Duke Energy Carolinas, LLC
Docket No. E-7, Sub 1214
Public Staff Data Request No. 167-1
Distribution Vegetation Management
As of December 31, 2019

Question #5

5. For TVM and DVM, please provide an annual itemized list of both budgeted and actual expenditures and miles maintained during the years 2014 through 2018 and 2019 year to date. Please include a detailed explanation for each instance in which actual miles or expenditures for a calendar year vary from budgeted expenditures for that year by 5% or more. Include all requested data for the company's entire system and for the North Carolina service territory only. Categories to include are, but, not limited to:

a. Maintenance/trimming
b. Hazard/Danger tree removal
c. Reactive maintenance
d. Herbicide

Data updated through YE 2019

Dist Veg Mgmt Response

Programs	2014				2015			
DEC Distribution Veg Mgmt	Budget	Actual	Variance	Variance Explanation	Budget	Actual	Variance	Variance Explanation
Reactive	$ 3,216,212	$ 2,861,882	-11%	Costs associated with resolving customer issues less than forecast	$ 3,312,700	$ 3,087,378	-7%	Costs associated with resolving customer issues less than forecast
Maintenance/Trimming	$ 39,872,889	$ 40,112,764	1%		$ 41,068,546	$ 41,774,818	2%	
Herbicide	$ 3,497,195	$ 3,101,904	-11%	Herbicide plan costs less than projected due to less stem density resulting in use of less herbicide	$ 3,100,646	$ 3,047,272	-2%	
Contract Inspectors	$ 618,996	$ 534,191	-14%	Timing of open positions	$ 637,572	$ 679,854	7%	Added additional Contract Foresters to focus on contractor safety
Hazard Tree	$ 7,680,011	$ 7,204,371	-6%	Less hazard trees identified than original forecast.	$ 10,436,935	$ 8,131,608	-22%	Less hazard trees identified than original forecast.

Workplan Summary	2014				2015			
DEC Distribution Veg Mgmt	Annual Plan (Miles)	Actual Completed (Miles)	Variance	Variance Explanation	Annual Plan (Miles)	Actual Completed (Miles)	Variance	Variance Explanation
Total Annual Maintenance Trim Miles	5,830	5,878	1%		5,755	5,897	2%	
Total Herbicide/Sprayed Miles	17,254	17,245	0%		15,321	15,321	0%	

Programs	2016				2017			
DEC Distribution Veg Mgmt	Budget	Actual	Variance	Variance Explanation	Budget	Actual	Variance	Variance Explanation
Reactive	$ 2,645,518	$ 2,343,515	-11%	Customer requested work less than budgeted	$ 2,645,518	$ 2,325,560	-12%	Costs associated with resolving customer issues less than forecast
Maintenance/Trimming	$ 44,525,936	$ 41,936,101	-6%	Cost per mile less than forecast due to less complex miles in the work plan	$ 38,772,590	$ 38,159,696	-2%	
Herbicide	$ 3,162,659	$ 3,058,933	-3%		$ 3,100,380	$ 3,033,740	-2%	
Contract Inspectors	$ 650,323	$ 779,156	20%	Added additional Contract Foresters to focus on contractor safety	$ 1,094,923	$ 976,425	-11%	Reduction in Contract Forester positions to match workload and safey oversight accountabilities
Hazard Tree	$ 9,345,367	$ 8,152,707	-13%	Less hazard trees identified than original forecast.	$ 9,121,275	$ 12,049,526	32%	Less hazard trees identified than original forecast.

Workplan Summary	2016				2017			
DEC Distribution Veg Mgmt	Annual Plan (Miles)	Actual Completed (Miles)	Variance	Variance Explanation	Annual Plan (Miles)	Actual Completed (Miles)	Variance	Variance Explanation
Total Annual Maintenance Trim Miles	5,492	5,807	6%	Cost/mile favorability allowed resources to complete more miles than targeted	4,988	4,850	-3%	
Total Herbicide/Sprayed Miles	15,883	15,883	0%		16,914	16,914	0%	

Programs	2018				2019			
DEC Distribution Veg Mgmt	Budget	Actual	Variance	Variance Explanation	Budget	Actual	Variance	Variance Explanation
Reactive	$ 2,654,934	$ 2,159,025	-19%	Costs associated with resolving customer issues less than forecast	$ 2,847,680	$ 2,725,442	-4%	Costs associated with resolving customer issues less than forecast
Maintenance/Trimming	$ 49,524,781	$ 48,357,856	-2%		$ 60,161,146	$ 66,147,626	10%	Additional miles and dollars added to the plan to support the revised vegetatation management plan approved by the NCUC in August of 2019.
Herbicide	$ 3,148,392	$ 3,343,623	6%	Herbicide plan costs more than projected due to increased stem count resulting in use of more herbicide	$ 3,242,844	$ 2,839,369	-12%	Herbicide plan costs less than projected due to less miles due for treatment .
Contract Inspectors	$ 731,484	$ 696,536	-5%	Reduction in Contract Forester positions to match workload and safey oversight accountabilities	$ 816,112	$ 643,501	-21%	Reallocation of contract forester time to include capital inspections.
Hazard Tree	$ 12,189,145	$ 11,142,972	-9%	Less hazard trees identified than original forecast.	$ 12,846,788	$ 15,007,912	17%	More hazard trees than planned in the original forecast. Expanded hazard tree program to include some single phase.

Workplan Summary	2018				2019			
DEC Distribution Veg Mgmt	Annual Plan (Miles)	Actual Completed (Miles)	Variance	Variance Explanation	Annual Plan (Miles)	Actual Completed (Miles)	Variance	Variance Explanation
Total Annual Maintenance Trim Miles	5,159	5,559	8%	Cost/mile favorability allowed resources to complete more miles than targeted	6,368	6,956	9%	Additional miles and dollars added to the plan to support the revised vegetatation management plan approved by the NCUC in August of 2019.
Total Herbicide/Sprayed Miles	16,808	16,808	0%		15,708	15,708	0%	

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Public Staff Data Request No. 6.4 and 6.5

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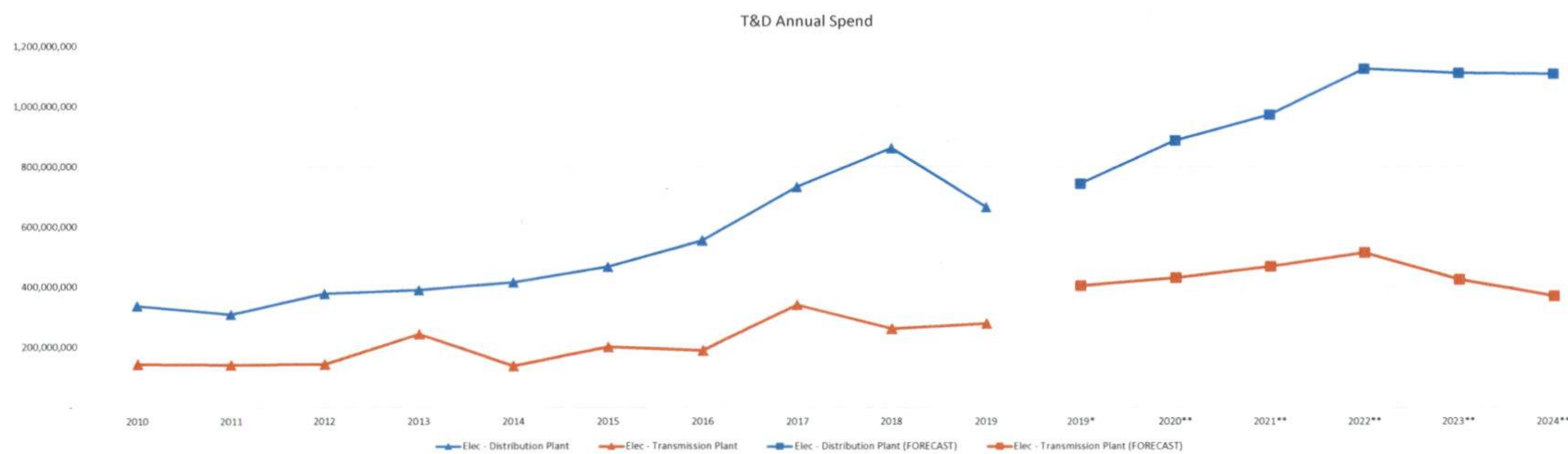
	2010 FERC Form 1	2011 FERC Form 1	2012 FERC Form 1	2013 FERC Form 1	2014 FERC Form 1	2015 FERC Form 1	2016 FERC Form 1	2017 FERC Form 1	2018 FERC Form 1	2019 YTD actual (thru August) Internal Reporting
Elec - Distribution Plant	337,698,682	309,414,417	377,254,485	389,737,879	414,986,088	467,466,433	554,486,461	733,301,069	861,928,953	666,267,640
Elec - Transmission Plant	144,031,672	141,862,611	142,904,967	243,440,920	137,959,818	201,451,690	189,141,094	340,598,836	260,617,660	277,989,580
Elec - Distribution Plant (FORECAST)										
Elec - Transmission Plant (FORECAST)										

	2019* projection Internal Reporting	2020** forecast	2021** forecast	2022** forecast	2023** forecast	2024** forecast
Elec - Distribution Plant						
Elec - Transmission Plant						
Elec - Distribution Plant (FORECAST)	743,762,000	887,601,971	973,546,001	1,124,987,567	1,110,835,632	1,107,922,582
Elec - Transmission Plant (FORECAST)	403,155,000	430,372,983	467,858,880	513,388,729	423,890,576	368,510,472

*** 2019 forecast is based on the 12x0 and is subject to change**
**** Projected forecasts that are subject to change.**



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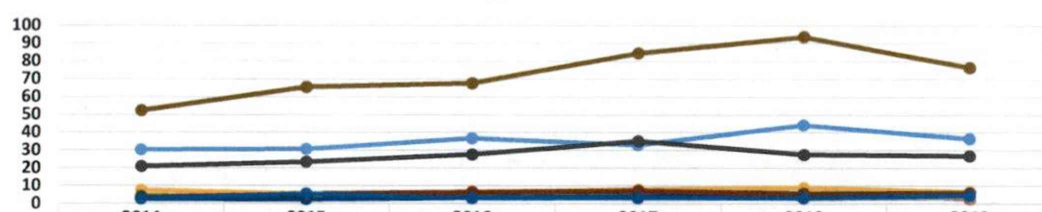
	Reliability SAIDI					
Row Labels	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
DEC NC	**130.74**	**147.91**	**163.14**	**190.82**	**202.46**	**174.66**
Design Issue	3.47	3.10	4.16	4.39	5.71	2.81
Duke Error	3.29	2.60	3.46	4.60	3.11	3.41
Environment	7.53	5.40	6.53	7.85	8.90	6.53
Equipment Failure	30.36	30.78	36.78	33.00	44.19	36.65
Other	4.27	3.84	4.58	6.98	5.90	6.03
Other Human Events	2.62	2.42	3.11	4.03	4.67	5.56
Planned Work	3.30	5.30	6.39	7.16	5.47	5.91
Public Accident	20.90	23.36	27.58	35.11	27.57	26.82
Vegetation	52.28	65.47	67.58	84.49	93.67	76.30
Wildlife	2.71	5.63	2.98	3.20	3.29	4.64

DEC NC SAIDI Outage Causes



	2014	2015	2016	2017	2018	2019
Design Issue	3.47	3.10	4.16	4.39	5.71	2.81
Duke Error	3.29	2.60	3.46	4.60	3.11	3.41
Environment	7.53	5.40	6.53	7.85	8.90	6.53
Equipment Failure	30.36	30.78	36.78	33.00	44.19	36.65
Other	4.27	3.84	4.58	6.98	5.90	6.03
Other Human Events	2.62	2.42	3.11	4.03	4.67	5.56
Planned Work	3.30	5.30	6.39	7.16	5.47	5.91
Public Accident	20.90	23.36	27.58	35.11	27.57	26.82
Vegetation	52.28	65.47	67.58	84.49	93.67	76.30
Wildlife	2.71	5.63	2.98	3.20	3.29	4.64

