Ratios are developed in Exhibit JRW-3.

Panel B - Alternative Cost of Capital Recommendation

Capital Source	Capitalization Ratios*	Cost Rate	Weighted Cost Rate
Long-Term Debt	48.5%	4.11%	1.99%
Common Equity	51.5%	8.40%	4.32%
Total Capitalization	100.00%		6.32%

* Capital Structure Ratios are developed in Exhibit JRW-3.

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Exhibit JRW-2

Duke Energy Progress, LLC

Panel A
Electric Proxy Group

Company	Operating Revenue ($mil)	Percent Reg Elec Revenue	Percent Reg Gas Revenue	Net Plant ($mil)	Market Cap ($mil)	S&P Issuer Credit Rating	Moody's Long Term Rating	Pre-Tax Interest Coverage	Primary Service Area	Common Equity Ratio	Return on Equity	Market to Book Ratio
ALLETE, Inc. (NYSE-ALE)	$1,240.5	84%	0%	$4,405.6	$3,983.2	BBB+	Baa1	2.89x	MN, WI	56.1%	8.5%	1.78
Alliant Energy Corporation (NYSE-LNT)	$3,647.7	84%	12%	$13,527.1	$14,177.5	A-	Baa1	2.63x	WI,IA,IL,MN	43.6%	11.4%	2.72
Ameren Corporation (NYSE-AEE)	$5,646.0	80%	13%	$24,412.0	$21,439.4	BBB+	Baa1	3.56x	IL,MO	44.7%	10.6%	2.66
American Electric Power Co. (NYSE-AEP)	$15,561.4	96%	0%	$61,095.5	$49,306.3	A-	Baa1	2.67x	10 States	38.6%	9.9%	2.51
Avangrid (NYSE-AGR)	$6,338.0	56%	23%	$25,421.0	$16,661.6	BBB+	Baa1	3.14x	NY,CT,ME	64.2%	4.6%	1.09
Avista Corporation (NYSE-AVA)	$1,345.6	64%	22%	$4,944.9	$3,488.8	BBB	Baa2	2.21x	WA,OR,AK,ID	45.7%	10.6%	1.80
CMS Energy Corporation (NYSE-CMS)	$6,845.0	65%	28%	$18,973.0	$19,402.5	BBB+	Baa1	2.54x	MI	27.3%	13.9%	3.87
Consolidated Edison, Inc. (NYSE-ED)	$12,574.0	64%	17%	$44,747.0	$29,375.6	BBB+	A3	2.58x	NY,PA	44.2%	7.7%	1.62
Dominion Energy Inc. (NYSE-D)	$16,572.0	67%	34%	$69,581.0	$74,607.2	BBB+	NA	2.49x	VA,NC,SC,OH,WV,UT	40.5%	5.4%	2.52
Duke Energy Corporation (NYSE-DUK)	$24,658.0	91%	7%	$102,339.0	$74,542.2	A-	Baa1	2.59x	NC,OH,FL,SC,KY	40.5%	8.3%	1.66
Edison International (NYSE-EIX)	$12,347.0	100%	0%	$44,849.0	$25,437.9	BBB	Baa3	2.54x	CA	37.9%	10.8%	1.91
Entergy Corporation (NYSE-ETR)	$10,878.7	88%	0%	$35,515.6	$25,636.9	BBB+	Baa2	2.15x	LA,AR,MS,TX	33.4%	13.0%	2.50
Evergy, Inc. (NYSE-EVRG)	$5,147.8	100%	0%	$19,216.9	$16,564.2	A-	Baa1	3.07x	KS,MO	46.0%	7.2%	1.93
Eversource Energy (NYSE-ES)	$8,526.5	82%	12%	$27,635.4	$32,513.5	A-	Baa1	3.49x	CT,NH,MA	44.4%	7.5%	2.57
Exelon Corporation (NYSE-EXC)	$34,438.0	59%	4%	$78,749.0	$45,617.6	BBB+	Baa2	2.80x	PA,NJ,IL,MD,DCDE	43.6%	9.3%	1.41
FirstEnergy Corporation (NYSE-FE)	$10,844.0	100%	0%	$31,881.0	$26,224.6	BBB	Baa3	1.82x	OH,PA,NY,NJ,WV,MD	24.7%	13.1%	3.76
Hawaiian Electric Industries (NYSE-HE)	$2,874.6	89%	0%	$5,308.8	$5,109.8	BBB-	NA	3.73x	HI	47.7%	9.8%	2.24
IDACORP, Inc. (NYSE-IDA)	$1,346.4	100%	0%	$4,531.5	$5,372.7	BBB	Baa1	2.96x	ID	57.2%	9.6%	2.18
MGE Energy, Inc. (NYSE-MGEE)	$555.0	70%	30%	$1,643.4	$2,631.0	AA-	Aa2	4.95x	WI	60.3%	10.4%	3.07
NextEra Energy, Inc. (NYSE-NEE)	$19,204.0	71%	0%	$82,010.0	$137,996.0	A-	Baa1	2.43x	FL	43.8%	10.6%	3.73
NorthWestern Corporation (NYSE-NWE)	$1,257.9	78%	22%	$4,704.6	$3,932.3	BBB	NA	2.83x	MT,SD,NE	47.5%	10.2%	1.93
OGE Energy Corp. (NYSE-OGE)	$2,231.6	100%	100%	$8,964.8	$8,015.1	BBB+	Baa1	3.36x	OK,AR	55.2%	10.6%	1.94
Otter Tail Corporation (NDQ-OTTR)	$919.5	50%	0%	$1,775.7	$2,065.4	BBB	Baa2	4.16	MN,ND,SD	52.1%	11.5%	2.64
Pinnacle West Capital Corp. (NYSE-PNW)	$3,471.2	95%	0%	$14,254.3	$11,273.2	A-	A3	2.95x	AZ	47.8%	10.1%	2.08
PNM Resources, Inc. (NYSE-PNM)	$1,457.6	100%	0%	$5,509.9	$4,149.2	BBB+	Baa3	1.14x	NM,TX	33.0%	4.6%	2.47
Portland General Electric Company (NYSE-POR)	$2,123.0	100%	0%	$6,820.0	$5,325.9	BBB+	A3	2.62x	OR	48.1%	8.4%	2.06
PPL Corporation (NYSE-PPL)	$7,769.0	91%	8%	$36,578.0	$24,708.2	A-	Baa2	3.18x	PA,KY	35.9%	14.2%	1.90
Sempra Energy (NYSE-SRE)	$10,829.0	56%	44%	$37,043.0	$43,210.1	BBB+	Baa1	2.31x	CA,TX	36.5%	10.4%	2.44
Southern Company (NYSE-SO)	$21,419.0	73%	14%	$84,420.0	$71,408.9	A-	Baa2	3.20x	GA,FL,NJ,IL,VA,TN,MS	34.1%	18.1%	2.60
WEC Energy Group (NYSE-WEC)	$7,523.1	58%	42%	$23,661.5	$32,871.4	A-	Baa1	3.12x	WI,IL,MN,MI	43.9%	11.4%	3.25
Xcel Energy Inc. (NYSE-XEL)	$11,529.0	83%	16%	$40,781.0	$36,307.1	A-	Baa1	2.69x	MN,WI,ND,SD,MI	39.2%	10.8%	2.74
Mean	$8,745.8	80%	14%	$31,138.7	$28,172.8	BBB+	Baa1	2.86		43.8%	10.1%	2.37
Median	$6,845.0	83%	8%	$24,412.0	$21,439.4	BBB+	Baa1	2.80		43.9%	10.4%	2.44

Data Source Company 2019 SEC 10-K filings, S&P Capital IQ; *Value Line Investment Survey* , 2019.

Panel B
Hevert Proxy Group

Company	Operating Revenue ($mil)	Percent Reg Elec Revenue	Percent Reg Gas Revenue	Net Plant ($mil)	Market Cap ($mil)	S&P Issuer Credit Rating	Moody's Long Term Rating	Pre-Tax Interest Coverage	Primary Service Area	Common Equity Ratio	Return on Equity	Market to Book Ratio
ALLETE, Inc. (NYSE-ALE)	$1,240.5	84%	0%	$4,405.6	$3,983.2	BBB+	Baa1	2.89x	MN, WI	56.1%	8.5%	1.78
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Ameren Corporation (NYSE-AEE)	$5,646.0	80%	13%	$24,412.0	$21,439.4	BBB+	Baa1	3.56x	IL,MO	44.7%	10.6%	2.66
American Electric Power Co. (NYSE-AEP)	$15,561.4	96%	0%	$61,095.5	$49,306.3	A-	Baa1	2.67x	10 States	38.6%	9.9%	2.51
Avangrid (NYSE-AGR)	$6,338.0	56%	23%	$25,421.0	$16,661.6	BBB+	Baa1	3.14x	NY,CT,ME	64.2%	4.6%	1.09
CMS Energy Corporation (NYSE-CMS)	$6,845.0	65%	28%	$18,973.0	$19,402.5	BBB+	Baa1	2.54x	MI	27.3%	13.9%	3.87
DTE Energy Company (NYSE-DTE)	$12,669.0	41%	16%	$25,486.0	$22,935.5	BBB+	Baa1	2.65x	MI	39.6%	10.7%	1.96
Evergy, Inc. (NYSE-EVRG)	$5,147.8	100%	0%	$19,216.9	$16,564.2	A-	Baa1	3.07x	KS,MO	46.0%	7.2%	1.93
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NorthWestern Corporation (NYSE-NWE)	$1,257.9	78%	22%	$4,704.6	$3,932.3	BBB	NA	2.83x	MT,SD,NE	47.5%	10.2%	1.93
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Pinnacle West Capital Corp. (NYSE-PNW)	$3,471.2	95%	0%	$14,254.3	$11,273.2	A-	A3	2.95x	AZ	47.8%	10.1%	2.08
PNM Resources, Inc. (NYSE-PNM)	$1,457.6	100%	0%	$5,509.9	$4,149.2	BBB+	Baa3	1.14x	NM,TX	33.0%	4.6%	2.47
Portland General Electric Company (NYSE-POR)	$2,123.0	100%	0%	$6,820.0	$5,325.9	BBB+	A3	2.62x	OR	48.1%	8.4%	2.06
Southern Company (NYSE-SO)	$21,419.0	73%	14%	$84,420.0	$71,408.9	A-	Baa2	3.20x	GA,FL,NJ,IL,VA,TN,MS	34.1%	18.1%	2.60
WEC Energy Group (NYSE-WEC)	$7,523.1	58%	42%	$23,661.5	$32,871.4	A-	Baa1	3.12x	WI,IL,MN,MI	43.9%	11.4%	3.25
Xcel Energy Inc. (NYSE-XEL)	$11,529.0	83%	16%	$40,781.0	$36,307.1	A-	Baa1	2.69x	MN,WI,ND,SD,MI	39.2%	10.8%	2.74
Mean	$6,900.3	79%	15%	$24,776.2	$25,417.1	BBB+	Baa1	2.91		44.9%	10.2%	2.43
Median	$5,147.8	83%	12%	$18,973.0	$16,564.2	BBB+	Baa1	2.89		44.7%	10.6%	2.47

Data Source Company 2019 SEC 10-K filings, S&P Capital IQ; *Value Line Investment Survey* , 2019.