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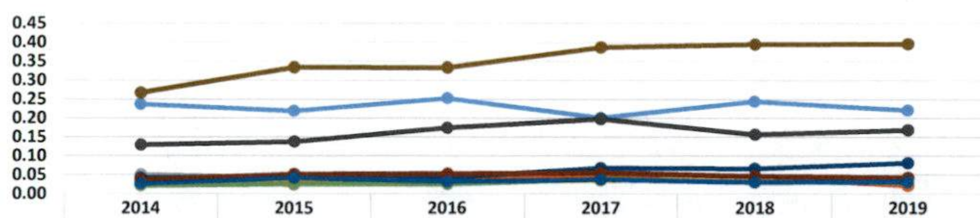
Row Labels	Reliability SAIFI 2014	2015	2016	2017	2018	2019
DEC NC	**0.879**	**0.952**	**1.027**	**1.123**	**1.088**	**1.070**
Design Issue	0.031	0.025	0.036	0.043	0.044	0.022
Duke Error	0.050	0.043	0.045	0.060	0.036	0.042
Environment	0.039	0.033	0.033	0.036	0.039	0.034
Equipment Failure	0.236	0.219	0.253	0.201	0.244	0.221
Other	0.022	0.025	0.026	0.039	0.031	0.030
Other Human Events	0.042	0.043	0.042	0.068	0.067	0.082
Planned Work	0.037	0.051	0.052	0.055	0.046	0.042
Public Accident	0.129	0.138	0.174	0.198	0.157	0.169
Vegetation	0.267	0.334	0.333	0.387	0.395	0.396
Wildlife	0.026	0.042	0.032	0.037	0.030	0.032

DEC NC SAIFI Outage Causes



	2014	2015	2016	2017	2018	2019
Design Issue	0.031	0.025	0.036	0.043	0.044	0.022
Duke Error	0.050	0.043	0.045	0.060	0.036	0.042
Environment	0.039	0.033	0.033	0.036	0.039	0.034
Equipment Failure	0.236	0.219	0.253	0.201	0.244	0.221
Other	0.022	0.025	0.026	0.039	0.031	0.030
Other Human Events	0.042	0.043	0.042	0.068	0.067	0.082
Planned Work	0.037	0.051	0.052	0.055	0.046	0.042
Public Accident	0.129	0.138	0.174	0.198	0.157	0.169
Vegetation	0.267	0.334	0.333	0.387	0.395	0.396
Wildlife	0.026	0.042	0.032	0.037	0.030	0.032

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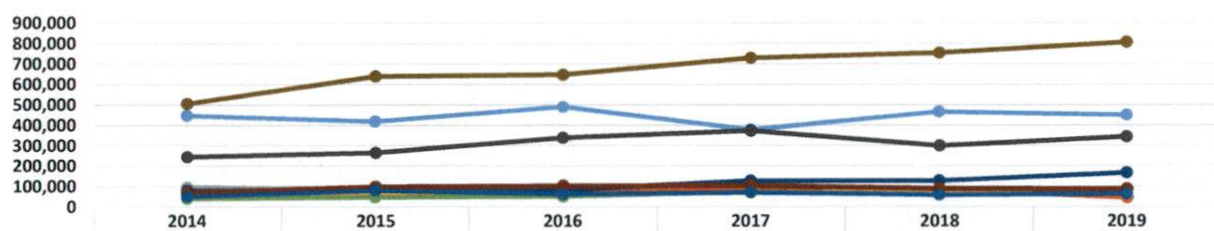
Row Labels	Customer CI					
	2014	2015	2016	2017	2018	2019
DEC NC	**1,665,180**	**1,822,450**	**1,992,157**	**2,115,567**	**2,079,537**	**2,177,414**
Design Issue	57,970	47,405	69,173	81,178	84,055	44,583
Duke Error	95,097	82,420	86,447	113,216	67,873	84,880
Environment	73,473	62,984	64,622	67,805	74,897	70,186
Equipment Failure	447,930	419,181	490,603	377,888	466,872	449,631
Other	40,776	47,638	50,492	72,732	59,029	61,600
Other Human Events	80,053	82,042	81,908	127,802	127,168	165,978
Planned Work	69,646	97,531	101,677	103,801	87,576	85,522
Public Accident	244,681	263,747	338,561	372,357	299,524	343,755
Vegetation	505,637	639,211	646,873	728,514	754,355	806,120
Wildlife	49,917	80,291	61,801	70,274	58,188	65,159

DEC NC Customer CI Outage Causes



	2014	2015	2016	2017	2018	2019
Design Issue	57,970	47,405	69,173	81,178	84,055	44,583
Duke Error	95,097	82,420	86,447	113,216	67,873	84,880
Environment	73,473	62,984	64,622	67,805	74,897	70,186
Equipment Failure	447,930	419,181	490,603	377,888	466,872	449,631
Other	40,776	47,638	50,492	72,732	59,029	61,600
Other Human Events	80,053	82,042	81,908	127,802	127,168	165,978
Planned Work	69,646	97,531	101,677	103,801	87,576	85,522
Public Accident	244,681	263,747	338,561	372,357	299,524	343,755
Vegetation	505,637	639,211	646,873	728,514	754,355	806,120
Wildlife	49,917	80,291	61,801	70,274	58,188	65,159

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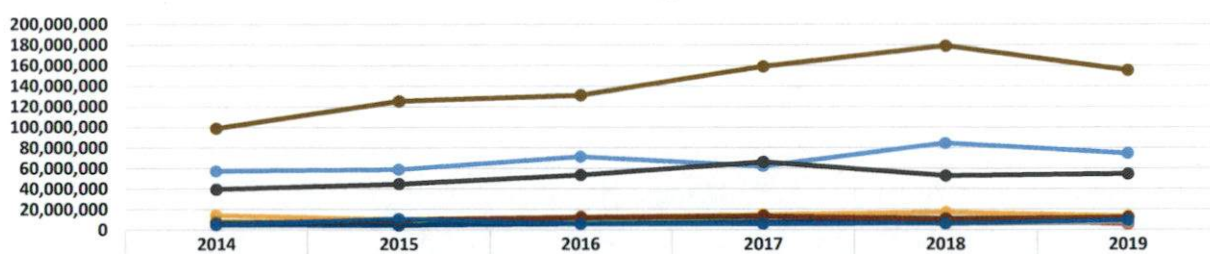
	Customer CMI					
Row Labels	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
DEC NC	**247,675,550**	**283,166,221**	**316,584,796**	**359,349,170**	**387,016,784**	**355,540,177**
Design Issue	6,568,801	5,935,477	8,065,752	8,274,341	10,910,953	5,723,100
Duke Error	6,234,013	4,984,027	6,723,936	8,660,983	5,935,732	6,937,270
Environment	14,272,912	10,334,338	12,674,840	14,783,898	17,009,124	13,282,594
Equipment Failure	57,514,191	58,932,382	71,367,509	62,149,098	84,481,327	74,613,629
Other	8,095,483	7,354,019	8,883,039	13,139,880	11,269,111	12,266,736
Other Human Events	4,963,967	4,625,342	6,036,269	7,581,775	8,930,579	11,321,464
Planned Work	6,253,187	10,149,401	12,396,267	13,491,054	10,447,615	12,039,249
Public Accident	39,594,532	44,726,498	53,524,344	66,120,294	52,697,329	54,592,234
Vegetation	99,050,924	125,337,852	131,138,735	159,115,007	179,053,372	155,312,014
Wildlife	5,127,541	10,786,885	5,774,106	6,032,841	6,281,640	9,451,887

DEC NC Customer CMI Outage Causes



	2014	2015	2016	2017	2018	2019
Design Issue	6,568,801	5,935,477	8,065,752	8,274,341	10,910,953	5,723,100
Duke Error	6,234,013	4,984,027	6,723,936	8,660,983	5,935,732	6,937,270
Environment	14,272,912	10,334,338	12,674,840	14,783,898	17,009,124	13,282,594
Equipment Failure	57,514,191	58,932,382	71,367,509	62,149,098	84,481,327	74,613,629
Other	8,095,483	7,354,019	8,883,039	13,139,880	11,269,111	12,266,736
Other Human Events	4,963,967	4,625,342	6,036,269	7,581,775	8,930,579	11,321,464
Planned Work	6,253,187	10,149,401	12,396,267	13,491,054	10,447,615	12,039,249
Public Accident	39,594,532	44,726,498	53,524,344	66,120,294	52,697,329	54,592,234
Vegetation	99,050,924	125,337,852	131,138,735	159,115,007	179,053,372	155,312,014
Wildlife	5,127,541	10,786,885	5,774,106	6,032,841	6,281,640	9,451,887

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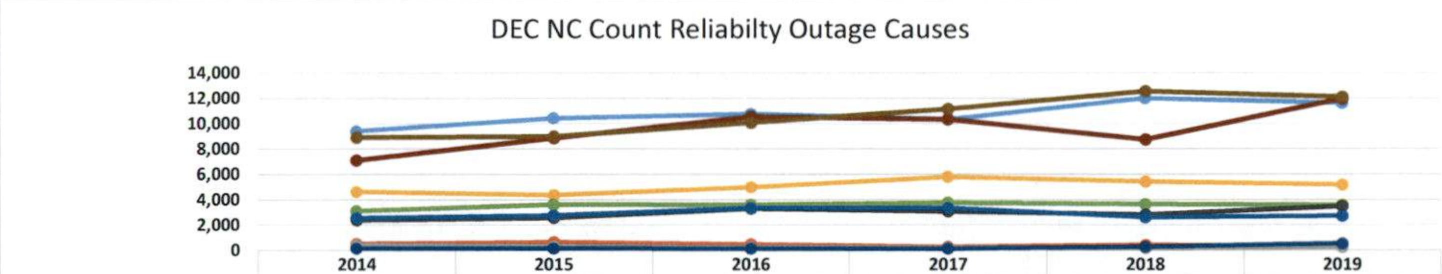
Row Labels	Counts Reliability Outages 2014	2015	2016	2017	2018	2019
DEC NC	**39,125**	**42,761**	**47,448**	**48,328**	**48,634**	**51,682**
Design Issue	503	640	461	256	405	309
Duke Error	389	330	240	196	178	231
Environment	4,621	4,375	4,987	5,790	5,432	5,174
Equipment Failure	9,418	10,444	10,780	10,327	12,007	11,617
Other	3,108	3,616	3,587	3,749	3,623	3,582
Other Human Events	153	157	129	129	266	524
Planned Work	7,102	8,881	10,540	10,340	8,744	11,956
Public Accident	2,374	2,568	3,298	3,059	2,810	3,472
Vegetation	8,917	8,998	10,093	11,162	12,571	12,105
Wildlife	2,540	2,752	3,333	3,320	2,598	2,712



	2014	2015	2016	2017	2018	2019
Design Issue	503	640	461	256	405	309
Duke Error	389	330	240	196	178	231
Environment	4,621	4,375	4,987	5,790	5,432	5,174
Equipment Failure	9,418	10,444	10,780	10,327	12,007	11,617
Other	3,108	3,616	3,587	3,749	3,623	3,582
Other Human Events	153	157	129	129	266	524
Planned Work	7,102	8,881	10,540	10,340	8,744	11,956
Public Accident	2,374	2,568	3,298	3,059	2,810	3,472
Vegetation	8,917	8,998	10,093	11,162	12,571	12,105
Wildlife	2,540	2,752	3,333	3,320	2,598	2,712

Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

		Focus	Optimize	Optimize	Optimize	Optimize
		Program Number (Oliver Exhibit 10)	1	1	1	1
		Component Number	1	2	3	4
		Reference	**1.1**	**1.2**	**1.3**	**1.4**
		Program	**Self Optimizing Grid**			
Weight	**Metric**	**Component** **Metric Rankings**	**Capacity Projects**	**Connectivity Projects**	**Automation Projects**	**Advanced Distribution Management System (ADMS)**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	1.0	1.0	3.0	3.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	1.0	2.0	2.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	3.0	3.0	3.0	3.0
	Weighted Grid Transformation Score (min=4; max=12)		**6**	**6**	**11**	**11**