Exhibit JRW-2

Duke Energy Progress, LLC
***Value Line* Risk Metrics**

Panel A
Electric Proxy Group

Company	Beta	Financial Strength	Safety	Earnings Predictability	Stock Price Stability
ALLETE, Inc. (NYSE-ALE)	0.60	A	2	80	95
Alliant Energy Corporation (NYSE-LNT)	0.55	A	2	90	100
Ameren Corporation (NYSE-AEE)	0.50	A	2	85	100
American Electric Power Co. (NYSE-AEP)	0.50	A+	1	85	100
Avangrid (NYSE-AGR)	0.40	B++	2	NMF	95
Avista Corporation (NYSE-AVA)	0.60	A	2	65	90
CMS Energy Corporation (NYSE-CMS)	0.50	B++	2	85	100
Consolidated Edison, Inc. (NYSE-ED)	0.40	A+	1	100	100
Dominion Energy Inc. (NYSE-D)	0.50	B++	2	60	100
Duke Energy Corporation (NYSE-DUK)	0.45	A	2	90	100
Edison International (NYSE-EIX)	0.55	B+	3	10	85
Entergy Corporation (NYSE-ETR)	0.60	B++	2	60	95
Evergy, Inc. (NYSE-EVRG)	NMF	B++	2	NMF	NMF
Eversource Energy (NYSE-ES)	0.55	A	1	95	100
Exelon Corporation (NYSE-EXC)	0.65	B++	2	55	95
FirstEnergy Corporation (NYSE-FE)	0.60	B++	2	40	95
Hawaiian Electric Industries (NYSE-HE)	0.55	A	2	60	100
IDACORP, Inc. (NYSE-IDA)	0.55	A	2	95	100
MGE Energy, Inc. (NYSE-MGEE)	0.50	A	1	95	90
NextEra Energy, Inc. (NYSE-NEE)	0.50	A+	1	70	100
NorthWestern Corporation (NYSE-NWE)	0.60	B++	2	85	100
OGE Energy Corp. (NYSE-OGE)	0.70	A	2	80	100
Otter Tail Corporation (NDQ-OTTR)	0.70	A	2	65	90
Pinnacle West Capital Corp. (NYSE-PNW)	0.50	A+	1	95	100
PNM Resources, Inc. (NYSE-PNM)	0.60	B+	3	75	85
Portland General Electric Company (NYSE-POR)	0.55	B++	2	85	95
PPL Corporation (NYSE-PPL)	0.65	B++	2	70	95
Sempra Energy (NYSE-SRE)	0.70	A	2	70	95
Southern Company (NYSE-SO)	0.50	A	2	85	100
WEC Energy Group (NYSE-WEC)	0.45	A+	1	90	95
Xcel Energy Inc. (NYSE-XEL)	0.50	A+	1	100	100
Mean	0.55	A	1.8	77	97

Data Source: *Value Line Investment Survey* , 2020.

Panel B
Hevert Proxy Group

Company	Beta	Financial Strength	Safety	Earnings Predictability	Stock Price Stability
ALLETE, Inc. (NYSE-ALE)	0.60	A	2	80	95
Alliant Energy Corporation (NYSE-LNT)	0.55	A	2	90	100
Ameren Corporation (NYSE-AEE)	0.50	A	2	85	100
American Electric Power Co. (NYSE-AEP)	0.50	A+	1	85	100
Avangrid (NYSE-AGR)	0.40	B++	2	NMF	95
CMS Energy Corporation (NYSE-CMS)	0.50	B++	2	85	100
DTE Energy Company (NYSE-DTE)	0.50	B++	2	85	100
Evergy, Inc. (NYSE-EVRG)	NMF	B++	2	NMF	NMF
Hawaiian Electric Industries (NYSE-HE)	0.55	A	2	60	100
NextEra Energy, Inc. (NYSE-NEE)	0.50	A+	1	70	100
NorthWestern Corporation (NYSE-NWE)	0.60	B++	2	85	100
OGE Energy Corp. (NYSE-OGE)	0.70	A	2	80	100
Otter Tail Corporation (NDQ-OTTR)	0.70	A	2	65	90
Pinnacle West Capital Corp. (NYSE-PNW)	0.50	A+	1	95	100
PNM Resources, Inc. (NYSE-PNM)	0.60	B+	3	75	85
Portland General Electric Company (NYSE-POR)	0.55	B++	2	85	95
Southern Company (NYSE-SO)	0.50	A	2	85	100
WEC Energy Group (NYSE-WEC)	0.45	A+	1	90	95
Xcel Energy Inc. (NYSE-XEL)	0.50	A+	1	100	100
Mean	0.54	A	1.8	82	98

Data Source: *Value Line Investment Survey* , 2020.

Value Line Risk Metrics

Beta

A relative measure of the historical sensitivity of a stock's price to overall fluctuations in the New York Stock Exchange Composite Index. A beta of 1.50 indicates a stock tends to rise (or fall) 50% more than the New York Stock Exchange Composite Index. The ''coefficient'' is derived from a regression analysis of the relationship between weekly percentage changes in the price of a stock and weekly percentage changes in the NYSE Index over a period of five years. In the case of shorter price histories, a smaller time period is used, but two years is the minimum. Betas are adjusted for their long-term tendency to converge toward 1.00.

Financial Strength

A relative measure of the companies reviewed by *Value Line* . The relative ratings range from A++ (strongest) down to C (weakest).

Safety Rank

A measurement of potential risk associated with individual common stocks. The Safety Rank is computed by averaging two other *Value Line* indexes the Price Stability Index and the Financial strength Rating. Safety Ranks range from 1 (Highest) to 5 (Lowest). Conservative investors should try to limit their purchases to equities ranked 1 (Highest) and 2 (Above Average) for Safety.

Earnings Predictability

A measure of the reliability of an earnings forecast. Earnings Predictability is based upon the stability of year-to-year comparisons, with recent years being weighted more heavily than earlier ones. The most reliable forecasts tend to be those with the highest rating (100); the least reliable, the lowest (5). The earnings stability is derived from the standard deviation of percentage changes in quarterly earnings over an eight-year period. Special adjustments are made for comparisons around zero and from plus to minus.

Stock Price Stability

A measure of the stability of a stock's price. It includes sensitivity to the market (see Beta as well as the stock's inherent volatility. *Value Line's* Stability ratings range from 1 (highest) to 5 (lowest).

Source: *Value Line Investment Analyzer* .

Exhibit JRW-3

Duke Energy Progress, LLC
Capital Structure Ratios and Debt Cost Rate

Panel A - DEP's Proposed Capital Structure and Debt Cost Rates

	Percent of Total	Cost
Long-Term Debt	47.00%	4.11%
Common Equity	53.00%	
Total Capital	100.00%	

Panel B - Duke Energy Progress, LLC and Duke Energy Corporation Capital Structure Ratios

Duke Energy Progress, LLC	Ratios
Short-Term Debt	47.4%
Common Equity	52.6%
Total Capital	100.0%

Duke Energy Corporation	Ratios
Long-Term Debt	55.4%
Preferred Stock	0.7%
Common Equity	43.9%
Total Capital	100.0%

See page 2 of Exhibit JRW-3.

Panel C - Public Staff's Pramary Capital Structure Ratios and Debt Cost Rates

	DEP Proposed	Adjustment	Staff Proposed	Cost
Long-Term Debt	47.00%	1.063830	50.00%	4.11%
Common Equity	53.00%	0.943396	50.00%	
Total Capital	100.00%		100.00%	

Panel D - Public Staff's Alternative Capital Structure and Debt Cost Rates*

	Percent of Total	Cost
Long-Term Debt	48.5%	4.11%
Common Equity	51.5%	
Total Capital	100.00%	

See page 2 of Exhibit JRW-3 - DEP Capital Structure as of 12-31-20.

Duke Energy Progress, LLC and Duke Energy Corporation Capital Structure Ratios
Quarterly - 2018-2019

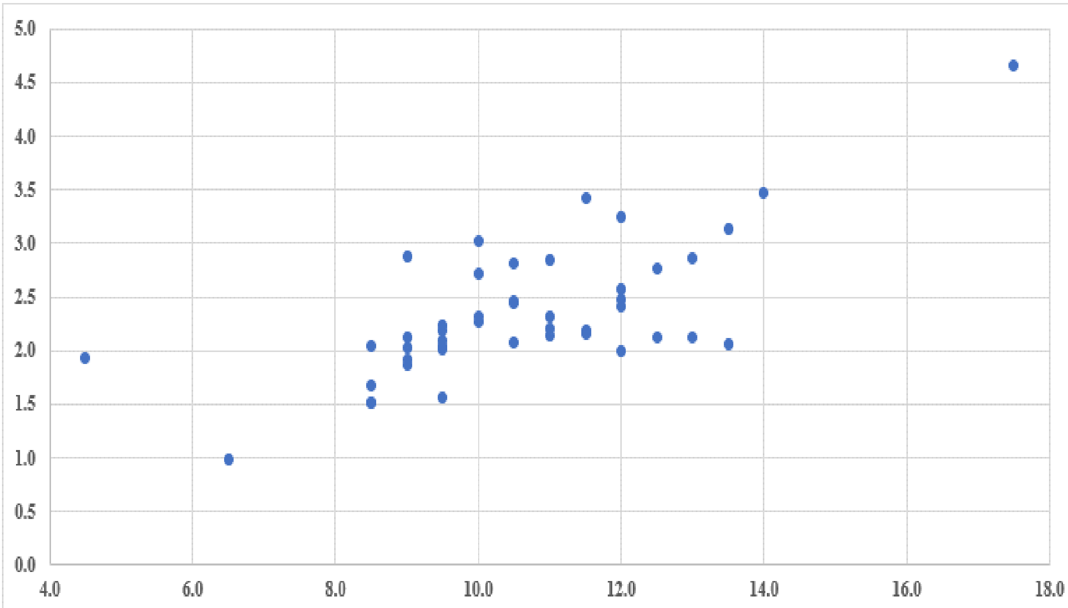
	2018 FQ1	*2018 FQ2*	*2018 FQ3*	*2018 FQ4*	*2019 FQ1*	*2019 FQ2*	*2019 FQ3*	*2019 FQ4*	
Duke Energy Progress, LLC	**3/31/2018**	**6/30/2018**	**9/30/2018**	**12/31/2018**	**3/31/2019**	**6/30/2019**	**9/30/2019**	**12/31/2019**	**Average**
Long-Term Debt	46.4%	46.4%	46.9%	47.1%	47.4%	48.1%	48.6%	48.5%	47.4%
Common Equity	53.6%	53.6%	53.1%	52.9%	52.6%	51.9%	51.4%	51.5%	52.6%
Total Capital	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	2018 FQ1	*2018 FQ2*	*2018 FQ3*	*2018 FQ4*	*2019 FQ1*	*2019 FQ2*	*2019 FQ3*	*2019 FQ4*	
Duke Energy Corporation	**3/31/2018**	**6/30/2018**	**9/30/2018**	**12/31/2018**	**3/31/2019**	**6/30/2019**	**9/30/2019**	**12/31/2019**	**Average**
Long-Term Debt	55.9%	55.4%	55.6%	55.4%	55.5%	55.7%	55.0%	54.8%	55.4%
Preferred Stock	0.0%	0.0%	0.0%	0.0%	1.0%	1.0%	1.9%	1.8%	0.7%
Common Equity	44.1%	44.6%	44.4%	44.6%	43.5%	43.3%	43.1%	43.4%	43.9%
Total Capital	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Source DEP Response to NCPS No. 24-6, Updated 1/30/20.

DOCKET NO. E-2, SUB 1219
Exhibit JRW-4
The Relationship Between Expected ROE and Market-to-Book Ratios
Page 1 of 1

Exhibit JRW-4
Electric Utilities and Gas Distribution Companies

Market-to-Book



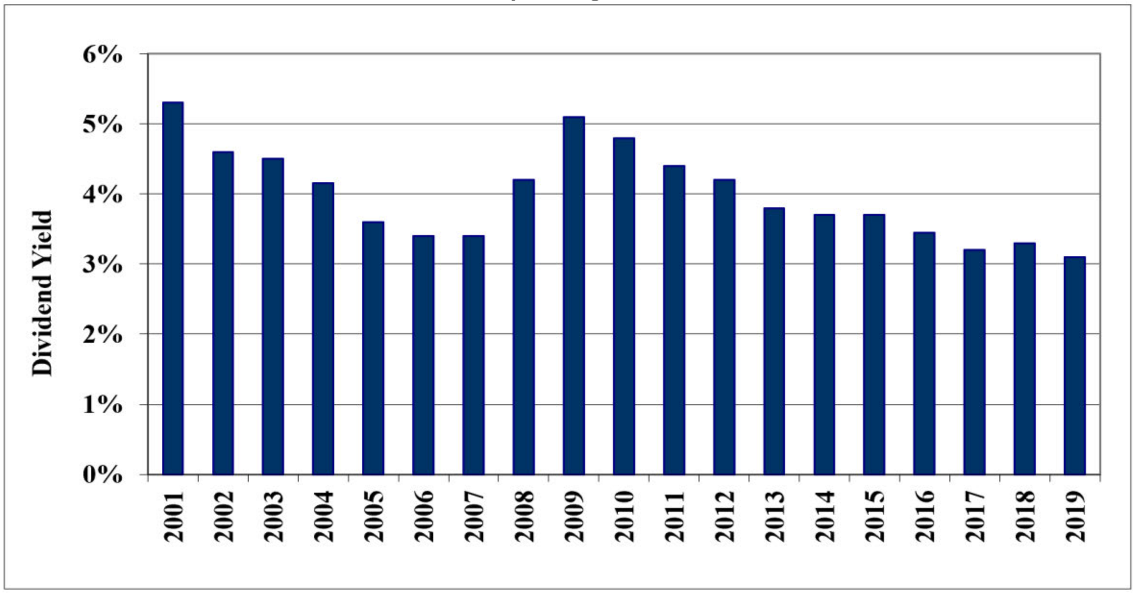
Expected Return on Equity
R-Square = .50, N=43