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Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

		Focus	Optimize	Optimize	Optimize	Optimize	Optimize
		Program Number (Oliver Exhibit 10)	2	3	4	5	5
		Component Number				1	2
		Reference	**2.**	**3.**	**4.**	**5.1**	**5.2**
		Program	**Distribution Hardening and Resiliency - Flood Hardening**	**Distribution Transformer Retrofit**	**IVVC**	**Transmission Hard Resiliency**	
Weight	**Metric**	**Component** / **Metric Rankings**				**Line H&R**	**Substation Flooding H&R**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	1.0	1.0	3.0	1.0	1.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	1.0	2.0	1.0	1.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	1.0	3.0	2.0	1.0	1.0
	Weighted Grid Transformation Score (min=4; max=12)		**4**	**6**	**10**	**4**	**4**

Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

		Focus	Optimize	Optimize	Modernize	Optimize
		Program Number (Oliver Exhibit 10)	5	6	7	8
		Component Number	3			1
		Reference	**5.3**	**6.**	**7.**	**8.1**
		Program	**ening &**	**Transformer Bank Replacements**	**Transmission System Intelligence**	**Oil Breaker Re**
Weight	**Metric**	**Component** **Metric Rankings**	**Substation Animal Mitigation**			**Transmission Class (SF6)**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	1.0	1.0	3.0	1.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	1.0	2.0	1.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	1.0	3.0	3.0	3.0
	Weighted Grid Transformation Score (min=4; max=12)		**4**	**6**	**11**	**6**

Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

		Focus	Optimize	Optimize	Optimize	Modernize
		Program Number (Oliver Exhibit 10)	8	9	11	12
		Component Number	2			1
		Reference	**8.2**	**9.**	**11.**	**12.1**
		Program	**placements**	**Targeted Underground (TUG)**	**Long Duration Int/High Impact Sites**	
Weight	**Metric**	**Component** / **Metric Rankings**	**Distribution Class (Vacuum)**			**Next Generation Cellular**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	1.0	1.0	1.0	1.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	1.0	1.0	3.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	3.0	3.0	1.0	3.0
	Weighted Grid Transformation Score (min=4; max=12)		**6**	**6**	**4**	**8**

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T AND D WILLIAMSON
EXHIBIT 4
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Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

		Focus	Modernize	Modernize	Modernize	Modernize
		Program Number (Oliver Exhibit 10)	12	12	12	12
		Component Number	2	3	4	5
		Reference	**12.2**	**12.3**	**12.4**	**12.5**
		Program	**Enterprise Communi**			
Weight	**Metric**	**Component** **Metric Rankings**	**Mission Critical Voice**	**POC**	**BizWAN**	**GridWAN**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	1.0	1.0	1.0	1.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	1.0	1.0	1.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	3.0	1.0	3.0	3.0
	Weighted Grid Transformation Score (min=4; max=12)		**6**	**4**	**6**	**6**

Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

		Focus	Modernize	Modernize	Modernize	Modernize
		Program Number (Oliver Exhibit 10)	12	12	12	12
		Component Number	6	7	8	9
		Reference	**12.6**	**12.7**	**12.8**	**12.9**
		Prog am	**cations**			
Weight	**Metric**	**Component** / **Metric Rankings**	**Mission Critical Transport**	**Tower, shelters, and Power Supplies**	**Network Asset Systems**	**Vehicle Area Network**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	1.0	1.0	1.0	1.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	1.0	2.0	2.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	3.0	3.0	2.0	2.0
	Weighted Grid Transformation Score (min=4; max=12)		**6**	**6**	**6**	**6**

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EXHIBIT 4

Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

		Focus	Modernize	Modernize	Modernize	Modernize
		Program Number (Oliver Exhibit 10)	13	13	13	13
		Component Number	1	2	3	4
		Reference	**13.1**	**13.2**	**13.3**	**13.4**
		Program	**Distribution Automation**			
Weight	**Metric**	**Component** / **Metric Rankings**	**Hydraulic to Electronic Recloser**	**System Intelligence and Monitoring**	**Fuse Replacement**	**UG System Automation**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	2.0	2.0	2.0	3.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	1.0	1.0	2.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	3.0	3.0	3.0	3.0
	Weighted Grid Transformation Score (min=4; max=12)		**8**	**8**	**8**	**11**

Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

Weight	Metric					
		Focus	Modernize	Modernize	Modernize	Modernize
		Program Number (Oliver Exhibit 10)	14	15	16	18
		Component Number				
		Reference	**14.**	**15.**	**16.**	**18.**
		Program / **Component** / **Metric Rankings**	**Enterprise Applications**	**ISOP**	**DER Dispatch Tool**	**Power Electronics for Volt/VAR Control**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	2.0	3.0	2.0	2.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	3.0	1.0	2.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	2.0	3.0	2.0	3.0
	Weighted Grid Transformation Score (min=4; max=12)		**7**	**12**	**7**	**9**

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Grid Transformation Matrix

Driving Question: What is "grid transformation", and how do we determine whether each program fits that designation?

		Focus	Protect	Protect	Protect	Protect	Protect
		Program Number (Oliver Exhibit 10)	19	19	19	19	19
		Component Number	1	2	3	4	5
		Reference	**19.1**	**19.2**	**19.3**	**19.4**	**19.5**
		Program	**Physical and Cyber Security**				
Weight	**Metric**	**Component** / **Metric Rankings**	**Substation Physical security**	**Windows Based unit change outs**	**Device entry alert system**	**Secure Access Device Management**	**Line Device Protection**
2	**TRANSFORMATIVE:** Does the program allow the utility to do something **on the grid** that it could not do before?	1 = No new capabilities; current procedures provide similar capabilities 2 = Adds some limited new capabilities 3 = Adds significant new capabilities	1.0	1.0	2.0	2.0	2.0
1	**TIMING:** What is the level of urgency to complete this program?	1 = Ongoing work; continue normal pace 2 = New work; 3-year timeline is not critical to grid op 3 = Urgent; 3-year timeline is critical to grid op	1.0	1.0	1.0	1.0	1.0
1	**GRID ARCHITECTURE:** How does this program fit into the broader grid modernization architecture?	1 = This program is standalone and operates outside grid modernization architecture. 2 = This program is an application dependent upon core components. 3 = This program is a core component of grid mod (foundational).	1.0	1.0	3.0	2.0	3.0
	Weighted Grid Transformation Score (min=4; max=12)		**4**	**4**	**8**	**7**	**8**

Docket No. E-7, Subs 1213 and 1214
T and D Williamson Exhibit 5

Summary	DEC 2020	DEC 2021	DEC 2022	DEC Total
Total Grid Improvement Plan (NC only)	$335	$461	$592	**$1387.9**
Total Requested Deferral	$327	$454	$550	**$1331.4**
Electric 'Extraordinary TYPE'	$95	$204	$193	**$491.8**

All dollars in millions; reflects capital budget allocated to North Carolina

Description	Forward to Acounting as Extraordinary TYPE	Requested Deferral	DEC 2020	DEC 2021	DEC 2022	DEC Total
IVVC	YES	Yes	$30.8	$86.3	$89.6	**$206.7**
SOG Automation + Control	YES	Yes	$25.1	$75.4	$76.2	**$176.6**
Transmission System Intelligence	YES	Yes	$24.0	$30.3	$8.4	**$62.7**
SOG ADMS	YES	Yes	$9.3	$8.8	$11.5	**$29.6**
UG System automation	YES	Yes	$2.7	$2.7	$6.6	**$12.1**
ISOP	YES	Yes	$3.0	$0.4	$0.7	**$4.2**
SOG Capacity & Connectivity	No	Yes	$56.2	$69.5	$88.1	**$213.9**
Trans CB Replace - SF6	No	Yes	$22.4	$48.2	$31.0	**$101.7**
Trans Line H&R	No	Yes	$12.0	$20.4	$68.1	**$100.4**
Mission Critical Transport	No	Yes	$16.8	$24.1	$23.4	**$64.3**
Fuse Replacement	No	Yes	$4.6	$14.3	$42.1	**$61.0**
TUG	No	Yes	$6.4	$15.3	$38.1	**$59.8**
Storage	No	No	$8.2	$6.2	$42.1	**$56.5**
Subst physical security	No	Yes	$47.1	$7.3	-	**$54.4**
Hydraulic recloser replace	No	Yes	$27.0	-	$10.2	**$37.2**
TX Bank Replacements	No	Yes	$6.2	$18.2	$9.3	**$33.6**
Enterprise applicaions	No	Yes	$4.3	$3.1	$9.6	**$17.0**
Towers, shelters	No	Yes	$2.5	$7.0	$4.8	**$14.2**
Dist CB Replace - Vacuum	No	Yes	$5.8	$5.8	$2.4	**$14.0**
Long Duration outage	No	Yes	$2.4	$5.7	$3.2	**$11.3**
Mission Critical Voice	No	Yes	$0.2	-	$10.1	**$10.3**
Dist Tx Retrofit	No	Yes	-	-	$8.3	**$8.3**
GridWAN	No	Yes	$4.2	$1.2	$0.7	**$6.2**
Next Gen Cellular	No	Yes	$1.8	$2.9	$1.4	**$6.1**
Dist System intell/monitor	No	Yes	$1.8	$0.9	$2.5	**$5.2**
DER Dispatch	No	Yes	$1.7	$2.0	$0.8	**$4.5**
Secure Access Device Mgmt.	No	Yes	$1.7	$1.5	$1.0	**$4.3**
Line Device Protection	No	Yes	$1.0	$1.4	$1.3	**$3.7**
Trans Animal mitigation	No	Yes	$2.0	-	-	**$2.0**
Device Entry Alert System	No	Yes	$1.2	$0.7	-	**$1.9**
Network Asset Systems	No	Yes	$0.3	$0.4	$0.3	**$1.0**
Vehicle Area Network	No	Yes	$0.8	$0.1	-	**$1.0**
Windows PC replace	No	Yes	$0.8	-	-	**$0.8**
Power Electronics	No	Yes	-	$0.3	$0.3	**$0.7**
POC	No	Yes	$0.4	-	-	**$0.4**
BizWAN	No	Yes	-	$0.1	$0.1	**$0.3**
Dist H&R Flooding	No	Yes	-	-	-	-

Description	Forward to Acounting as Extraordinary TYPE	Requested Deferral	DEC 2020	DEC 2021	DEC 2022	DEC Total
Trans H&R Flooding	No	Yes	-	-	-	-
Electric Transportation	No	No	-	-	-	-
TOTAL			$335.0	$460.7	$592.2	$1387.9
TOTAL EXTRAORDINARY TYPE			$95.0	$203.9	$193.0	$491.8

Public Staff
Hinton Exhibit 1

Docket No. E-7, Sub 1214

CONFIDENTIAL

Public Staff
Hinton Exhibit 2

Docket No. E-7, Sub 1214

CONFIDENTIAL

Public Staff
Hinton Exhibit 3
Docket No. E-7, Sub 1214

MOODY'S
INVESTORS SERVICE

CREDIT OPINION
31 October 2019

Update

Rate this Research

RATINGS

Duke Energy Carolinas, LLC

Domicile	Charlotte, North Carolina, United States
Long Term Rating	A1
Type	LT Issuer Rating
Outlook	Stable

Please see the ratings section at the end of this report for more information. The ratings and outlook shown reflect information as of the publication date.