Exhibit JRW-5
Long-Term 'A' Rated Public Utility Bonds

Data Source: Mergent Bond Record

Exhibit JRW-5

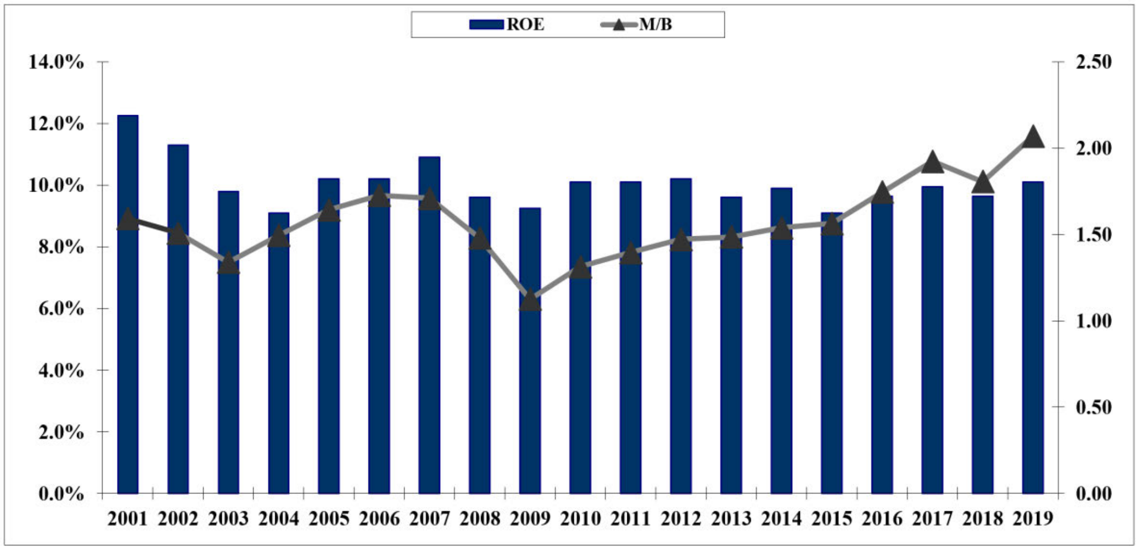
Electric Utility Average Dividend Yield



Data Source: ***Value Line Investment Survey.***

Exhibit JRW-5

Electric Utility Average Return on Equity and Market-to-Book Ratios



Data Source: ***Value Line Investment Survey.***

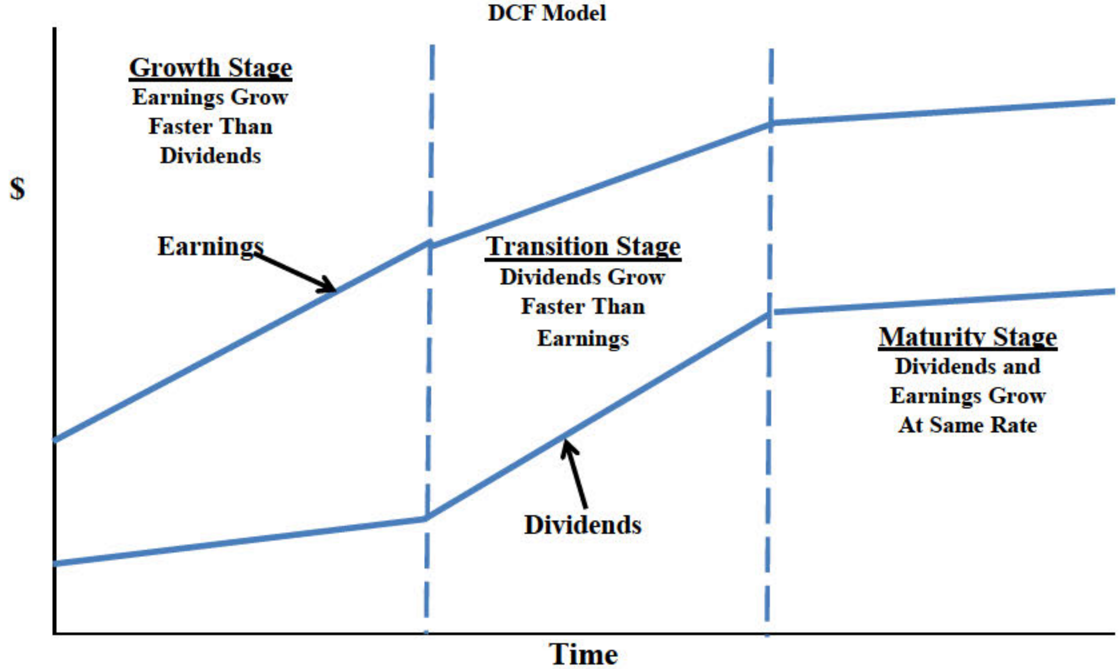
Exhibit JRW-5
Industry Average Betas*
Value Line Investment Survey* Betas*
20-Jan-20

Rank	Industry	Beta	Rank	Industry	Beta	Rank	Industry	Beta
1	Petroleum (Producing)	1.81	34	Precision Instrument	1.18	67	Cable TV	1.05
2	Natural Gas (Div.)	1.77	35	Apparel	1.18	68	Funeral Services	1.04
3	Oilfield Svcs/Equip.	1.74	36	Paper/Forest Products	1.18	69	IT Services	1.04
4	Metals & Mining (Div.)	1.58	37	Advertising	1.16	70	Foreign Electronics	1.02
5	Steel	1.58	38	Homebuilding	1.16	71	Retail (Softlines)	1.02
6	Maritime	1.45	39	Retail Building Supply	1.16	72	Pharmacy Services	1.02
7	Metal Fabricating	1.44	40	Bank (Midwest)	1.16	73	Med Supp Non-Invasive	1.00
8	Oil/Gas Distribution	1.43	41	Internet	1.15	74	Healthcare Information	1.00
9	Chemical (Specialty)	1.39	42	Newspaper	1.15	75	Information Services	0.98
10	Petroleum (Integrated)	1.36	43	Entertainment	1.15	76	Retail Store	0.98
11	Chemical (Basic)	1.34	44	Computer Software	1.15	77	Med Supp Invasive	0.98
12	Chemical (Diversified)	1.33	45	Public/Private Equity	1.14	78	Educational Services	0.96
13	Engineering & Const	1.32	46	Drug	1.14	79	Investment Co.(Foreign)	0.94
14	Heavy Truck & Equip	1.31	47	Human Resources	1.14	80	Environmental	0.94
15	Hotel/Gaming	1.31	48	Telecom. Equipment	1.14	81	Thrift	0.93
16	Pipeline MLPs	1.29	49	Shoe	1.14	82	Reinsurance	0.93
17	Auto Parts	1.29	50	Power	1.14	83	Insurance (Prop/Cas.)	0.89
18	Office Equip/Supplies	1.29	51	Retail Automotive	1.14	84	Restaurant	0.88
19	Building Materials	1.28	52	Diversified Co.	1.13	85	Household Products	0.87
20	Electronics	1.28	53	Financial Svcs. (Div.)	1.13	86	Investment Co.	0.86
21	Computers/Peripherals	1.27	54	Packaging & Container	1.13	87	Beverage	0.84
22	Railroad	1.23	55	Bank	1.13	88	R.E.I.T.	0.84
23	Semiconductor	1.23	56	Wireless Networking	1.13	89	Tobacco	0.83
24	Semiconductor Equip	1.23	57	Furn/Home Furnishings	1.12	90	Food Processing	0.80
25	Machinery	1.22	58	Publishing	1.09	91	Retail/Wholesale Food	0.80
26	Electrical Equipment	1.21	59	Telecom. Utility	1.09	92	Water Utility	0.68
27	Air Transport	1.21	60	Medical Services	1.09	93	Natural Gas Utility	0.67
28	E-Commerce	1.20	61	Entertainment Tech	1.08	94	Precious Metals	0.64
29	Insurance (Life)	1.20	62	Industrial Services	1.07	95	Electric Util. (Central)	0.61
30	Automotive	1.20	63	Telecom. Services	1.06	96	Electric Utility (West)	0.59
31	Biotechnology	1.19	64	Toiletries/Cosmetics	1.06	97	Electric Utility (East)	0.56
32	Retail (Hardlines)	1.19	65	Recreation	1.06			
33	Trucking	1.19	66	Aerospace/Defense	1.05		Mean	1.12

* Industry averages for 97 industries using *Value Line*'s database of 1,706 companies - Updated 1-20-20.

** *Value Line* computes betas using monthly returns regressed against the New York Stock Exchange Index for five years. These betas are then adjusted as follows: *VL* Beta = [{(2/3) * Regressed Beta} + {(1/3) * (1.0)}] to account to tendency for Betas to regress toward average of 1.0. See M. Blume, “On the Assessment of Risk,” *Journal of Finance*, March 1971.

Exhibit JRW-6
DCF Model



I/A

Exhibit JRW-7

Duke Energy Progress, LLC
Discounted Cash Flow Analysis

Panel A
Electric Proxy Group

Dividend Yield*	3.05%
Adjustment Factor	1.025
Adjusted Dividend Yield	3.13%
Growth Rate**	5.00%
Equity Cost Rate	8.15%

* Page 2 of Exhibit JRW-7
** Based on data provided on pages 3, 4, 5, and 6 of Exhibit JRW-7

Panel B
Hevert Proxy Group

Dividend Yield*	2.90%
Adjustment Factor	1.027
Adjusted Dividend Yield	2.98%
Growth Rate**	5.40%
Equity Cost Rate	8.40%

* Page 2 of Exhibit JRW-7
** Based on data provided on pages 3, 4, 5, and 6 of Exhibit JRW-7

Exhibit JRW-7

Duke Energy Progress, LLC
Monthly Dividend Yields

Panel A
Electric Proxy Group*

Company	Annual Dividend	Dividend Yield 30 Day	Dividend Yield 90 Day	Dividend Yield 180 Day
ALLETE, Inc. (NYSE-ALE)	$2.47	3.0%	3.0%	2.9%
Alliant Energy Corporation (NYSE-LNT)	$1.52	2.7%	2.8%	2.9%
Ameren Corporation (NYSE-AEE)	$1.98	2.5%	2.6%	2.6%
American Electric Power Co. (NYSE-AEP)	$2.80	2.8%	3.0%	3.0%
Avangrid (NYSE-AGR)	$1.76	3.4%	3.5%	3.5%
Avista Corporation (NYSE-AVA)	$1.62	3.3%	3.4%	3.4%
CMS Energy Corporation (NYSE-CMS)	$1.63	2.5%	2.6%	2.6%
Consolidated Edison, Inc. (NYSE-ED)	$3.06	3.4%	3.4%	3.4%
Dominion Energy Inc. (NYSE-D)	$3.76	4.5%	4.6%	4.7%
Duke Energy Corporation (NYSE-DUK)	$3.78	4.0%	4.1%	4.1%
Edison International (NYSE-EIX)	$2.55	3.3%	3.5%	3.6%
Entergy Corporation (NYSE-ETR)	$3.72	3.0%	3.1%	3.3%
Evergy, Inc. (NYSE-EVRG)	$2.02	3.0%	3.1%	3.2%
Eversource Energy (NYSE-ES)	$2.27	2.6%	2.7%	2.8%
Exelon Corporation (NYSE-EXC)	$1.53	3.3%	3.3%	3.3%
FirstEnergy Corporation (NYSE-FE)	$1.56	3.2%	3.2%	3.3%
Hawaiian Electric Industries (NYSE-HE)	$1.28	2.7%	2.8%	2.9%
IDACORP, Inc. (NYSE-IDA)	$2.68	2.5%	2.5%	2.5%
MGE Energy, Inc. (NYSE-MGEE)	$1.41	1.8%	1.8%	1.9%
NextEra Energy, Inc. (NYSE-NEE)	$5.00	2.0%	2.1%	2.2%
NorthWestern Corporation (NYSE-NWE)	$2.30	3.1%	3.2%	3.2%
OGE Energy Corp. (NYSE-OGE)	$1.55	3.4%	3.5%	3.6%
Otter Tail Corporation (NDQ-OTTR)	$1.48	2.8%	2.8%	2.8%
Pinnacle West Capital Corp. (NYSE-PNW)	$3.13	3.3%	3.4%	3.4%
PNM Resources, Inc. (NYSE-PNM)	$1.23	2.4%	2.4%	2.4%
Portland General Electric Company (NYSE-POR)	$1.54	2.6%	2.7%	2.7%
PPL Corporation (NYSE-PPL)	$1.65	4.6%	4.8%	5.1%
Sempra Energy (NYSE-SRE)	$3.87	2.5%	2.6%	2.7%
Southern Company (NYSE-SO)	$2.48	3.7%	3.9%	4.1%
WEC Energy Group (NYSE-WEC)	$2.53	2.6%	2.7%	2.8%
Xcel Energy Inc. (NYSE-XEL)	$1.62	2.5%	2.6%	2.6%
Mean		3.0%	3.1%	3.1%
Median		3.0%	3.0%	3.0%

Data Sources: http://quote yahoo com, February, 2020

Panel B
Hevert Proxy Group

Company	Annual Dividend	Dividend Yield 30 Day	Dividend Yield 90 Day	Dividend Yield 180 Day
ALLETE, Inc. (NYSE-ALE)	$2.47	3.0%	3.0%	2.9%
Alliant Energy Corporation (NYSE-LNT)	$1.52	2.7%	2.8%	2.9%
Ameren Corporation (NYSE-AEE)	$1.98	2.5%	2.6%	2.6%
American Electric Power Co. (NYSE-AEP)	$2.80	2.8%	3.0%	3.0%
Avangrid (NYSE-AGR)	$1.76	3.4%	3.5%	3.5%
CMS Energy Corporation (NYSE-CMS)	$1.63	2.5%	2.6%	2.6%
DTE Energy Company (NYSE-DTE)	$4.05	3.1%	3.2%	3.1%
Evergy (NYSE-EVRG)	$2.02	3.0%	3.1%	3.2%
Hawaiian Electric Industries (NYSE-HE)	$1.28	2.7%	2.8%	2.9%
NextEra Energy, Inc. (NYSE-NEE)	$5.00	2.0%	2.1%	2.2%
NorthWestern Corporation (NYSE-NWE)	$2.30	3.1%	3.2%	3.2%
OGE Energy Corp. (NYSE-OGE)	$1.55	3.4%	3.5%	3.6%
Otter Tail Corporation (NDQ-OTTR)	$1.48	2.8%	2.8%	2.8%
Pinnacle West Capital Corp. (NYSE-PNW)	$3.13	3.3%	3.4%	3.4%
PNM Resources, Inc. (NYSE-PNM)	$1.23	2.4%	2.4%	2.4%
Portland General Electric Company (NYSE-POR)	$1.54	2.6%	2.7%	2.7%
Southern Company (NYSE-SO)	$2.48	3.7%	3.9%	4.1%
WEC Energy Group (NYSE-WEC)	$2.53	2.6%	2.7%	2.8%
Xcel Energy Inc. (NYSE-XEL)	$1.62	2.5%	2.6%	2.6%
Mean		2.9%	2.9%	3.0%
Median		2.8%	2.8%	2.9%

Data Sources: http://quote yahoo com, February, 2020

Exhibit JRW-7

Duke Energy Progress, LLC
DCF Equity Cost Growth Rate Measures
***Value Line* Historic Growth Rates**

Panel A
Electric Proxy Group

Company	*Value Line* Historic Growth: Past 10 Years			Past 5 Years		
	Earnings	Dividends	Book Value	Earnings	Dividends	Book Value
ALLETE, Inc. (NYSE-ALE)	2.5	3.0	5.0	4.0	3.5	5.0
Alliant Energy Corporation (NYSE-LNT)	5.0	7.0	4.0	5.0	7.0	5.0
Ameren Corporation (NYSE-AEE)	1.0	-2.0	-0.5	6.5	3.0	2.5
American Electric Power Co. (NYSE-AEP)	3.0	4.5	4.0	4.0	5.5	3.0
Avangrid (NYSE-AGR)						
Avista Corporation (NYSE-AVA)	5.5	8.5	4.0	5.0	4.5	4.5
CMS Energy Corporation (NYSE-CMS)	9.5	15.0	4.5	7.0	7.0	5.5
Consolidated Edison, Inc. (NYSE-ED)	2.5	2.0	4.0	2.0	2.5	4.0
Dominion Energy Inc. (NYSE-D)	3.0	7.5	4.5	3.5	7.5	6.5
Duke Energy Corporation (NYSE-DUK)	2.5	7.0	1.0	0.5	3.0	1.5
Edison International (NYSE-EIX)	-3.5	6.5	3.0	-9.0	11.0	3.0
Entergy Corporation (NYSE-ETR)	-0.5	2.5	1.0	0.5	1.5	-2.5
Evergy, Inc. (NYSE-EVRG)						
Eversource Energy (NYSE-ES)	8.0	9.5	6.5	7.0	8.0	5.0
Exelon Corporation (NYSE-EXC)	-5.5	-3.5	7.0	-3.5	-7.0	4.5
FirstEnergy Corporation (NYSE-FE)	-7.0	-2.5	-8.0	-2.5	-5.0	-17.5
Hawaiian Electric Industries (NYSE-HE)	5.0		3.0	4.0		3.5
IDACORP, Inc. (NYSE-IDA)	7.0	6.5	5.5	4.0	10.0	5.0
MGE Energy, Inc. (NYSE-MGEE)	4.5	3.5	5.5	2.5	4.0	5.5
Nextera Energy, Inc. (NYSE-NEE)	6.0	9.0	8.5	6.0	10.5	9.5
NorthWestern Corporation (NYSE-NWE)	8.5	5.0	5.5	7.0	7.0	8.0
OGE Energy Corp. (NYSE-OGE)	5.0	7.0	7.0	2.0	10.0	5.5
Otter Tail Corporation (NDQ-OTTR)	5.5	1.5		9.0	2.5	4.5
Pinnacle West Capital Corp. (NYSE-PNW)	4.5	2.5	2.5	5.0	3.0	4.5
PNM Resources, Inc. (NYSE-PNM)	7.0	2.5		6.0	11.0	1.0
Portland General Electric Company (NYSE-POR)	3.5	4.5	2.5	4.0	4.5	3.5
PPL Corporation (NYSE-PPL)		2.5	1.0	-0.5	2.0	-4.0
Sempra Energy (NYSE-SRE)	1.0	10.0	5.5	2.0	7.5	4.0
Southern Company (NYSE-SO)	3.0	3.5	4.0	2.5	3.5	3.0
WEC Energy Group (NYSE-WEC)	8.5	14.5	8.0	6.0	9.5	10.5
Xcel Energy Inc. (NYSE-XEL)	5.5	4.5	4.5	5.0	6.0	4.5
Mean	3.6	5.1	3.8	3.3	5.1	3.4
Median	4.5	4.5	4.0	4.0	5.0	4.5
Data Source: *Value Line Investment Survey.*	Average of Median Figures =			4.4		

Panel B
Hevert Proxy Group

Company	*Value Line* Historic Growth: Past 10 Years			Past 5 Years		
	Earnings	Dividends	Book Value	Earnings	Dividends	Book Value
ALLETE, Inc. (NYSE-ALE)	2.5	3.0	5.0	4.0	3.5	5.0
Alliant Energy Corporation (NYSE-LNT)	5.0	7.0	4.0	5.0	7.0	5.0
Ameren Corporation (NYSE-AEE)	1.0	-2.0	-0.5	6.5	3.0	2.5
American Electric Power Co. (NYSE-AEP)	3.0	4.5	4.0	4.0	5.5	3.0
Avangrid (NYSE-AGR)						
CMS Energy Corporation (NYSE-CMS)	9.5	15.0	4.5	7.0	7.0	5.5
DTE Energy Company (NYSE-DTE)	8.0	5.5	4.5	7.5	7.0	5.0
Evergy (NYSE-EVRG)						
Hawaiian Electric Industries (NYSE-HE)	5.0		3.0	4.0		3.5
Nextera Energy, Inc. (NYSE-NEE)	6.0	9.0	8.5	6.0	10.5	9.5
NorthWestern Corporation (NYSE-NWE)	8.5	5.0	5.5	7.0	7.0	8.0
OGE Energy Corp. (NYSE-OGE)	5.0	7.0	7.0	2.0	10.0	5.5
Otter Tail Corporation (NDQ-OTTR)	5.5	1.5		9.0	2.5	4.5
Pinnacle West Capital Corp. (NYSE-PNW)	4.5	2.5	2.5	5.0	3.0	4.5
PNM Resources, Inc. (NYSE-PNM)	7.0	2.5		6.0	11.0	1.0
Portland General Electric Company (NYSE-POR)	3.5	4.5	2.5	4.0	4.5	3.5
Southern Company (NYSE-SO)	3.0	3.5	4.0	2.5	3.5	3.0
WEC Energy Group (NYSE-WEC)	8.5	15.5	8.5	6.0	11.0	10.5
Xcel Energy Inc. (NYSE-XEL)	5.5	4.5	4.5	5.0	6.0	4.5
Mean	5.4	5.5	4.5	5.3	6.4	4.9
Median	5.0	4.5	4.5	5.0	6.5	4.5
Data Source: *Value Line Investment Survey.*	Average of Median Figures =			5.0		

Exhibit JRW-7

Duke Energy Progress, LLC
DCF Equity Cost Growth Rate Measures
***Value Line* Projected Growth Rates**

Panel A
Electric Proxy Group

Company	*Value Line* Projected Growth Est'd. '16-'18 to '22-'24 Earnings	Dividends	Book Value	*Value Line* Sustainable Growth Return on Equity	Retention Rate	Internal Growth
ALLETE, Inc. (NYSE-ALE)	5.5	5.5	4.5	8.5%	33.0%	2.8%
Alliant Energy Corporation (NYSE-LNT)	6.5	5.5	7.5	10.5%	33.0%	3.5%
Ameren Corporation (NYSE-AEE)	6.0	5.0	6.0	10.0%	46.0%	4.6%
American Electric Power Co. (NYSE-AEP)	5.0	5.5	4.5	10.5%	30.0%	3.2%
Avangrid (NYSE-AGR)	8.5	3.6	1.5	6.0%	33.0%	2.0%
Avista Corporation (NYSE-AVA)	3.5	3.5	3.5	8.0%	32.0%	2.6%
CMS Energy Corporation (NYSE-CMS)	7.5	7.0	7.5	13.5%	39.0%	5.3%
Consolidated Edison, Inc. (NYSE-ED)	3.0	3.5	3.5	8.5%	33.0%	2.8%
Dominion Energy Inc. (NYSE-D)	7.0	4.5	6.5	13.5%	24.0%	3.2%
Duke Energy Corporation (NYSE-DUK)	6.0	2.5	2.5	8.5%	32.0%	2.7%
Edison International (NYSE-EIX)	NMF	4.5	5.5	11.0%	41.0%	4.5%
Entergy Corporation (NYSE-ETR)	3.0	4.0	5.0	11.0%	35.0%	3.9%
Evergy, Inc. (NYSE-EVRG)	NMF	NMF	NMF	8.5%	35.0%	3.0%
Eversource Energy (NYSE-ES)	5.5	6.0	5.0	9.5%	38.0%	3.6%
Exelon Corporation (NYSE-EXC)	8.0	5.5	5.0	9.0%	52.0%	4.7%
FirstEnergy Corporation (NYSE-FE)	7.0	3.0	8.5	15.0%	40.0%	6.0%
Hawaiian Electric Industries (NYSE-HE)	2.5	3.0	3.5	9.0%	32.0%	2.9%
IDACORP, Inc. (NYSE-IDA)	3.5	7.0	4.0	9.5%	37.0%	3.5%
MGE Energy, Inc. (NYSE-MGEE)	5.5	5.5	5.0	10.5%	46.0%	4.8%
Nextera Energy, Inc. (NYSE-NEE)	10.0	10.5	7.0	13.0%	36.0%	4.7%
NorthWestern Corporation (NYSE-NWE)	2.0	4.5	3.5	9.0%	31.0%	2.8%
OGE Energy Corp. (NYSE-OGE)	4.5	6.0	3.5	11.0%	28.0%	3.1%
Otter Tail Corporation (NDQ-OTTR)	5.0	5.0	5.0	11.5%	35.0%	4.0%
Pinnacle West Capital Corp. (NYSE-PNW)	4.0	6.0	3.5	10.0%	32.0%	3.2%
PNM Resources, Inc. (NYSE-PNM)	7.0	7.0	5.0	9.0%	42.0%	3.8%
Portland General Electric Company (NYSE-POR)	4.5	6.5	3.0	9.0%	34.0%	3.1%
PPL Corporation (NYSE-PPL)	2.5	2.0	6.0	13.5%	42.0%	5.7%
Sempra Energy (NYSE-SRE)	11.0	8.0	6.5	11.5%	42.0%	4.8%
Southern Company (NYSE-SO)	4.0	3.0	4.0	13.0%	29.0%	3.8%
WEC Energy Group (NYSE-WEC)	6.0	6.5	3.5	12.5%	32.0%	4.0%
Xcel Energy Inc. (NYSE-XEL)	5.5	6.0	5.5	10.5%	36.0%	3.8%
Mean	5.5	5.2	4.8	10.5%	35.8%	3.7%
Median	5.5	5.5	5.0	10.5%	35.0%	3.6%
Average of Median Figures =		5.3			Median =	3.6%