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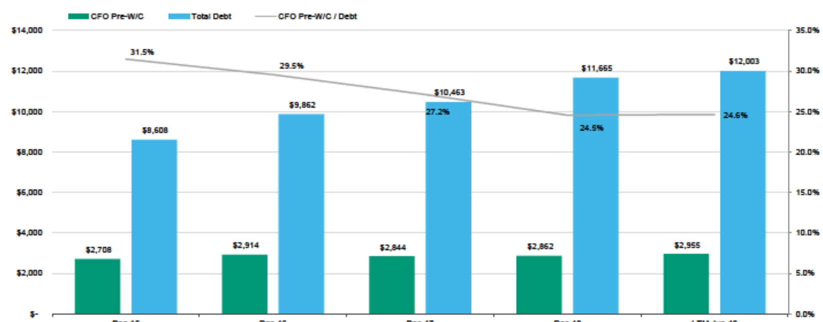
Duke Energy Carolinas, LLC

Update to credit analysis

Summary

Our view of Duke Energy Carolinas' (Duke Carolinas) credit reflects its low business and operating risk profile and historically supportive regulatory environments in both North and South Carolina. Our view is tempered by the utility's weaker financial credit metrics, but also considers the company's position as the largest subsidiary within the Duke Energy Corporation family, making up about a third of its rate base. Our view recognizes the benefits of scale and the potential for operational efficiencies that are enabled by joint management with affiliate Duke Energy Progress.

Exhibit 1
Historical CFO Pre-WC, Total Debt and CFO Pre-WC to Debt ($ MM)



Source: Moody's Financial Metrics

Credit Strengths

» Credit supportive regulatory environments

» Approved recovery for the majority of coal ash related expenditures

» Growing service territories

» Position as part of Duke Energy utility system

Credit Challenges

» High capital expenditures

» Increasing regulatory uncertainty surrounding coal ash remediation spending

» Financial metrics are under pressure

Rating Outlook

The stable rating outlook considers the utility's relatively low business risk profile and primarily credit supportive regulatory frameworks in both North and South Carolina. The outlook reflects our expectation that management will manage and finance Duke Carolinas relatively large capital expenditure program in a manner that allows the utility to demonstrate financial credit metrics that are consistent with its credit profile. The stable outlook also reflects our expectation that the company will continue to be able to fully recover the majority of its coal ash closure and remediation costs in rates.

Factors that Could Lead to an Upgrade

» Credit positive changes in the utility's regulatory framework, including more riders and trackers to reduce regulatory lag for ongoing capital investment, and real time recovery of coal ash remediation costs

» A sustained improvement in cash flow credit metrics, for example if the ratio of cash from operations excluding changes in working capital (CFO pre-W/C) to debt were to move above 30% on a sustained basis

Factors that Could Lead to a Downgrade

» A decline in the credit supportiveness of Duke Carolina's regulatory relationships in North or South Carolina, particularly with regards to coal ash remediation recovery in North Carolina

» Additional capital expenditures or other capital needs that result in a material increase in debt levels or are not recoverable

» A ratio of CFO pre-W/C to debt remaining below 25% on a sustained basis

Key Indicators

Duke Energy Carolinas, LLC [1]

	Dec-15	Dec-16	Dec-17	Dec-18	LTM Jun-19
CFO Pre-W/C + Interest / Interest	6.9x	7.2x	7.0x	6.9x	7.0x
CFO Pre-W/C / Debt	31.5%	29.5%	27.2%	24.5%	24.6%
CFO Pre-W/C – Dividends / Debt	26.8%	9.3%	21.2%	18.1%	22.5%
Debt / Capitalization	32.8%	36.4%	41.6%	43.3%	43.0%

[1]All ratios are based on 'Adjusted' financial data and incorporate Moody's Global Standard Adjustments for Non-Financial Corporations.
Source: Moody's Financial Metrics

Corporate Profile

Duke Carolinas is a vertically integrated electric utility serving approximately 2.6 million customers in North Carolina (about 2 million) and South Carolina. The utility is the largest subsidiary of Duke Energy Corporation (Duke Energy, Baa1 stable) and is regulated by the North Carolina Utilities Commission (NCUC) and the Public Service Commission of South Carolina (PSCSC).

Detailed Credit Considerations

Historically credit supportive regulatory environments, but uncertainty is increasing

The regulatory environments in both North and South Carolina have historically been credit supportive. While the PSCSC's May 2019 order in Duke Carolina's recent rate case denied recovery of around 25% of Duke Carolinas' spending on coal ash remediation, the balance of the order (which included recovery of development costs associated with a canceled nuclear project and an approved 53% equity ratio) was generally credit supportive. Duke Energy is planning to appeal the coal ash disallowance. On a positive note, the South Carolina order did continue authorization of the utility's ability to earn a full weighted average cost of capital return on its approved coal ash remediation spending. The order also shortened the recovery period to five years, versus a previously approved fifteen years.

In North Carolina (71% of retail rate base), the utility's July 2018 rate order authorized a partial settlement agreement with respect to certain traditional rate making parameters, such as return on equity (9.9%) and equity ratio (52%). The order also deemed spending for coal ash remediation to be reasonable and prudent and, with the exception of a specific, manageable penalty, authorized the company to recover its prior expenditures over five years with a full debt and equity return. Ongoing expenditures will continue to be deferred for future recovery, and thus remain subject to regulatory lag.

We view Duke Carolinas ability to earn a full return on its coal ash remediation expenditures, and to recover them over reasonable time frames, as credit positive. As a result of this rate base like treatment, we currently view the spending for coal ash remediation to be akin to a capital expenditure. We note however that there is increasing regulatory uncertainty as a portion of these expenditures have been disallowed in South Carolina, while the North Carolina decision authorizing recovery has been appealed by the state Attorney General and the Public Staff. Depending on the outcome of these appeals, we may modify our treatment of the portion of expenditures that are not recoverable.

In both of Duke Carolinas' jurisdictions, the utility has historically been able to recover its prudently incurred costs, and it has been authorized equity returns and approved equity layers in the capital structure that have been among the most credit supportive in the U.S. However, Duke Carolinas' requests for rider recovery for grid modernization investments and ongoing coal ash remediation have been denied, a credit negative as it maintains the utility's exposure to regulatory lag.

In North Carolina, Duke has been working with lawmakers in an attempt to pass legislation that would allow securitization of storm costs as well as the consideration of alternative rate adjustment mechanisms such as rider recovery, multiyear plans, incentive mechanisms or ROE bands. On October 30th, the North Carolina House and Senate both approved a bill that, if signed by the Governor, will authorize securitization of storm costs; however, the more controversial proposal that would have allowed the implementation of alternative rate plans was dropped. Our stable outlook assumes that, in the absence of alternative rate mechanisms the company will continue to file frequent, likely annual, rate cases. The outlook also assumes and that regulatory outcomes will provide an opportunity for Duke Carolinas to maintain cash flow based credit metrics at levels that are supportive of its current credit quality.

In September 2019, Duke Carolinas filed a base rate case in North Carolina requesting an approximate 6% increase in revenue premised on a 53% equity ratio and a 10.3% return on equity. The filing also seeks recovery of $480 million of coal ash remediation costs deferred from January 2018-January 2020 over five years. The utility requested rates become effective no later than August 2020. Our stable outlook assumes Duke Carolinas will continue to be allowed to recover the majority of its coal ash remediation spending, and that it will be able to earn a return on the deferred balance.

Capital expenditures expected to remain elevated

Capital expenditures (inclusive of coal ash remediation spending) at Duke Carolinas have been on the rise, growing steadily from about $1.7 billion in 2013 to around $3 billion for the twelve months ending June 2019. We expect spending to remain near these levels for at least the next year or so as spending for new generation, environmental compliance and grid modernization investments in transmission and distribution continue.

Duke Carolina's current profile incorporates our expectation that the utility will continue to recover its capital expenditures as part of its rate proceedings. Although there will likely be some regulatory lag, particularly with regard to coal ash as discussed below, we expect the utility to seek to mitigate the lag through frequent rate case filings.

Coal ash remediation is well underway, but costs are rising and uncertainty is increasing

In 2014, North Carolina lawmakers overwhelmingly passed the Coal Ash Management Act which regulates and requires the closure of coal ash basins at all coal plant sites throughout the state. The legislation, which was amended in 2016, required Duke to take costly, immediate action to excavate and close coal ash basins at three of its highest risk sites by the end of 2019. These basins were all successfully closed ahead of schedule by July 2019. A fourth basin is required to be closed by August 2022. The 2016 amendment required the remaining sites to be closed by either 2024 or 2029, depending on their priority designation.

In April 2019, the North Carolina Department of Environmental Quality (NCDEQ) ordered Duke Energy to excavate coal ash at all of its low-risk sites in North Carolina where specific closure plans had not been determined. The decision is credit negative as it will cost substantially more than alternative closure options proposed by Duke for these six sites - Duke estimated full excavation would cost \$4-\$5 billion more than its previously projected aggregate cost of \$5.6 billion to close all basins in the Carolinas. The company also believes in some cases excavation may take decades, stretching well beyond current state and federal deadlines. The company is required to submit closure plans by December 31, 2019. Duke has appealed the order to the North Carolina Office of Administrative Hearings. In August and October 2019 the court issued orders dismissing several of Duke's claims relating to procedure, but allowing the substantive claims to move forward. The company expects the process will take 9-12 months.

Through June 2019, Duke Carolinas had spent approximately \$1 billion on coal ash remediation. Management continues to refine the estimated cost of its coal ash remediation obligations as work continues on the sites and there is additional information around closure requirements. As of June 2019, Duke Energy's total asset retirement obligation relating to coal ash was reported at \$6.5 billion (versus \$4.8 billion in June 2018) and included \$5.7 billion for the Carolinas. Duke Carolinas asset retirement obligation was reported as \$2.9 billion versus \$1.8 billion in June 2018.

As noted above, in its most recent South Carolina rate case, recovery of certain coal ash costs were denied. We expect the company to appeal this decision and note that it represents a relatively modest portion of total incurred costs. Depending on the outcome of the appeal, we may modify our treatment of the portion of expenditures that are not recoverable.

Historically strong financial coverage metrics are being impacted by storm activity, coal ash remediation spend and delayed rate relief

Duke Carolinas' historically strong financial coverage metrics have been under pressure in recent years as the company has been spending for coal ash remediation, new generation, and grid modernization, while rates have essentially remained at levels established in 2013. Duke Carolina's 2018 rate order established a new base-line, and determined the utility's spending on coal ash remediation should be recovered over five years with a full return, a credit positive. However, the authorized increase in rates was entirely offset by a reduction in revenue due to the lower corporate tax rate.

In addition, in the second half of 2018, a succession of unusually severe storms resulted in over \$1 billion of unplanned costs across Duke's territories in the Carolinas and Florida. The impact of the storms put downward pressure on financial metrics for all of the impacted utilities. For the twelve months ending June 2019, Duke Carolinas' ratio of CFO pre-WC to debt was around 25%. Absent the unusual storm activity, we estimate this ratio would have been around 26%.

Going forward, lag in the recovery of ongoing coal ash remediation spending and grid modernization will maintain negative pressure on financial credit metrics. As a result, Duke Carolinas will need to file regular, possibly annual, rate cases to help sustain credit metrics. In its current rate case filed in October, Duke Carolinas is requesting an approximate \$290 million (6% rate increase) with rates to become effective no later than August 2020. Our stable outlook assumes that management will manage and finance Duke Carolinas relatively large capital expenditure program with a balanced mix of debt and equity, including the retention of utility cash flow, in a manner enables the utility to demonstrate financial credit metrics that are consistent with its credit profile. For example, a ratio of CFO pre-WC to debt above 25%, which is in the middle of the "A" scoring range for this factor in our rating methodology for regulated electric and gas utilities.

Environmental, social and governance considerations

Duke Carolinas has a moderate carbon transition risk within the regulated utility sector because, as an integrated utility, its generation ownership places it at a higher risk profile than transmission and distribution companies. As of December 31, 2018, approximately 33% of Duke Carolinas' 20,209 MW generation portfolio is coal fired. In 2018, Duke Carolina's generated energy was produced approximately 52% from nuclear fuel, which lowers the company's carbon footprint, 26% from coal, and 19% from natural gas. When considering all sources of energy, purchased power (which includes renewables), made up 11% of the energy supply, with nuclear contributing 46%, coal 23%, natural gas 17% and owned renewables 3%.