* 'Est'd. '16-'17 to '22-'24' is the estimated growth rate from the base period 2016 to 2018 until the future period 2022 to 2024.
Data Source: *Value Line Investment Survey.*

Panel B
Hevert Proxy Group

Company	*Value Line* Projected Growth Est'd. '16-'18 to '22-'24 Earnings	Dividends	Book Value	*Value Line* Sustainable Growth Return on Equity	Retention Rate	Internal Growth
ALLETE, Inc. (NYSE-ALE)	5.5	5.5	4.5	8.5%	33.0%	2.8%
Alliant Energy Corporation (NYSE-LNT)	6.5	5.5	7.5	10.5%	33.0%	3.5%
Ameren Corporation (NYSE-AEE)	6.0	5.0	6.0	10.0%	46.0%	4.6%
American Electric Power Co. (NYSE-AEP)	5.0	5.5	4.5	10.5%	30.0%	3.2%
Avangrid (NYSE-AGR)	8.5	3.6	1.5	6.0%	33.0%	2.0%
CMS Energy Corporation (NYSE-CMS)	7.5	7.0	7.5	13.5%	39.0%	5.3%
DTE Energy Company (NYSE-DTE)	5.0	6.5	5.5	10.5%	37.0%	3.9%
Evergy (NYSE-EVRG)	NMF	NMF	NMF	8.5%	35.0%	3.0%
Hawaiian Electric Industries (NYSE-HE)	2.5	3.0	3.5	9.0%	32.0%	2.9%
Nextera Energy, Inc. (NYSE-NEE)	10.0	10.5	7.0	13.0%	36.0%	4.7%
NorthWestern Corporation (NYSE-NWE)	2.0	4.5	3.5	9.0%	31.0%	2.8%
OGE Energy Corp. (NYSE-OGE)	4.5	6.0	3.5	11.0%	28.0%	3.1%
Otter Tail Corporation (NDQ-OTTR)	5.0	5.0	5.0	11.5%	35.0%	4.0%
Pinnacle West Capital Corp. (NYSE-PNW)	4.0	6.0	3.5	10.0%	32.0%	3.2%
PNM Resources, Inc. (NYSE-PNM)	7.0	7.0	5.0	9.0%	42.0%	3.8%
Portland General Electric Company (NYSE-POR)	4.5	6.5	3.0	9.0%	34.0%	3.1%
Southern Company (NYSE-SO)	4.0	3.0	4.0	13.0%	29.0%	3.8%
WEC Energy Group (NYSE-WEC)	6.0	6.0	3.5	12.0%	33.0%	4.0%
Xcel Energy Inc. (NYSE-XEL)	5.5	6.0	5.5	10.5%	36.0%	3.8%
Mean	5.5	5.7	4.7	10.3%	34.4%	3.5%
Median	5.3	5.8	4.5	10.5%	33.0%	3.5%
Average of Median Figures =		5.2			Median =	3.5%

* 'Est'd. '16-'17 to '22-'24' is the estimated growth rate from the base period 2016 to 2018 until the future period 2022 to 2024.
Data Source: *Value Line Investment Survey.*

Exhibit JRW-7

Duke Energy Progress, LLC
DCF Equity Cost Growth Rate Measures
Analysts Projected EPS Growth Rate Estimates

Panel A
Electric Proxy Group

Company	Yahoo	Zacks	Mean
ALLETE, Inc. (NYSE-ALE)	7.0%	7.2%	7.1%
Alliant Energy Corporation (NYSE-LNT)	5.4%	5.5%	5.4%
Ameren Corporation (NYSE-AEE)	6.1%	5.7%	5.9%
American Electric Power Co. (NYSE-AEP)	4.6%	6.2%	5.4%
Avangrid (NYSE-AGR)	3.5%	3.4%	3.4%
Avista Corporation (NYSE-AVA)	6.2%	7.4%	6.8%
CMS Energy Corporation (NYSE-CMS)	7.5%	6.4%	7.0%
Consolidated Edison, Inc. (NYSE-ED)	2.4%	2.0%	2.2%
Dominion Energy Inc. (NYSE-D)	4.4%	4.8%	4.6%
Duke Energy Corporation (NYSE-DUK)	4.4%	4.8%	4.6%
Edison International (NYSE-EIX)	3.9%	5.4%	4.7%
Entergy Corporation (NYSE-ETR)	-1.5%	7.0%	
Evergy, Inc. (NYSE-EVRG)	6.7%	6.6%	6.6%
Eversource Energy (NYSE-ES)	5.5%	5.6%	5.5%
Exelon Corporation (NYSE-EXC)	0.5%	4.2%	2.3%
FirstEnergy Corporation (NYSE-FE)	-6.6%	6.0%	
Hawaiian Electric Industries (NYSE-HE)	3.4%	4.2%	3.8%
IDACORP, Inc. (NYSE-IDA)	2.5%	3.9%	3.2%
MGE Energy, Inc. (NYSE-MGEE)	4.0%	N/A	4.0%
Nextera Energy, Inc. (NYSE-NEE)	8.0%	8.0%	8.0%
NorthWestern Corporation (NYSE-NWE)	3.2%	2.8%	3.0%
OGE Energy Corp. (NYSE-OGE)	3.5%	4.3%	3.9%
Otter Tail Corporation (NDQ-OTTR)	9.0%	7.0%	8.0%
Pinnacle West Capital Corp. (NYSE-PNW)	4.1%	4.9%	4.5%
PNM Resources, Inc. (NYSE-PNM)	6.3%	5.4%	5.8%
Portland General Electric Company (NYSE-POR)	4.8%	4.8%	4.8%
PPL Corporation (NYSE-PPL)	0.5%	N/A	0.5%
Sempra Energy (NYSE-SRE)	10.1%	7.7%	8.9%
Southern Company (NYSE-SO)	1.5%	4.5%	3.0%
WEC Energy Group (NYSE-WEC)	6.1%	6.1%	6.1%
Xcel Energy Inc. (NYSE-XEL)	6.1%	5.4%	5.8%
Mean	4.3%	5.4%	5.0%
Median	4.4%	5.4%	4.8%

Data Sources: www zacks com, http://quote yahoo com, February, 2020
* Entergy and FirstEnergy were excluded from the DCF analysis due to negative projected EPS growth rates

Panel B
Hevert Proxy Group

Company	Yahoo	Zacks	Mean
ALLETE, Inc. (NYSE-ALE)	7.0%	7.2%	7.1%
Alliant Energy Corporation (NYSE-LNT)	5.4%	5.5%	5.4%
Ameren Corporation (NYSE-AEE)	6.1%	5.7%	5.9%
American Electric Power Co. (NYSE-AEP)	4.6%	6.2%	5.4%
Avangrid (NYSE-AVG)	3.5%	3.4%	3.4%
CMS Energy Corporation (NYSE-CMS)	7.5%	6.4%	7.0%
DTE Energy Company (NYSE-DTE)	4.8%	6.0%	5.4%
Evergy (NYSE-EVRG)	6.7%	6.6%	6.6%
Hawaiian Electric Industries (NYSE-HE)	3.4%	4.2%	3.8%
Nextera Energy, Inc. (NYSE-NEE)	8.0%	8.0%	8.0%
NorthWestern Corporation (NYSE-NWE)	3.2%	2.8%	3.0%
OGE Energy Corp. (NYSE-OGE)	3.5%	4.3%	3.9%
Otter Tail Corporation (NDQ-OTTR)	9.0%	7.0%	8.0%
Pinnacle West Capital Corp. (NYSE-PNW)	4.1%	4.9%	4.5%
PNM Resources, Inc. (NYSE-PNM)	6.3%	5.4%	5.8%
Portland General Electric Company (NYSE-POR)	4.8%	4.8%	4.8%
Southern Company (NYSE-SO)	1.5%	4.5%	3.0%
WEC Energy Group (NYSE-WEC)	6.1%	6.1%	6.1%
Xcel Energy Inc. (NYSE-XEL)	6.1%	5.4%	5.8%
Mean	5.3%	5.5%	5.4%
Median	5.4%	5.5%	5.4%

Data Sources: www zacks com, http://quote yahoo com, February, 2020

Exhibit JRW-7

Duke Energy Progress, LLC
DCF Growth Rate Indicators

Electric and Hevert Proxy Groups

Growth Rate Indicator	Electric Proxy Group	Hevert Proxy Group
Historic *Value Line* Growth in EPS, DPS, and BVPS	4.4%	5.0%
Projected *Value Line* Growth in EPS, DPS, and BVPS	5.3%	5.2%
Sustainable Growth ROE * Retention Rate	3.6%	3.5%
Projected EPS Growth from Yahoo, Zacks, and Reuters - Mean/Median	5.0%/4.8%	5.4%/5.4%

I/A

Exhibit JRW-8

Duke Energy Progress, LLC
Capital Asset Pricing Model

Panel A
Electric Proxy Group

Risk-Free Interest Rate	**3.50%**
Beta*	**0.55**
Ex Ante Equity Risk Premium**	**5.75%**
CAPM Cost of Equity	**6.7%**

* See page 3 of Exhibit JRW-8

** See pages 5 and 6 of Exhibit JRW-8

Panel B
Hevert Proxy Group

Risk-Free Interest Rate	**3.50%**
Beta*	**0.55**
Ex Ante Equity Risk Premium**	**5.75%**
CAPM Cost of Equity	**6.7%**

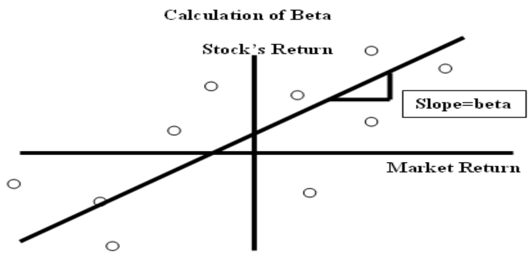
* See page 3 of Exhibit JRW-8

** See pages 5 and 6 of Exhibit JRW-8

Exhibit JRW-8

Thirty-Year U.S. Treasury Yields
2013-2020

Source: Federal Reserve Bank of St Louis, FRED Database



Panel A
Electric Proxy Group

Company Name	Beta
ALLETE, Inc. (NYSE-ALE)	0.60
Alliant Energy Corporation (NYSE-LNT)	0.55
Ameren Corporation (NYSE-AEE)	0.50
American Electric Power Co. (NYSE-AEP)	0.50
Avangrid (NYSE-AGR)	0.40
Avista Corporation (NYSE-AVA)	0.60
CMS Energy Corporation (NYSE-CMS)	0.50
Consolidated Edison, Inc. (NYSE-ED)	0.40
Dominion Energy Inc. (NYSE-D)	0.50
Duke Energy Corporation (NYSE-DUK)	0.45
Edison International (NYSE-EIX)	0.55
Entergy Corporation (NYSE-ETR)	0.60
Evergy, Inc. (NYSE-EVRG)	NMF
Eversource Energy (NYSE-ES)	0.55
Exelon Corporation (NYSE-EXC)	0.65
FirstEnergy Corporation (NYSE-FE)	0.60
Hawaiian Electric Industries (NYSE-HE)	0.55
IDACORP, Inc. (NYSE-IDA)	0.55
MGE Energy, Inc. (NYSE-MGEE)	0.50
NextEra Energy, Inc. (NYSE-NEE)	0.50
NorthWestern Corporation (NYSE-NWE)	0.60
OGE Energy Corp. (NYSE-OGE)	0.70
Otter Tail Corporation (NDQ-OTTR)	0.70
Pinnacle West Capital Corp. (NYSE-PNW)	0.50
PNM Resources, Inc. (NYSE-PNM)	0.60
Portland General Electric Company (NYSE-POR)	0.55
PPL Corporation (NYSE-PPL)	0.65
Sempra Energy (NYSE-SRE)	0.70
Southern Company (NYSE-SO)	0.50
WEC Energy Group (NYSE-WEC)	0.45
Xcel Energy Inc. (NYSE-XEL)	0.50
Mean	0.56
Median	0.55

Data Source *Value Line Investment Survey* , 2020.

Panel B
Hevert Proxy Group

Company Name	Beta
ALLETE, Inc. (NYSE-ALE)	0.60
Alliant Energy Corporation (NYSE-LNT)	0.55
Ameren Corporation (NYSE-AEE)	0.50
American Electric Power Co. (NYSE-AEP)	0.50
Avangrid (NYSE-AGR)	0.40
CMS Energy Corporation (NYSE-CMS)	0.50
DTE Energy Company (NYSE-DTE)	0.50
Evergy, Inc. (NYSE-EVRG)	NMF
Hawaiian Electric Industries (NYSE-HE)	0.55
NextEra Energy, Inc. (NYSE-NEE)	0.50
NorthWestern Corporation (NYSE-NWE)	0.60
OGE Energy Corp. (NYSE-OGE)	0.70
Otter Tail Corporation (NDQ-OTTR)	0.70
Pinnacle West Capital Corp. (NYSE-PNW)	0.50
PNM Resources, Inc. (NYSE-PNM)	0.60
Portland General Electric Company (NYSE-POR)	0.55
Southern Company (NYSE-SO)	0.50
WEC Energy Group (NYSE-WEC)	0.45
Xcel Energy Inc. (NYSE-XEL)	0.50
Mean	0.55
Median	0.55

Data Source *Value Line Investment Survey* , 2020.

Exhibit JRW-8
Risk Premium Approaches

	Historical Ex Post Returns	Surveys	Expected Return Models and Market Data
Means of Assessing The Market Risk Premium	Historical Average Stock Minus Bond Returns	Surveys of CFOs, Financial Forecasters, Companies, Analysts on Expected Returns and Market Risk Premiums	Use Market Prices and Market Fundamentals (such as Growth Rates) to Compute Expected Returns and Market Risk Premiums
Problems/Debated Issues	Time Variation in Required Returns, Measurement and Time Period Issues, and Biases such as Market and Company Survivorship Bias	Questions Regarding Survey Histories, Responses, and Representativeness Surveys may be Subject to Biases, such as Extrapolation	Assumptions Regarding Expectations, Especially Growth

Source: Adapted from Antti Ilmanen, Expected Returns on Stocks and Bonds," *Journal of Portfolio Management* , (Winter 2003)

Exhibit JRW-8

Capital Asset Pricing Model
Market Risk Premium

Category	Study Authors	Publication Date	Time Period Of Study	Methodology	Return Measure	Range Low	Range High	Midpoint of Range	Mean	Median
Historical Risk Premium										
	Ibbotson	2016	1928-2015	Historical Stock Returns - Bond Returns	Arithmetic				6.00%	
					Geometric				4.40%	
	Damodaran	2020	1928-2019	Historical Stock Returns - Bond Returns	Arithmetic				6.43%	
					Geometric				4.83%	
	Dimson, Marsh, Staunton _Credit Suisse Report	2019	1900-2018	Historical Stock Returns - Bond Returns	Arithmetic				5.50%	
					Geometric					
	Bate	2008	1900-2007	Historical Stock Returns - Bond Returns	Geometric				4.50%	
	Shiller	2006	1926-2005	Historical Stock Returns - Bond Returns	Arithmetic				7.00%	
					Geometric				5.50%	
	Siegel	2005	1926-2005	Historical Stock Returns - Bond Returns	Arithmetic				6.10%	
					Geometric				4.60%	
	Dimson, Marsh, and Staunton	2006	1900-2005	Historical Stock Returns - Bond Returns	Arithmetic				5.50%	
	Goyal & Welch	2006	1872-2004	Historical Stock Returns - Bond Returns					4.77%	
	Median									5.50%
Ex Ante Models (Puzzle Research)										
	Claus Thomas	2001	1985-1998	Abnormal Earnings Model					3.00%	
	Arnott and Bernstein	2002	1810-2001	Fundamentals - Div Yld + Growth					2.40%	
	Constantinides	2002	1872-2000	Historical Returns & Fundamentals - P/D & P/E					6.90%	
	Cornell	1999	1926-1997	Historical Returns & Fundamental GDP/Earnings		3.50%	5.50%	4.50%	4.50%	
	Easton, Taylor, et al	2002	1981-1998	Residual Income Model					5.30%	
	Fama French	2002	1951-2000	Fundamental DCF with EPS and DPS Growth		2.55%	4.32%		3.44%	
	Harris & Marston	2001	1982-1998	Fundamental DCF with Analysts' EPS Growth					7.14%	
	McKinsey	2002	1962-2002	Fundamental (P/E, D/P, & Earnings Growth)		3.50%	4.00%		3.75%	
	Siegel	2005	1802-2001	Historical Earnings Yield					2.50%	
	Grabowski	2006	1926-2005	Historical and Projected		3.50%	6.00%	4.75%	4.75%	
	Maheu & McCurdy	2006	1885-2003	Historical Excess Returns, Structural Breaks,		4.02%	5.10%	4.56%	4.56%	
	Bostock	2004	1960-2002	Bond Yields, Credit Risk, and Income Volatility		3.90%	1.30%	2.60%	2.60%	
	Bakshi & Chen	2005	1982-1998	Fundamentals - Interest Rates					7.31%	
	Donaldson, Kamstra, & Kramer	2006	1952-2004	Fundamental, Dividend yld., Returns,, & Volatility		3.00%	4.00%	3.50%	3.50%	
	Campbell	2008	1982-2007	Historical & Projections (D/P & Earnings Growth)		4.10%	5.40%		4.75%	
	Best & Byrne	2001	Projection	Fundamentals - Div Yld + Growth					2.00%	
	Fernandez	2007	Projection	Required Equity Risk Premium					4.00%	
	DeLong & Magin	2008	Projection	Earnings Yield - TIPS					3.22%	
	Siegel - Rethink ERP	2011	Projection	Real Stock Returns and Components					5.50%	
	Duff & Phelps	2019	Projection	Normalized with 3.5% Long-Term Treasury Yield					5.50%	
	Mschchowski - VL - 2014	2014	Projection	Fundamentals - Expected Return Minus 10-Year Treasury Rate					5.50%	
	American Appraisal Quarterly ERP	2015	Projection	Fundamental Economic and Market Factors					6.00%	
	Market Risk Premia	2019	Projection	Fundamental Economic and Market Factors					4.29%	
	KPMG	2019	Projection	Fundamental Economic and Market Factors					5.75%	
	Damodaran - 1-1-20	2020	Projection	Fundamentals - Implied from FCF to Equity Model (Trailing 12 month, with adjusted payout)					4.79%	
	Social Security									
	Office of Chief Actuary		1900-1995							
	John Campbell	2001	1860-2000	Historical & Projections (D/P & Earnings Growth)	Arithmetic	3.00%	4.00%	3.50%	3.50%	
			Projected for 75 Years		Geometric	1.50%	2.50%	2.00%	2.00%	
	Peter Diamond	2001	Projected for 75 Years	Fundamentals (D/P, GDP Growth)		3.00%	4.80%	3.90%	3.90%	
	John Shoven	2001	Projected for 75 Years	Fundamentals (D/P P/E GDP Growth)		3.00%	3.50%	3.25%	3.25%	
	Median									4.29%
Surveys										
	New York Fed	2015	Five-Year	Survey of Wall Street Firms					5.70%	
	Survey of Financial Forecasters	2019	10-Year Projection	About 20 Financial Forecastsers					1.85%	
	Duke - CFO Magazine Survey	2019	10-Year Projection	Approximately 200 CFOs					4.05%	
	Welch - Academics	2008	30-Year Projection	Random Academics		5.00%	5.74%	5.37%	5.37%	
	Fernandez - Academics Analysts and Compani	2019	Long-Term	Survey of Academics Analysts and Companies					5.60%	
	Median									5.37%
Building Block										
	Ibbotson and Chen	2015	Projection	Historical Supply Model (D/P & Earnings Growth)	Arithmetic			6.22%	5.21%	
					Geometric			4.20%		
	Chen - Rethink ERP	2010	20-Year Projection	Combination Supply Model (Historic and Projection	Geometric				4.00%	
	Ilmanen - Rethink ERP	2010	Projection	Current Supply Model (D/P & Earnings Growth)	Geometric				3.00%	
	Grinold, Kroner, Siegel - Rethink ERP	2011	Projection	Current Supply Model (D/P & Earnings Growth)	Arithmetic			4.63%	4.12%	
					Geometric			3.60%		
	Median									4.06%
Mean										**4.80%**
Median										**4.83%**

Exhibit JRW-8

Capital Asset Pricing Model
Market Risk Premium

Summary of 2010-20 Equity Risk Premium Studies

Category	Study Authors	Publication Date	Time Period Of Study	Methodology	Return Measure	Range Low	Range High	Midpoint of Range	Mean	Average
Historical Risk Premium										
	Ibbotson	2016	1928-2015	Historical Stock Returns - Bond Returns	Arithmetic				6.00%	
					Geometric				4.40%	
	Damodaran	2020	1928-2019	Historical Stock Returns - Bond Returns	Arithmetic				6.43%	
					Geometric				4.83%	
	Dimson, Marsh, Staunton _Credit Suisse Report	2019	1900-2018	Historical Stock Returns - Bond Returns	Arithmetic				5.50%	
					Geometric					
	Median									5.43%
Ex Ante Models (Puzzle Research)										
	Siegel - Rethink ERP	2011	Projection	Real Stock Returns and Components					5.50%	
	Duff & Phelps	2019	Projection	Normalized with 3.5% Long-Term Treasury Yield					5.50%	
	Mschchowski - VL - 2014	2014	Projection	Fundamentals - Expected Return Minus 10-Year Treasury Rate					5.50%	
	American Appraisal Quarterly ERP	2015	Projection	Fundamental Economic and Market Factors					6.00%	
	Market Risk Premia	2019	Projection	Fundamental Economic and Market Factors					4.29%	
	KPMG	2019	Projection	Fundamental Economic and Market Factors					5.75%	
	Damodaran - 1-1-20	2020	Projection	Fundamentals - Implied from FCF to Equity Model (Trailing 12 month with adjusted payout)					4.79%	
	Median									5.50%
Surveys										
	New York Fed	2015	Five-Year	Survey of Wall Street Firms					5.70%	
	Survey of Financial Forecasters	2019	10-Year Projection	About 20 Financial Forecastsers					1.85%	
	Duke - CFO Magazine Survey	2019	10-Year Projection	Approximately 200 CFOs					4.05%	
	Fernandez - Academics Analysts and Companies	2019	Long-Term	Survey of Academics Analysts and Companies					5.60%	
	Median									4.83%
Building Block										
	Ibbotson and Chen	2015	Projection	Historical Supply Model (D/P & Earnings Growth)	Arithmetic			6.22%	5.21%	
					Geometric			4.20%		
	Chen - Rethink ERP	2010	20-Year Projection	Combination Supply Model (Historic and Projection)	Geometric				4.00%	
	Ilmanen - Rethink ERP	2010	Projection	Current Supply Model (D/P & Earnings Growth)	Geometric				3.00%	
	Grinold, Kroner, Siegel - Rethink ERP	2011	Projection	Current Supply Model (D/P & Earnings Growth)	Arithmetic			4.63%	4.12%	
					Geometric			3.60%		
	Median									4.06%
Mean										**4.95%**
Median										**5.13%**