Natural gas is playing an important role in the company's plans to transition to a cleaner generation mix, and we expect the proportion of energy supplied by natural gas to increase as coal declines. In 2019, gas co-firing capability was added at the 1,388 MW Rodgers plant, and the 560 MW Ashville combined cycle plant is scheduled to come on line. By 2024, Duke Carolinas plans to retire three coal fired units at its Allen Station (totaling 604 MW) and to add 468 MW of gas-fired capacity at its Lincoln Station. By 2021, gas-firing optionality is planned at Duke Carolinas 2,220 MW Belews Creek and its 2,060 MW Marshall plants. The remaining two coal-fired Allen units (totaling 526 MW) are expected to be retired by 2028.

Liquidity Analysis

Given its large capital expenditure program, continuing dividends, and current borrowing capacity under Duke Energy's bank credit facility, Duke Carolinas is reliant on market access to maintain adequate liquidity. For the twelve months ended June 30, 2019, Duke Carolinas generated approximately $2.6 billion of cash from operations (CFO), invested approximately $2.8 billion in capital expenditures and up streamed approximately $250 million in dividend payments to parent Duke Energy, resulting in negative free cash flow (FCF) of $424 million. In 2018, Duke Carolinas generated approximately $2.5 billion of CFO, invested about $2.7 billion in capital expenditures and up streamed $750 million in dividend payments, resulting in negative FCF of $926 million. Going forward, we expect Duke Carolinas will remain cash flow negative.

Duke Carolinas' alternate liquidity sources include access to funding from the parent company's commercial paper program through the Duke Energy system money pool, and direct borrowings from the money pool. As of June 2019, the utility had $1.75 billion of borrowing capacity under Duke Energy's $8 billion master credit facility. As of June 2019, the utility had $1.1 billion of commercial paper outstanding, $4 million of letters of credit outstanding, and $250 million set aside to meet its obligations related to a May 2015 Plea Agreement with the US Department of Justice related to coal ash, reducing available capacity to $397 million from the parent master credit facility.

Duke Energy's $8 billion master credit facility terminates in March 2024. The facility does not contain a material adverse change clause for new borrowings and has a single financial covenant requiring that Duke Energy and its utility subsidiaries each maintain a consolidated debt to capitalization ratio of no more than 65%, except for Piedmont. The debt to capitalization covenant for Piedmont is a maximum of 70%. As of June 2019, we estimate Duke Carolinas' ratio to be about 49%. Duke Carolinas' nearest long-term debt maturity is $450 million of first mortgage bonds due in June 2020.

Rating Methodology and Scorecard Factors

Exhibit 3
Rating Factors
Duke Energy Carolinas, LLC

Regulated Electric and Gas Utilities Industry Scorecard [1][2]	Current LTM 6/30/2019		Moody's 12-18 Month Forward View As of Date Published [3]	
Factor 1 : Regulatory Framework (25%)	**Measure**	**Score**	**Measure**	**Score**
a) Legislative and Judicial Underpinnings of the Regulatory Framework	A	A	A	A
b) Consistency and Predictability of Regulation	Aa	Aa	Aa	Aa
Factor 2 : Ability to Recover Costs and Earn Returns (25%)				
a) Timeliness of Recovery of Operating and Capital Costs	A	A	A	A
b) Sufficiency of Rates and Returns	A	A	A	A
Factor 3 : Diversification (10%)				
a) Market Position	A	A	A	A
b) Generation and Fuel Diversity	A	A	A	A
Factor 4 : Financial Strength (40%)				
a) CFO pre-WC + Interest / Interest (3 Year Avg)	7.1x	Aa	6.5x - 7x	Aa
b) CFO pre-WC / Debt (3 Year Avg)	26.2%	A	24% - 26%	A
c) CFO pre-WC – Dividends / Debt (3 Year Avg)	19.7%	A	16% - 19%	A
d) Debt / Capitalization (3 Year Avg)	41.2%	A	40% - 43%	A
Rating:				
Grid-Indicated Outcome Before Notching Adjustment		A1		A1
HoldCo Structural Subordination Notching	0	0	0	0
a) Scorecard-Indicated Outcome		A1		A1
b) Actual Rating Assigned		A1		A1

[1] All ratios are based on 'Adjusted' financial data and incorporate Moody's Global Standard Adjustments for Non-Financial Corporations.
[2] As of 6/30/2019(L)
[3]This represents Moody's forward view; not the view of the issuer; and unless noted in the text, does not incorporate significant acquisitions and divestitures.
Source: Moody's Financial Metrics

Appendix

Exhibit 4

Cash Flow and Credit Metrics [1]

CF Metrics	Dec-15	Dec-16	Dec-17	Dec-18	LTM Jun-19
As Adjusted					
FFO	2,694	2,883	2,915	3,129	3,130
+/- Other	14	31	(71)	(267)	(175)
CFO Pre-WC	2,708	2,914	2,844	2,862	2,955
+/- ΔWC	(128)	349	54	(96)	(83)
CFO	2,580	3,263	2,898	2,766	2,872
- Div	401	2,000	625	750	250
- Capex	2,097	2,507	2,788	2,942	3,048
FCF	82	(1,244)	(515)	(926)	(426)
(CFO Pre-W/C) / Debt	31.5%	29.5%	27.2%	24.5%	24.6%
(CFO Pre-W/C - Dividends) / Debt	26.8%	9.3%	21.2%	18.1%	22.5%
FFO / Debt	31.3%	29.2%	27.9%	26.8%	26.1%
RCF / Debt	26.6%	9.0%	21.9%	20.4%	24.0%
Revenue	7,229	7,322	7,302	7,300	7,322
Cost of Good Sold	1,872	1,789	1,803	1,800	1,787
Interest Expense	456	469	474	482	491
Net Income	985	1,127	1,160	1,025	1,033
Total Assets	35,553	36,657	37,851	40,121	42,442
Total Liabilities	24,027	25,975	26,585	28,542	30,270
Total Equity	11,526	10,682	11,266	11,579	12,172

[1] All figures and ratios are calculated using Moody's estimates and standard adjustments. Periods are Financial Year-End unless indicated. LTM=Last Twelve Months
Source: Moody's Financial Metrics

Exhibit 5

Peer Comparison Table [1]

	Duke Energy Carolinas, LLC A1 Stable			Duke Energy Progress, LLC A2 Stable			Alabama Power Company A1 Stable			Virginia Electric and Power Company A2 Stable		
	FYE	FYE	LTM	FYE	FYE	LTM	FYE	FYE	LTM	FYE	FYE	LTM
(in US millions)	Dec-17	Dec-18	Jun-19	Dec-17	Dec-18	Jun-19	Dec-17	Dec-18	Jun-19	Dec-17	Dec-18	Jun-19
Revenue	7,302	7,300	7,322	5,129	5,699	5,819	6,039	6,032	5,977	7,556	7,619	7,945
CFO Pre-W/C	2,844	2,862	2,955	1,947	1,763	1,752	2,016	1,879	2,167	2,931	3,198	2,606
Total Debt	10,463	11,665	12,003	8,215	8,975	9,639	7,933	8,500	8,396	13,275	13,697	14,006
CFO Pre-W/C / Debt	27.2%	24.5%	24.6%	23.7%	19.6%	18.2%	25.4%	22.1%	25.8%	22.1%	23.3%	18.6%
CFO Pre-W/C – Dividends / Debt	21.2%	18.1%	22.5%	22.2%	17.7%	16.4%	16.5%	12.7%	16.1%	13.1%	20.0%	15.8%
Debt / Capitalization	41.6%	43.3%	43.0%	45.7%	46.1%	46.8%	44.6%	44.3%	40.8%	47.2%	46.2%	46.8%

[1] All figures & ratios calculated using Moody's estimates & standard adjustments. FYE=Financial Year-End. LTM=Last Twelve Months. RUR*=Ratings Under Review, where UPG=for upgrade and DNG=for downgrade
Source: Moody's Financial Metrics

Ratings

Exhibit 6

Category	Moody's Rating
DUKE ENERGY CAROLINAS, LLC	
Outlook	Stable
Issuer Rating	A1
First Mortgage Bonds	Aa2
Bkd Senior Secured	Aa2
Senior Unsecured	A1
PARENT: DUKE ENERGY CORPORATION	
Outlook	Stable
Issuer Rating	Baa1
Sr Unsec Bank Credit Facility	Baa1
Senior Unsecured	Baa1
Jr Subordinate	Baa2
Pref. Stock	Baa3
Commercial Paper	P-2

Source: Moody's Investors Service

REPORT NUMBER 1197492

MOODY'S
INVESTORS SERVICE

Public Staff
Hinton Exhibit 4
Docket No. E-7, Sub 1214

Duke Energy Carolinas, LLC
First Mortgage Bonds
Moody's Historical Ratings

Date	Rating	Rating Action
01 Aug 2018	Aa2	RATING AFFIRMATION
12 May 2017	Aa2	RATING AFFIRMATION
13 Jan 2016	Aa2	RATING AFFIRMATION
27 Oct 2015	Aa2	RATING AFFIRMATION
05 Jun 2015	Aa2	RATING AFFIRMATION
31 Jan 2014	Aa2	Upgrade
08 Nov 2013	Aa3	ON WATCH for Possible Upgrade
25 Sep 2013	Aa3	Upgrade
09 Jul 2013	A1	ON WATCH for Possible Upgrade
03 Aug 2009	A1	Upgrade
06 Apr 2006	A2	Upgrade
29 Mar 2006	A3	ON WATCH for Possible Upgrade
17 Jun 2003	A3	Downgrade
31 Mar 2003	A2	ON WATCH for Possible Downgrade
23 Dec 2002	A2	Downgrade
20 Sep 2002	Aa3	ON WATCH for Possible Downgrade
21 Sep 2001	Aa3	Confirmed
20 Sep 1999	Aa3	Confirmed
03 Aug 1999	Aa3	Confirmed
30 Jul 1999	Aa3	Confirmed
18 Feb 1999	Aa3	Confirmed
23 Nov 1998	Aa3	Confirmed
01 Jul 1997	Aa3	Downgrade
25 Nov 1996	Aa2	ON WATCH for Possible Downgrade
14 Nov 1996	Aa2	Confirmed
13 Mar 1996	Aa2	Confirmed
10 Sep 1984	Aa2	Upgrade
02 May 1983	Aa3	Upgrade
26 Apr 1982	A1	Modified Rating Notation
12 Nov 1973	A	Downgrade

INFRASTRUCTURE AND PROJECT FINANCE

MOODY'S INVESTORS SERVICE

CREDIT OPINION
13 October 2019

Update

Rate this Research

RATINGS

Duke Energy Corporation

Domicile	Charlotte, North Carolina, United States
Long Term Rating	Baa1
Type	LT Issuer Rating - Dom Curr
Outlook	Stable

Please see the ratings section at the end of this report for more information. The ratings and outlook shown reflect information as of the publication date.

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Americas	1-212-553-1653
Asia Pacific	852-3551-3077
Japan	81-3-5408-4100
EMEA	44-20-7772-5454

Duke Energy Corporation

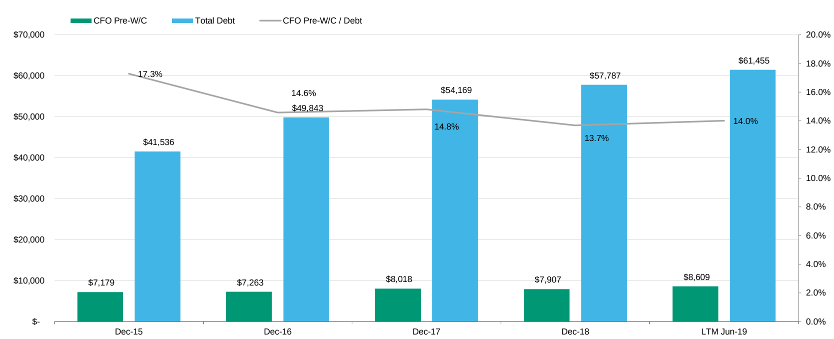
Update to credit analysis

Summary

Duke Energy Corporation (Duke) is one of the largest utility holding companies in the US. Its credit profile reflects the company's diverse, low business risk operations in which about 97% of earnings and cash flow are derived from rate regulated businesses in growing economies with supportive regulators. These credit supportive factors are balanced against weak financial metrics that we expect will improve somewhat in 2019, but dip again in 2020 before rebounding in 2021.