DOCKET NO. E-2, SUB 1219
Exhibit JRW-8
CAPM Study

Duff & Phelps Risk-Free Interest Rates and Equity Risk Premium Estimates

DUFF & PHELPS

Table: Equity Risk Premium & Risk-free Rates

December 31, 2019

Duff & Phelps Recommended U.S. Equity Risk Premium (ERP) and Corresponding Risk-free Rates (R_f); January 2008–Present

For additional information, please visit www.duffandphelps.com/CostofCapital

Date	Risk-free Rate (R_f)	R_f (%)	Duff & Phelps Recommended ERP (%)	What Changed
Current Guidance:				
December 19, 2019 – UNTIL FURTHER NOTICE	Normalized 20-year U.S. Treasury yield	3.00	5.00	ERP
September 30, 2019 – December 18, 2019	Normalized 20-year U.S. Treasury yield	3.00	5.50	R_f
December 31, 2018 – September 29, 2019	Normalized 20-year U.S. Treasury yield	3.50	5.50	ERP
September 5, 2017 – December 30, 2018	Normalized 20-year U.S. Treasury yield	3.50	5.00	ERP
November 15, 2016 – September 4, 2017	Normalized 20-year U.S. Treasury yield	3.50	5.50	R_f
January 31, 2016 – November 14, 2016	Normalized 20-year U.S. Treasury yield	4.00	5.50	ERP
December 31, 2015	Normalized 20-year U.S. Treasury yield	4.00	5.00	
December 31, 2014	Normalized 20-year U.S. Treasury yield	4.00	5.00	
December 31, 2013	Normalized 20-year U.S. Treasury yield	4.00	5.00	
February 28, 2013 – January 30, 2016	Normalized 20-year U.S. Treasury yield	4.00	5.00	ERP
December 31, 2012	Normalized 20-year U.S. Treasury yield	4.00	5.50	
January 15, 2012 – February 27, 2013	Normalized 20-year U.S. Treasury yield	4.00	5.50	ERP
December 31, 2011	Normalized 20-year U.S. Treasury yield	4.00	6.00	
September 30, 2011 – January 14, 2012	Normalized 20-year U.S. Treasury yield	4.00	6.00	ERP
July 1 2011 – September 29, 2011	Normalized 20-year U.S. Treasury yield	4.00	5.50	R_f
June 1, 2011 – June 30, 2011	Spot 20-year U.S. Treasury yield	Spot	5.50	R_f
May 1, 2011 – May 31, 2011	Normalized 20-year U.S. Treasury yield	4.00	5.50	R_f
December 31, 2010	Spot 20-year U.S. Treasury yield	Spot	5.50	
December 1, 2010 – April 30, 2011	Spot 20-year U.S. Treasury yield	Spot	5.50	R_f
June 1, 2010 – November 30, 2010	Normalized 20-year U.S. Treasury yield	4.00	5.50	R_f
December 31, 2009	Spot 20-year U.S. Treasury yield	Spot	5.50	
December 1, 2009 – May 31, 2010	Spot 20-year U.S. Treasury yield	Spot	5.50	ERP
June 1, 2009 – November 30, 2009	Spot 20-year U.S. Treasury yield	Spot	6.00	R_f
December 31, 2008	Normalized 20-year U.S. Treasury yield	4.50	6.00	
November 1, 2008 – May 31, 2009	Normalized 20-year U.S. Treasury yield	4.50	6.00	R_f
October 27, 2008 – October 31, 2008	Spot 20-year U.S. Treasury yield	Spot	6.00	ERP
January 1, 2008 – October 26, 2008	Spot 20-year U.S. Treasury yield	Spot	5.00	Initialized

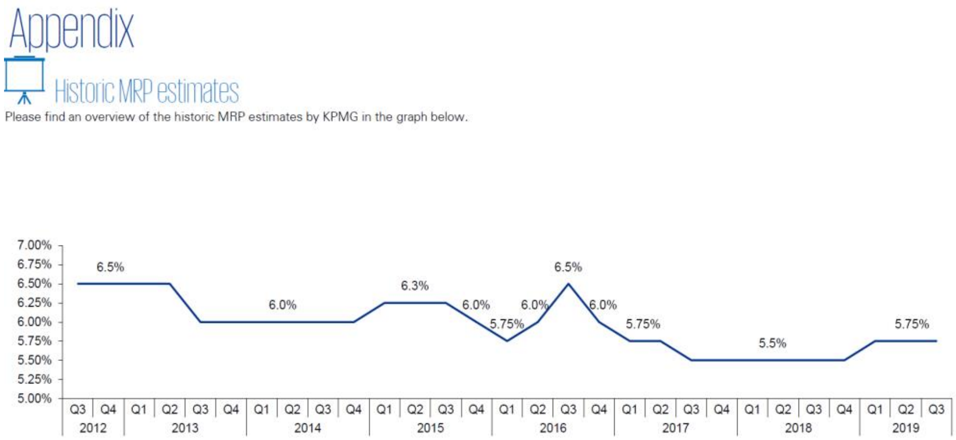
"Normalized" in this context means that in months where the risk-free rate is deemed to be abnormally low, a proxy for a longer-term sustainable risk-free rate is used.

To learn more about cost of capital issues, and to ensure that you are using the most recent Duff & Phelps Recommended ERP, visit www.duffandphelps.com/CostofCapital.
This and other related resources can also be found in the online Cost of Capital Navigator platform. To learn more about the Cost of Capital Navigator and other Duff & Phelps valuation and industry data products, visit www.DPCostofCapital.com.

Source: https://www.duffandphelps.com/-/media/assets/pdfs/publications/valuation/coc/erp-risk-free-rates-jan-2008-present.ashx?la=en

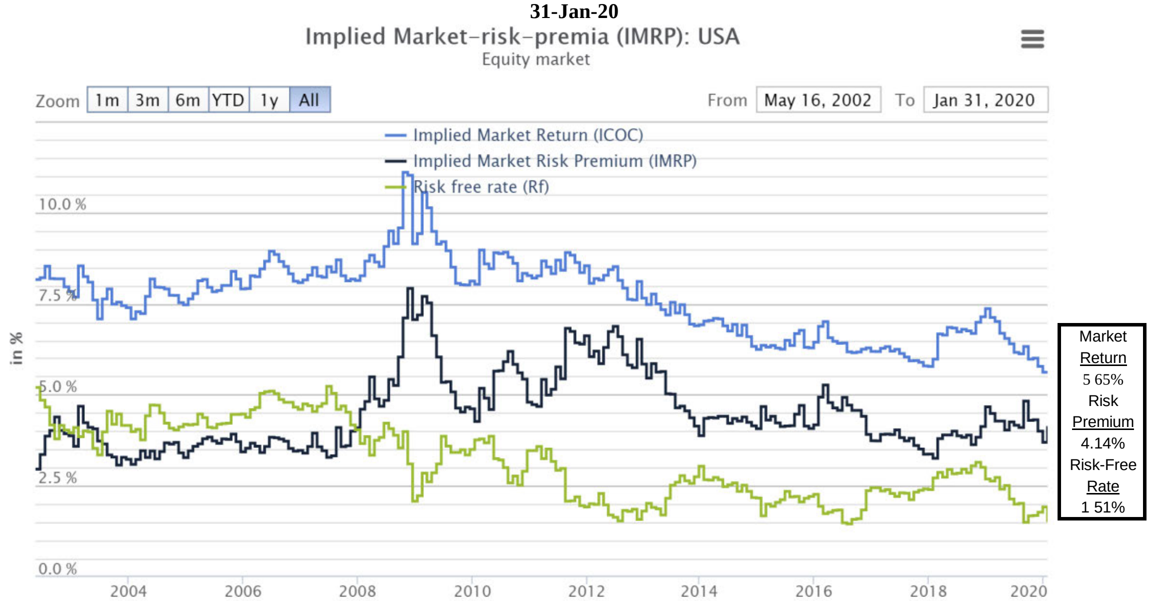
DOCKET NO. E-2, SUB 1219
Exhibit JRW-8
CAPM Study
Page 8 of 8

Panel A
KPMG Equity Risk Premium Recommendation



Source: https://assets.kpmg/content/dam/kpmg/nl/pdf/2019/advisory/equity-market-research-summary.pdf

Panel B
Market-Risk-Premia.com Implied Market Risk Premium
31-Jan-20



Source: http://www market-risk-premia com/

Duke Energy Progress, LLC Recommended Cost of Capital

Capital Source	Capitalization Ratios*	Cost Rate	Weighted Cost Rate
Long-Term Debt	47.00%	4.15%	1.95%
Common Equity	53.00%	10.50%	5.57%
Total Capitalization	100.00%		7.52%

Panel A
Mr. Hevert's DCF Results

	Mean	Mean High
30-Day Average	8.78%	9.67%
90-Day Average	8.84%	9.73%
180-Day Average	8.97%	9.85%

Panel B
Mr. Hevert's CAPM Results

CAPM	Bloomberg Derived Market Risk Premium	Value Line Derived Market Risk Premium
Average Bloomberg Beta Coefficient		
Current 30-Year Treasury (2.43%)	8.44%	8.52%
Near Term Projected 30-Year Treasury (2.65%)	8.66%	8.74%
Average Value Line Beta Coefficient		
Current 30-Year Treasury (2.43%)	9.32%	9.41%
Near Term Projected 30-Year Treasury (2.65%)	9.54%	9.62%
Empirical CAPM	**Bloomberg Derived Market Risk Premium**	**Value Line Derived Market Risk Premium**
Average Bloomberg Beta Coefficient		
Current 30-Year Treasury (2.43%)	9.95%	10.04%
Near Term Projected 30-Year Treasury (2.65%)	10.17%	10.26%
Average Value Line Beta Coefficient		
Current 30-Year Treasury (2.43%)	10.61%	10.71%
Near Term Projected 30-Year Treasury (2.65%)	10.83%	10.93%
Bond Yield Plus Risk Premium Approach		
Current 30-Year Treasury (2.43%)	9.91%	
Near Term Projected 30-Year Treasury (2.65%)	9.90%	
Long-Term Projected 30-Year Treasury (3.70%)	10.06%	

I/A

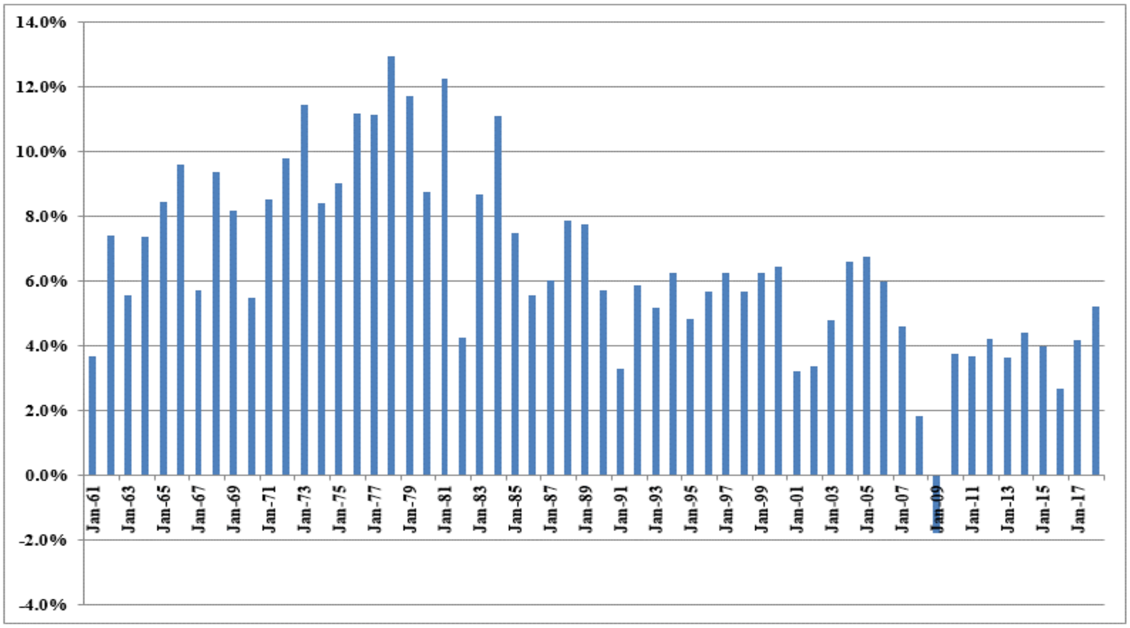
DOCKET NO. E-2, SUB 1219
Exhibit JRW-10
GDP and S&P 500 Growth Rates