Exhibit 1

Historical CFO Pre-WC, Total Debt and CFO Pre-WC to Debt ($MM) [1]



[1] CFO Pre-WC is defined as cash flow from operations excluding changes in working capital
Source: Moody's Financial Metrics

Credit strengths

» Diverse group of utilities operating in seven states in three geographic regions

» Credit supportive regulatory relationships

» Businesses are essentially all regulated or contracted

» Approved recovery of the majority of coal ash related expenditures

Credit challenges

» Weak consolidated credit metrics

» Significant, primarily debt financed, capital program

» Lag in the recovery of storm related costs and coal ash remediation spending

» Increasing regulatory uncertainty surrounding coal ash cost recovery

» Delays and cost increases at Atlantic Coast Pipeline (ACP) project

» Relatively high parent company debt levels

Rating outlook

The stable outlook reflects our expectation that Duke will maintain supportive regulatory relationships in all of its jurisdictions. The outlook also assumes management will manage its operating, capital and financing plans in a manner that supports credit quality and enables the maintenance of credit metrics that are consistent with our expectations. For example, we anticipate the company's ratio of cash flow from operations excluding working capital (CFO pre-WC) to debt will improve to the 15% range.

Factors that could lead to an upgrade

» Ratings could be upgraded if regulatory environments were to become more supportive, leading to increased cash flow and reduced leverage, and if the ratio of CFO pre-WC to debt can be maintained above 18%.

Factors that could lead to a downgrade

» A deterioration in the credit supportiveness or emergence of a more contentious regulatory relationship which negatively impacts cash flows or the timeliness of cost recovery, particularly with regards to coal ash remediation recovery in North Carolina

» A ratio of CFO pre-WC that we expect to remain below 15% beyond 2020, or an increase in parent company debt levels above 35% of total consolidated debt

Key indicators

Exhibit 2

Duke Energy Corporation [1]

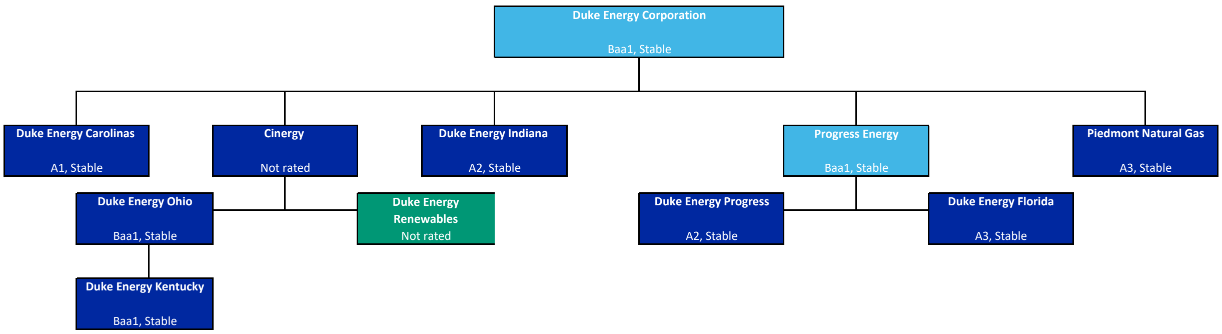
	Dec-15	Dec-16	Dec-17	Dec-18	LTM Jun-19
CFO Pre-W/C + Interest / Interest	5.3x	4.7x	4.7x	4.4x	4.6x
CFO Pre-W/C / Debt	17.3%	14.6%	14.8%	13.7%	14.0%
CFO Pre-W/C – Dividends / Debt	11.8%	9.9%	10.3%	9.4%	9.8%
Debt / Capitalization	44.2%	47.5%	53.0%	52.9%	53.6%

[1] All ratios are based on 'Adjusted' financial data and incorporate Moody's Global Standard Adjustments for Non-Financial Corporations.
Source: Moody's Financial Metrics

Profile

Duke is a large (2018 revenues of $24.5 billion), diversified energy company with mostly regulated utility operations headquartered in Charlotte, North Carolina. Its main business consists of its electric utilities and infrastructure business segment, which serves approximately 7.7 million retail electric customers in six US states and made up about 90% of Duke's 2018 earnings base. The company's gas utilities and infrastructure businesses provide natural gas to over 1.6 million customers located in five states. Duke has also formed a joint venture to build and own a 47% share of the estimated $7.0-$7.8 billion Atlantic Coast Pipeline, a 600-mile interstate natural gas pipeline from West Virginia to the Carolinas which has been experiencing permitting delays and increased costs. The company's relatively small (about 3% of 2018 adjusted earnings) commercial renewables business segment builds, develops and operates wind and solar generation projects throughout the continental US.

Exhibit 3
Duke Organizational Structure



Source: Moody's Investors Service, Company

Detailed credit considerations

Diverse group of utilities operating in credit supportive regulatory environments

Duke's overall credit profile is driven by seven regulated utilities operating in seven US states, which provide a high degree of regulatory and geographic diversity. We consider these regulatory jurisdictions to be supportive with rate settlements in place at most of its utilities. In addition, the company has achieved reasonably credit supportive outcomes in its major jurisdictions on issues related to the majority of its coal ash remediation spending and federal tax reform.

In Duke's largest electric jurisdiction, North Carolina, the North Carolina Utilities Commission (NCUC) issued orders in 2018 for both Duke Energy Carolinas and Duke Energy Progress (combined approximately 56% of Duke's 2018 regulated earnings base) that established revenues based on a 9.9% return on equity, and a 52% equity base. The orders followed settlement agreements on traditional rate making parameters. We view the ability to regularly settle on more traditional issues as a credit positive.

The North Carolina orders also resolved issues relating to the recovery of costs for coal ash remediation. Spending for coal ash remediation has been deemed reasonable and prudent and, with the exception of a specific manageable penalty assessed in each case, the companies have been authorized to recover their prior expenditures over five years with a full debt and equity return. Ongoing expenditures will continue to be deferred for future recovery. We view the ability to earn a full return on these expenditures, and to recover them over reasonable time frames, as credit positive. As a result of this rate base like treatment, we currently view the spending for coal ash remediation to be akin to a capital expenditure.

In 2018, the NCUC also addressed the impact of federal tax reform. During the year, both Duke Energy Carolinas and Duke Energy Progress' revenue requirements were reduced by the full amount of the change in tax rate to 21% from 35%. However, the utilities were allowed to retain all excess deferred taxes for three years, or until its next rate case, whichever is sooner. At that time, the NCUC will evaluate how to best return this value to customers. We believe the form of return could include accelerated recovery of certain expenses, or the avoidance of rate increases. We would view such outcomes as credit positive.

The NCUC did however deny Duke's requests for rider recovery for grid modernization investments and ongoing coal ash remediation, both credit negatives. As a result, there will continue to be regulatory lag associated with these expenditures and we expect the utilities will need to file frequent rate cases to minimize this exposure. Duke has been working with lawmakers in an attempt to pass legislation that would allow securitization of storm costs as well as the consideration of alternative rate adjustment mechanisms such as rider recovery, multiyear plans, incentive mechanisms or ROE bands. Last week, a North Carolina conference committee produced a compromise bill that would authorize securitization of storm costs immediately, but would delay the implementation of alternative rate plans until 2021. The bill was immediately approved by the Senate and must now be approved by the House before heading to the Governor. A vote in the House is expected in October. Our stable outlook assumes a continuation of regulatory outcomes that will allow the companies to maintain cash flow based credit metrics at levels that are supportive of their current credit quality.

In South Carolina, in May 2019, the Public Service Commission of South Carolina (PSCSC) issued an order for rate increases at Duke Energy Carolinas and Duke Energy Progress for $107 million and $41 million respectively based on a 9.5% ROE and a 53% equity ratio. New rates were effective June 1, 2019. In a credit negative development, the PSCSC denied the recovery of certain coal ash costs deemed to be related to the North Carolina Coal Ash Management Act and incremental to the federal Coal Combustion Residuals rule in the amount of $115 million and $65 million at Duke Energy Carolinas and Duke Energy Progress respectively. In May 2019, both Duke subsidiaries filed a petition for rehearing or reconsideration of the PSCSC's order contending substantial rights of Duke Energy Carolinas and Duke Energy Progress were prejudiced by unlawful, arbitrary and capricious rulings by the commission on certain issues, including its ability to fully recover its coal ash remediation spending. In June 2019, the PSCSC issued a directive denying the company's request for rehearing. Duke Energy Carolinas and Duke Energy Progress are currently awaiting the written order detailing the PSCSC's decision and are prepared to appeal portions of the case to the South Carolina Supreme Court. Depending on the outcome of the appeal, we may modify our treatment of the portion of expenditures that are not recoverable.

In Florida (approximately 18% of 2018 regulated earnings base), as part of a 2017 second revised and restated settlement agreement (which amended a 2013 settlement agreement), Duke Energy Florida will increase base rates by an incremental $67 million (subsequently adjusted to $55 million to reflect the effects of federal tax reform) each year from 2019 through 2021, subject to an ROE range of 9.5% to 11.5%. The order also included provisions that addressed the expected passage of federal tax reform and included the ability to use a portion of future benefits resulting from lower tax rates to accelerate the depreciation of existing coal plants rather than decreasing revenue. In January 2018, the Florida Public Service Commission authorized Duke Energy Florida to utilize the remainder of the benefits of lower tax rates to avoid a rate increase for power restoration costs associated with the company's 2017 response to Hurricane Irma. In June 2019, the FPSC approved the company's request to recover approximately $221 million of incremental operating costs incurred as a result of Hurricane Michael. We view the ability to utilize tax reform savings to offset storm costs as a credit positive. Approved storm costs are currently expected to be fully recovered around year-end 2022.

Duke Energy Florida also continues to benefit from a credit positive Generation Base Rate Adjustment (GBRA) mechanism for new generation built or purchased during 2016-2018 that allows recovery of prudently incurred costs through a base rate adjustment when the generation is placed in service. Duke Florida's 1,640 MW $1.5 billion Citrus County combined cycle plant was placed into service in 2018. The 2017 settlement included a similar mechanism for up to 700MW of new solar generation to be acquired or constructed between 2018 and 2022.

In Indiana (about 11% of 2018 regulated earnings base), in June 2016, the Indiana Utility Regulatory Commission (IURC) approved a settlement agreement between Duke Energy Indiana and key consumer groups on a seven year $1.4 billion grid modernization plan. As a result, in accordance with previously approved state legislation, 80% of the plan's costs will be recovered through a rate rider, with the remaining 20% recoverable through future base rate proceedings. In May 2017, Duke Energy Indiana received approval to recover 60% of the capital and 80% of the operating costs of complying with the US Environmental Protection Agency's Coal Combustion Residuals rules via an environmental mandate tracker, and to defer the remaining difference for recovery in the utility's next rate case. In June 2018, Duke Energy Indiana reached a settlement with key intervenors on tax reform. The settlement calls for a flow through of the reduction in tax rate to 21% from 35% beginning in September. However, the protected portion of excess deferred taxes will be retained until January 2020, after which it will be returned over approximately 26 years. The unprotected portion will be returned over 10 years, but to mitigate the impact on cash flow based credit metrics, the amount is lower in the first five years.

In July 2019, Duke Energy Indiana filed a request for a $395 million (approximately 15%) base rate increase premised on a 10.4% return on equity and a 53% equity component. This is Duke Energy Indiana's first base rate case filing in 16 years and is being driven by capital investments in generation, improvements in the grid to ensure reliability and a growing customer base. The request includes $138 million relating to a change in depreciation, primarily to accelerate the retirement of certain coal-fired units. The company is also requesting the use of a forward test year, which was authorized by law in 2013. Duke expects hearings to begin in early 2020 with new rates effective by mid 2020.

On the natural gas side, Duke's local gas distribution subsidiary Piedmont Natural Gas (Piedmont), has historically received supportive treatment from its regulators in North Carolina (73% of rate base), South Carolina (14%) and Tennessee (13%). In addition, all three states provide cost recovery mechanisms and frameworks that lead to reduced regulatory lag.

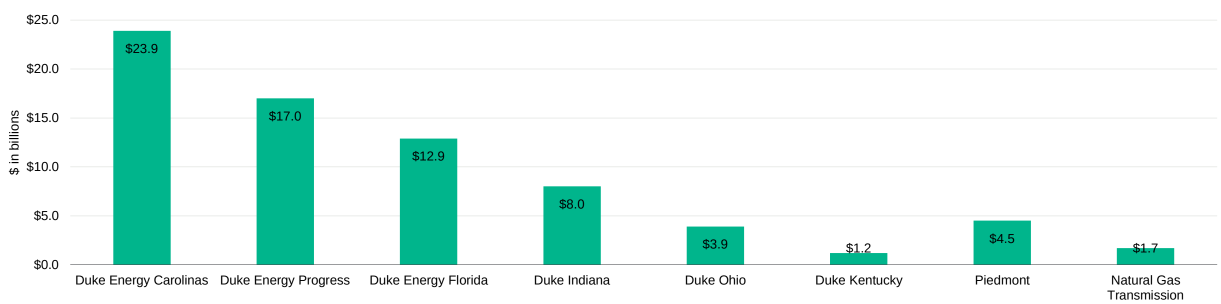
In August 2019 Piedmont reached a settlement agreement with the NCUC public staff for a base rate increase of approximately $109 million, after the expiration of various rider credits to flow back federal and state income tax credits. The agreed increase was based on a 9.7% ROE and a 52% equity layer. Piedmont initially requested an increase of $83 million (net of $37 million of reductions due to lower tax rates), based on a 10.6% ROE and a 52% equity layer. The settlement allows continuation of an integrity management rider for federally mandated safety and capital investments and establishes a new distribution integrity management program recovery mechanism. The settlement is subject to the review and approval of the NCUC.

Operations are essentially all regulated

In 2015, Duke successfully exited the merchant generating business with the sale of Duke Energy Ohio's competitive generating assets. In 2016, Duke sold its more volatile Latin American businesses and acquired Piedmont Natural Gas Company (Piedmont), expanding its relatively low risk local natural gas distribution operations in the historically credit supportive states of North Carolina, South Carolina and Tennessee. As a result, essentially all of its operations are now either state or federally regulated. Duke's commercial renewables segment provides services under long term contracts, and contributed under 5% of the company's 2018 earnings. The shift to lower business risk operations has helped to mitigate the decline in credit metrics that followed the Piedmont acquisition.

Exhibit 4

2018 Regulated Utilities Earnings Base



Source: Company

Consolidated financial credit metrics are weak

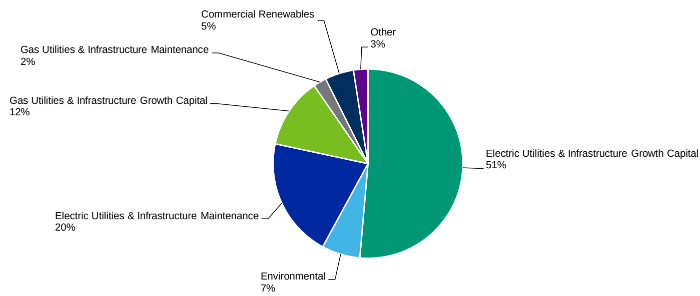
Duke's revenues and cash flow are being negatively impacted by the 2017 Tax Cuts and Jobs Act (TCJA), continued lag in recovery of coal ash remediation costs, severe storm activity, and lag in recovery of grid modernization investments. As a result, cash flow based credit metrics, which declined in 2016 following Duke's acquisition of Piedmont, have remained below our financial metric downgrade triggers. For example, for the last twelve months ended June 30, 2019, we calculate Duke's ratio of cash flow from operations excluding changes in working capital (CFO pre-WC) to debt to be about 14%, which is at the lower end of the "Baa" scoring range for this metric in our rating methodology for regulated electric and gas utilities and below our financial metric downgrade trigger of 15%. Absent the impact of the 2018 storms, we estimate the company's twelve month trailing ratio of CFO pre-WC to debt would be about 15%.

While we anticipate Duke's ratio of CFO pre-WC to debt will be around 15% for full year 2019, we believe it could fall toward 14% in 2020 before rebounding in 2021 as a result of rate case activity, operational enhancements, and lower dividend growth. In addition to planning regular rate cases in the Carolinas, Duke is also actively working with lawmakers on legislation that would allow the securitization of storm costs as well as alternative rate mechanisms that could reduce the lag in recovery, and would be credit positive. Our stable outlook assumes management will remain focused on achieving and maintaining a ratio of CFO pre-WC to debt in the 15-16% range, and that the metric will move into this range by 2021.

High capital spending for utility infrastructure and growth initiatives

Capital expenditures at Duke, inclusive of spending for coal ash remediation, have steadily increased year over year, nearly doubling from about $5.5 billion in 2014 to about $10.1 billion in 2018. As shown in the exhibit below, the largest portion of the plan represents what Duke terms "growth" capital driven by grid modernization in the Carolinas and natural gas infrastructure. In 2018, maintenance spending increased to $3.2 billion due in part to restoration efforts related to storm damages; going forward maintenance spending is expected to range between $2 and $2.5 billion per year.

Exhibit 5
2019-2023 Capital Expenditures Forecast ($50 Billion)



Source: Company

In addition to its core utility investment, Duke is growing its natural gas pipeline businesses and plans to continue to selectively invest in renewables. Included in the company's capital plan for 2019-2023 is about $2.9 billion for midstream pipelines, primarily the Atlantic Coast Pipeline (ACP), and about $2.5 billion for utility scale contracted renewables. Although we view the commercial renewables business as higher risk than its regulated utility business segment, these assets for the most part sell power to investor owned, cooperative, or municipal utilities under risk mitigating long-term contracts. Duke recently sold a minority share in its commercial renewables portfolio, generating pre-tax proceeds of approximately $415 million, which will likely also reduce the future capital needs of this segment.

Delays and cost increases at Atlantic Coast Pipeline (ACP) project

ACP is a 600-mile interstate natural gas pipeline being built by Dominion Energy, Inc. (Baa2 stable) from West Virginia to eastern North Carolina. Duke holds a 47% share in the project. The pipeline will supply natural gas from the Utica and Marcellus shale basins to natural gas generation at Duke Energy Carolinas and Duke Energy Progress, as well as to Piedmont and other utilities in the area.

Construction of ACP has been halted due to adverse court rulings on environmental issues, including a biological opinion and a permit to cross under the Appalachian Trail. As a result, the estimated cost to complete the project increased by about $1 billion, and its estimated completion schedule was extended by over a year. The pipeline is currently expected to cost between $7 and $7.8 billion ($3.3-$3.7 for Duke) and could be completed in two phases. Construction of the first phase, which does not cross the Appalachian Trail, could be restarted by year-end if there is a successful re-issuance of its biological opinion.

Construction of the second phase requires resolution of a Fourth Circuit Court of Appeals decision to vacate the permit issued by the U.S. Forest Service allowing ACP to cross under the Appalachian Trail. ACP has appealed the decision to the U.S. Supreme Court and just recently learned the Court has accepted the case. A decision is required by June 2020, which if favorable, would allow construction to begin next summer and the pipeline to be completed by the end of 2021. The increased costs, and delay of cash flow from this project, are maintaining downward pressure on Duke's credit metrics.

Lag in the recovery of storm related costs will pressure metrics in the near term

In the fall and winter of 2018, Duke's operations were impacted by a succession of severe storms. Hurricane Florence arrived in mid-September and affected the company's operations in North and South Carolina. One month later, Hurricane Michael came ashore in the gulf region and caused damage all the way from Florida through North and South Carolina. In December 2018, Winter Storm Diego was the third major storm to impact Duke Energy Progress and Duke Energy Carolinas service territories.

Total costs for the three storms was in excess of $1 billion, primarily in Duke Energy Progress' North Carolina and Duke Energy Florida's service territories. Utilities in these territories have a good history of storm recovery, albeit with some regulatory lag. Duke has been working with lawmakers to enact securitization legislation, which would assure recovery of costs at lower cost to customers; however recovery would likely not begin until 2020 and will be spread out over a number of years. In the meantime, Duke's consolidated debt balances are about $1 billion higher than previously forecast, which continues to add negative pressure to credit metrics.

Recovery of coal ash expenditures primarily resolved, but lag persists and uncertainty is increasing

In 2014, North Carolina lawmakers overwhelmingly passed the Coal Ash Management Act which regulates and requires the closure of coal ash basins at all coal plant sites throughout the state. The legislation, which was amended in 2016, required Duke to take costly, immediate action to excavate and close coal ash basins at three of its highest risk sites by the end of 2019. These basins were all successfully closed ahead of schedule by July 2019. A fourth basin is required to be closed by August 2022. The 2016 amendment required the remaining sites to be closed by either 2024 or 2029, depending on their priority designation.

In April 2019, the North Carolina Department of Environmental Quality (NCDEQ) ordered Duke Energy to excavate coal ash at all of its low-risk sites in North Carolina where specific closure plans had not been determined. The decision is credit negative as it will cost substantially more than the alternative closure options proposed by Duke for these six sites, and in some cases it may take decades, stretching well beyond current state and federal deadlines. The company is required to submit closure plans by December 31, 2019. Duke has appealed the order to the North Carolina Office of Administrative Hearings. In August 2019 the court issued an order dismissing several of Duke's claims relating to procedure, but allowing the substantive claims to move forward. The company expects the process will take 9-12 months.

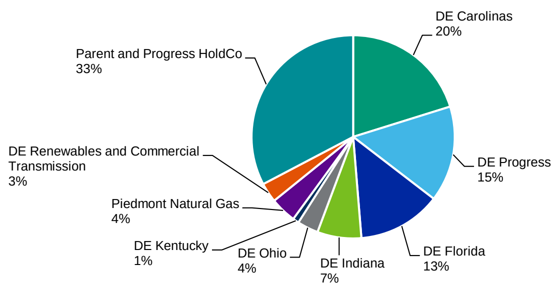
In 2014, Duke recognized a $3.5 billion Asset Retirement Obligation (ARO) for its estimated obligations to close its North Carolina coal ash basins. In the second quarter of 2015, after publication of the EPA's final Coal Combustion Rules, Duke incrementally increased the ARO by $1 billion as it created additional obligations for the company in South Carolina, Indiana, and Kentucky, putting its total ARO at $4.5 billion. Duke continues to refine its estimated obligations as work continues on the sites and there is additional information around closure requirements. As of June 30, 2019, Duke had spent approximately $2.1 billion and its total ARO had increased to approximately $6.5 billion ($2 billion more than reported as of December 2018).

In Duke's largest jurisdictions in North and South Carolina, coal ash basin closure and remediation spending is not recovered via trackers or other automatic cost recovery provisions and must be recovered via base rate case filings. As a result, there will likely continue to be regulatory lag in the recovery of these costs. To date, the majority of coal ash expenditures incurred have been recovered with rate base like treatment. Therefore we currently view the spending for coal ash remediation to be akin to a capital expenditure. However in their most recent South Carolina rate cases Duke Energy Progress and Duke Energy Carolinas were denied recovery of certain coal ash costs. The company plans to appeal this decision and we note that it represents a relatively modest portion of total incurred costs. Depending on the outcome of the appeal, we may modify our treatment of the portion of expenditures that are not recoverable.