Growth Rates
GDP, S&P 500 Price, EPS, and DPS

		GDP	S&P 500	S&P 500 EPS	S&P 500 DPS	
	1960	542 38	58.11	3.10	1 98	
1	1961	562 21	71.55	3.37	2.04	
2	1962	603 92	63.10	3.67	2 15	
3	1963	637 45	75.02	4.13	2 35	
4	1964	684 46	84.75	4.76	2 58	
5	1965	742 29	92.43	5.30	2.83	
6	1966	813 41	80.33	5.41	2.88	
7	1967	859 96	96.47	5.46	2 98	
8	1968	940 65	103.86	5.72	3.04	
9	1969	1017 62	92.06	6.10	3 24	
10	1970	1073 30	92.15	5.51	3 19	
11	1971	1164 85	102.09	5.57	3 16	
12	1972	1279 11	118.05	6.17	3 19	
13	1973	1425 38	97.55	7.96	3.61	
14	1974	1545 24	68.56	9.35	3.72	
15	1975	1684 90	90.19	7.71	3.73	
16	1976	1873 41	107.46	9.75	4 22	
17	1977	2081 83	95.10	10.87	4.86	
18	1978	2351 60	96.11	11.64	5 18	
19	1979	2627 33	107.94	14.55	5 97	
20	1980	2857 31	135.76	14.99	6.44	
21	1981	3207 04	122.55	15.18	6.83	
22	1982	3343 79	140.64	13.82	6 93	
23	1983	3634 04	164.93	13.29	7 12	
24	1984	4037 61	167.24	16.84	7.83	
25	1985	4338 98	211.28	15.68	8 20	
26	1986	4579 63	242.17	14.43	8 19	
27	1987	4855 22	247.08	16.04	9 17	
28	1988	5236 44	277.72	24.12	10.22	
29	1989	5641 58	353.40	24.32	11.73	
30	1990	5963 14	330.22	22.65	12.35	
31	1991	6158 13	417.09	19.30	12.97	
32	1992	6520 33	435.71	20.87	12.64	
33	1993	6858 56	466.45	26.90	12.69	
34	1994	7287 24	459.27	31.75	13.36	
35	1995	7639 75	615.93	37.70	14.17	
36	1996	8073 12	740.74	40.63	14.89	
37	1997	8577 55	970.43	44.09	15.52	
38	1998	9062 82	1229 23	44.27	16.20	
39	1999	9630 66	1469 25	51.68	16.71	
40	2000	10252 35	1320 28	56.13	16.27	
41	2001	10581 82	1148.09	38.85	15.74	
42	2002	10936 42	879.82	46.04	16.08	
43	2003	11458 25	1111 91	54.69	17.88	
44	2004	12213 73	1211 92	67.68	19.41	
45	2005	13036 64	1248 29	76.45	22.38	
46	2006	13814 61	1418 30	87.72	25.05	
47	2007	14451 86	1468 36	82.54	27.73	
48	2008	14712 85	903.25	65.39	28.05	
49	2009	14448 93	1115 10	59.65	22.31	
50	2010	14992 05	1257.64	83.66	23.12	
51	2011	15542 58	1257.60	97.05	26.02	
52	2012	16197 01	1426 19	102.47	30.44	
53	2013	16784 85	1848 36	107.45	36.28	
54	2014	17521 75	2058 90	113.01	39.44	
55	2015	18219 30	2043 94	106.32	43.16	
56	2016	18707 19	2238.83	108.86	45.03	
57	2017	19485 39	2673.61	124.94	49.73	
58	2018	20500 64	2506.85	148.34	53.61	**Average**
	Growth Rates	**6.46**	**6.71**	**6.89**	**5 85**	**6.48**

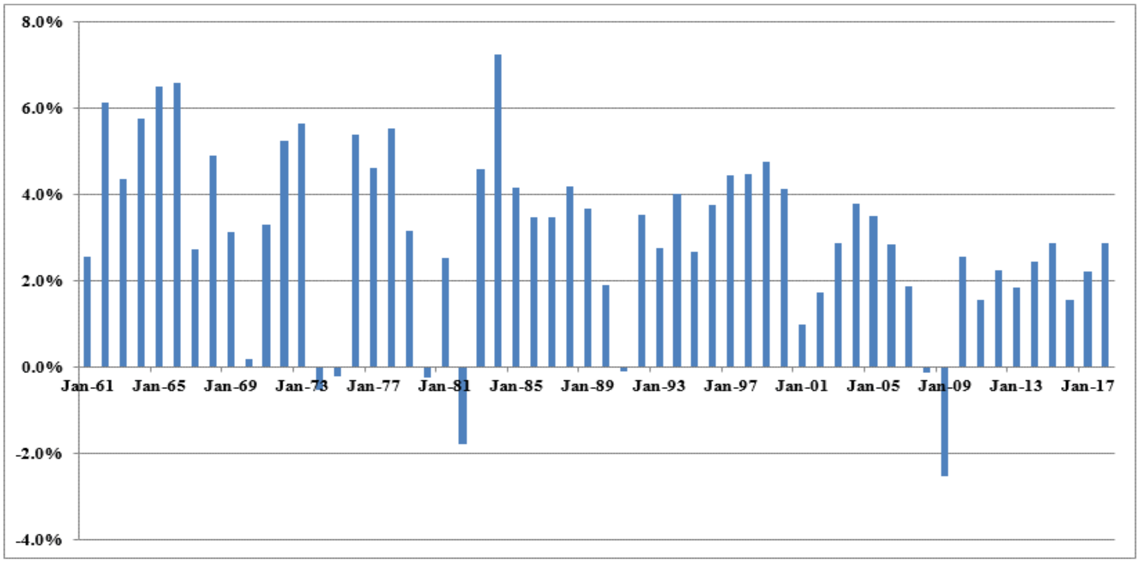
A -http://research stlouisfed org/fred2/series/GDPA/downloaddata
EPS and DPS - http://pages stern nyu edu/~adamodar/

Nominal GDP Growth Rates
Annual Growth Rates - 1961-2018



Data Sources: GDPA -https://fred stlouisfed org/series/GDPA

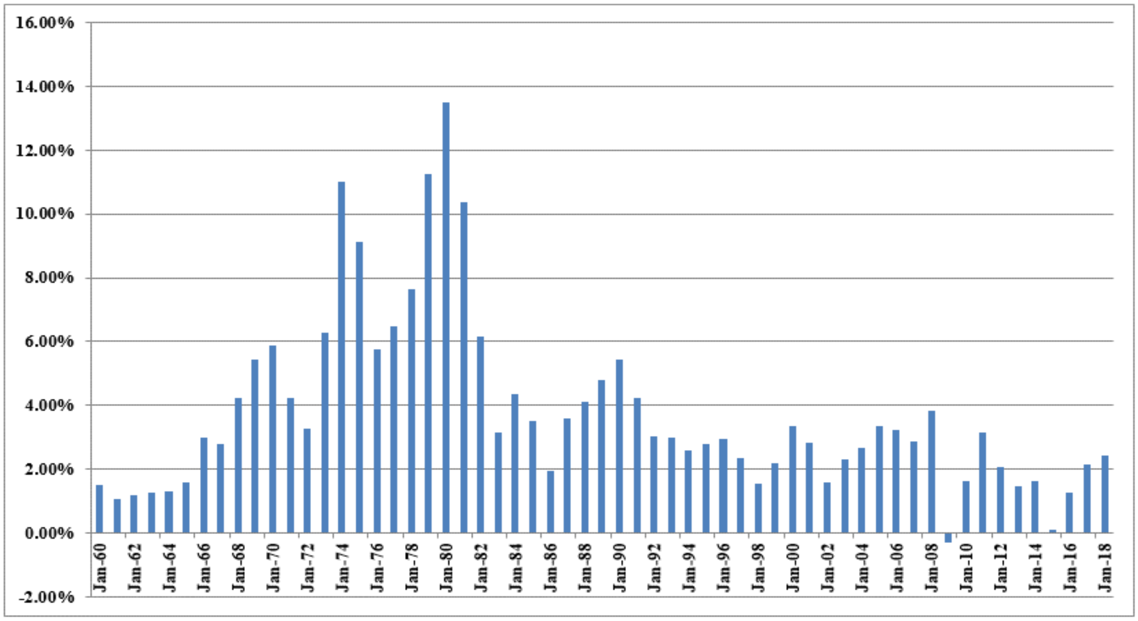
Annual Real GDP Growth Rates
1961-2018



Data Sources: GDPC1 - https://fred stlouisfed org/series/GDPCA

DOCKET NO. E-2, SUB 1219
Exhibit JRW-10
Inflation Rates

Annual Inflation Rates
1961-2018



Data Sources: CPIAUCSL - https://fred stlouisfed org/series/CPIAUCSL

Panel A
Historic GDP Growth Rates

10-Year Average		**3.37%**
20-Year Average		**4.17%**
30-Year Average		**4.65%**
40-Year Average		**5.56%**
50-Year Average		**6.36%**

Calculated using GDP data on Page 1 of Exhibit JRW-10

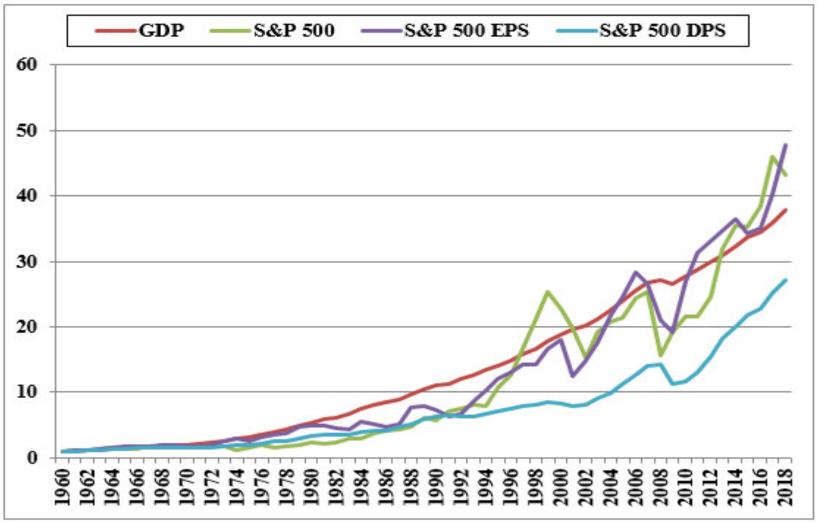
Panel B
Projected GDP Growth Rates

	Time Frame	Projected Nominal GDP Growth Rate
Congressional Budget Office	**2018-2048**	**4.0%**
Survey of Financial Forecasters	**Ten Year**	**4.3%**
Social Security Administration	**2018-2095**	**4.4%**
Energy Information Administration	**2017-2050**	**4.3%**

Sources:

Congressional Budget Office,The *2018 Long-Term Budget Outlook*, June 1, 2018.
https://www.cbo.gov/system/files?file=2018-06/53919-2018ltbo.pdf
U.S. Energy Information Administration, *Annual Energy Outlook 2018*, Table: Macroeconomic Indicators,
https://www.eia.gov/outlooks/aeo/data/browser/#/?id=18-AEO2018&sourcekey=0.
Social Security Administration, 2018 Annual Report of the Board of Trustees of the Old-Age, Survivors, and Disability Insurance (OASDI) Program, Table VI.G4, p. 211(June 15, 2018), https://www.ssa.gov/oact/tr/2018/lr6g4 html. The 4.4% represents the compounded growth rate in projected GDP from $20,307 trillion in 2018 to $548,108 trillion in 2095.
https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/

Long-Term Growth of GDP, S&P 500, S&P 500 EPS, and S&P 500 DPS



	GDP	S&P 500	S&P 500 EPS	S&P 500 DPS
Growth Rates	6.47	6.95	6.70	5.82