Equity issuance has contained parent leverage – but it will still be relatively high

Duke's $2 billion 2018 equity issuance, and its plans for ongoing issuance of $500 million per year, have helped control the company's need for parent level debt financing. Prior to the announced 2018 equity issuance, we expected the level of parent debt to spike in 2018 and 2019 due in part to investments in ACP. Currently, we expect the proportion of Duke parent debt as a percentage of total consolidated debt will remain under 35%. This is still relatively high when compared to some other regulated utility holding company peers, and a factor in the wide differential between Duke and most of its subsidiaries' credit quality.

Exhibit 6
2018 Reported Debt by Entity

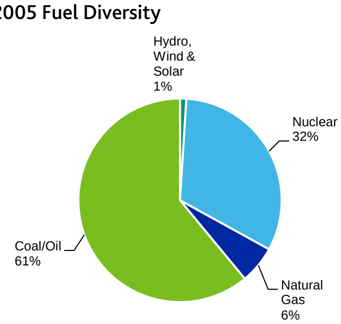


Source: Moody's Investors Service, Company

Environmental, social and governance considerations

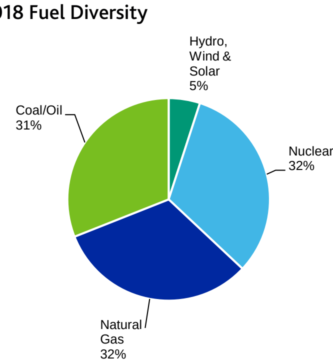
Duke has moderate carbon transition risk within the regulated utility sector as the majority of its energy is generated by fossil fuels. Since 2005, Duke has reduced carbon dioxide emissions by 31% and currently plans a 50% (increased from 40% in 2017) reduction by 2030. Furthermore Duke just announced a goal to achieve net-zero carbon emissions by 2050. As of 2018, the company's consolidated net output included about 31% from coal / oil fired resources, versus about 61% in 2005. By 2030 Duke estimates that 15% of its total company generation will be fired by coal.

Exhibit 7
2005 Fuel Diversity



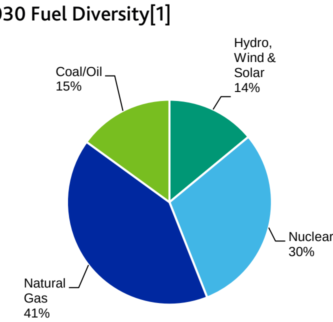
Source: Company

Exhibit 8
2018 Fuel Diversity



Source: Company

Exhibit 9
2030 Fuel Diversity[1]



[1] Company Estimate
Source: Company

Liquidity analysis

Given its large capital programs, Duke is reliant on external sources of liquidity. For the twelve months ending June 2019, Duke's consolidated cash flow from operations was approximately $7 billion while cash used for investing activities was about $10.5 billion and the company paid around $2.6 billion in dividends resulting in negative free cash flow of approximately $6 billion. The shortfall was funded via a combination of sources including subsidiary and parent level debt as well as preferred and common equity (about $2 billion).

As of June 2019, the Duke had $336 million of cash and short-term investments on hand, $3.9 billion available under its $8 billion master credit facility, and $500 million available under its $1 billion parent level revolving credit facility (May 2022 expiration). The master credit facility matures in March 2024 and includes sub-limits for each of its utility subsidiaries. As of June 30, 2019, Duke's parent company borrowing sub-limit under the master credit facility was $2.65 billion, and the subsidiary sub-limits were: $1.25 billion for Duke Energy Progress, $800 million for Duke Energy Florida, $1.75 billion for Duke Energy Carolinas, $600 million for Duke Energy Indiana, $450 million for Duke Energy Ohio, and $500 million for Piedmont Natural Gas.

The master credit facility supports a $4.85 billion commercial paper program. The facility does not contain a material adverse change clause for new borrowings and has a single financial covenant requiring that Duke and its utility subsidiaries each maintain a consolidated debt to capitalization ratio of no more than 65%, except for Piedmont. The debt to capital covenant for Piedmont is a maximum of 70%. As of June 30, 2019, we estimate Duke's consolidated ratio to be about 57%.

As of June 30, 2019, Duke had about $3.4 billion of commercial paper outstanding, including about $1 billion allocated to the parent company under its $2.65 billion credit facility sub-limit. Of the total $8 billion master credit facility, Duke and its utilities had about $3.9 billion of availability with $3.4 billion of commercial paper, $500 million of coal ash set-aside, $81 million of tax-exempt bonds, and $53 million of letters of credit outstanding. Duke also maintains a money pool arrangement among its utility subsidiaries allowing it to more efficiently utilize available cash balances throughout the organization.

As an additional source of liquidity Duke also has the ability to raise short-term debt through a variable rate demand note program called PremierNotes. The company's filings with the SEC indicate that no more than $1.5 billion of such notes will be outstanding. The notes have no stated maturity date and can be redeemed in whole or in part by Duke or at the investor's option at any time. As of June 30, 2019, Duke had about $991 million of PremierNotes outstanding. Although not explicitly backed by Duke's bank credit facility, the facility could be used to fund the maturities of such notes. These notes are classified as part of the $3.8 billion total notes payable and commercial paper outstanding as of June 30, 2019.

Duke's scheduled long-term debt maturities over the twelve months beginning June 30, 2019 total approximately $2.35 billion, including approximately $830 million at the parent level Duke Corp., $350 million at Progress Energy, $450 million at Duke Carolinas, $600 million at Duke Florida, $100 million at Duke Kentucky. We expect most of this debt will be refinanced.

Rating methodology and scorecard factors

Exhibit 10
Rating Factors
Duke Energy Corporation

Regulated Electric and Gas Utilities Industry Scorecard [1][2]	Current LTM 6/30/2019		Moody's 12-18 Month Forward View As of Date Published [3]	
Factor 1 : Regulatory Framework (25%)	**Measure**	**Score**	**Measure**	**Score**
a) Legislative and Judicial Underpinnings of the Regulatory Framework	A	A	A	A
b) Consistency and Predictability of Regulation	Aa	Aa	Aa	Aa
Factor 2 : Ability to Recover Costs and Earn Returns (25%)				
a) Timeliness of Recovery of Operating and Capital Costs	A	A	A	A
b) Sufficiency of Rates and Returns	Baa	Baa	Baa	Baa
Factor 3 : Diversification (10%)				
a) Market Position	Aa	Aa	Aa	Aa
b) Generation and Fuel Diversity	A	A	A	A
Factor 4 : Financial Strength (40%) [4]				
a) CFO pre-WC + Interest / Interest (3 Year Avg)	4.6x	A	4.6x - 5x	A
b) CFO pre-WC / Debt (3 Year Avg)	14.3%	Baa	14% - 16%	Baa
c) CFO pre-WC – Dividends / Debt (3 Year Avg)	10.0%	Baa	10% - 12%	Baa
d) Debt / Capitalization (3 Year Avg)	51.8%	Baa	50% - 54%	Baa
Rating:				
Scorecard-Indicated Outcome Before Notching Adjustment		A3		A3
HoldCo Structural Subordination Notching	-1	-1	-1	-1
a) Scorecard-Indicated Outcome		Baa1		Baa1
b) Actual Rating Assigned		Baa1		Baa1

[1] All ratios are based on 'Adjusted' financial data and incorporate Moody's Global Standard Adjustments for Non-Financial Corporations.
[2] As of 6/30/2019(L)
[3] This represents Moody's forward view; not the view of the issuer; and unless noted in the text, does not incorporate significant acquisitions and divestitures.
[4] Standard risk grid for financial strength
Source: Moody's Financial Metrics

Appendix

Exhibit 11

Cash Flow and Credit Metrics [1]

CF Metrics	Dec-15	Dec-16	Dec-17	Dec-18	LTM Jun-19
As Adjusted					
FFO	7,638	7,586	8,514	8,954	9,540
+/- Other	(459)	(323)	(496)	(1,047)	(931)
CFO Pre-WC	7,179	7,263	8,018	7,907	8,609
+/- ΔWC	181	394	(752)	(138)	(993)
CFO	7,360	7,657	7,266	7,769	7,616
- Div	2,269	2,338	2,457	2,484	2,587
- Capex	7,278	8,697	8,687	9,959	11,209
FCF	(2,187)	(3,378)	(3,878)	(4,674)	(6,179)
(CFO Pre-W/C) / Debt	17.3%	14.6%	14.8%	13.7%	14.0%
(CFO Pre-W/C - Dividends) / Debt	11.8%	9.9%	10.3%	9.4%	9.8%
FFO / Debt	18.4%	15.2%	15.7%	15.5%	15.5%
RCF / Debt	12.9%	10.5%	11.2%	11.2%	11.3%
Debt / EBITDA	4.4x	5.1x	5.0x	5.5x	5.6x
Revenue	22,371	22,743	23,565	24,521	24,779
Cost of Good Sold	7,338	6,789	6,863	7,396	7,390
EBITDA	9,417	9,728	10,737	10,480	10,927
Interest Expense	1,681	1,977	2,171	2,330	2,388
Net Income	2,530	2,119	3,106	2,281	2,627
Total Assets	119,812	131,655	136,911	144,659	151,314
Total Liabilities	80,026	90,739	95,410	101,027	106,786
Total Equity	39,785	40,916	41,501	43,633	44,529

[1] All figures and ratios are calculated using Moody's estimates and standard adjustments. Periods are Financial Year-End unless indicated. LTM = Last Twelve Months
Source: Moody's Financial Metrics

Exhibit 12

Peer Comparison Table [1]

	Duke Energy Corporation Baa1 Stable			American Electric Power Company, Inc. Baa1 Stable			Southern Company (The) Baa2 Stable			Xcel Energy Inc. Baa1 Stable		
(in US millions)	FYE Dec-17	FYE Dec-18	LTM Jun-19	FYE Dec-17	FYE Dec-18	LTM Jun-19	FYE Dec-17	FYE Dec-18	LTM Jun-19	FYE Dec-17	FYE Dec-18	LTM Jun-19
Revenue	23,565	24,521	24,779	15,425	16,196	15,765	23,031	23,495	22,006	11,404	11,537	11,646
CFO Pre-W/C	8,018	7,907	8,609	4,580	4,831	4,572	7,242	7,107	6,245	3,314	3,116	3,083
Total Debt	54,169	57,787	61,455	24,138	26,588	28,552	51,414	47,808	46,185	16,917	18,376	19,243
CFO Pre-W/C / Debt	14.8%	13.7%	14.0%	19.0%	18.2%	16.0%	14.1%	14.9%	13.5%	19.6%	17.0%	16.0%
CFO Pre-W/C – Dividends / Debt	10.3%	9.4%	9.8%	14.0%	13.4%	11.4%	9.4%	9.7%	5.3%	15.3%	13.0%	12.1%
Debt / Capitalization	53.0%	52.9%	53.6%	49.2%	50.6%	51.6%	60.2%	56.2%	53.3%	52.8%	53.2%	53.9%

[1] All figures & ratios calculated using Moody's estimates & standard adjustments. FYE = Financial Year-End. LTM = Last Twelve Months. RUR* = Ratings under Review, where UPG = for upgrade and DNG = for downgrade
Source: Moody's Financial Metrics

Ratings

Exhibit 13

Category	Moody's Rating
DUKE ENERGY CORPORATION	
Outlook	Stable
Issuer Rating	Baa1
Sr Unsec Bank Credit Facility	Baa1
Senior Unsecured	Baa1
Jr Subordinate	Baa2
Pref. Stock	Baa3
Commercial Paper	P-2
DUKE ENERGY CAROLINAS, LLC	
Outlook	Stable
Issuer Rating	A1
First Mortgage Bonds	Aa2
Bkd Senior Secured	Aa2
Senior Unsecured	A1
DUKE ENERGY PROGRESS, LLC	
Outlook	Stable
Issuer Rating	A2
First Mortgage Bonds	Aa3
Senior Secured	Aa3
DUKE ENERGY INDIANA, LLC.	
Outlook	Stable
Issuer Rating	A2
First Mortgage Bonds	Aa3
Senior Secured	Aa3
Senior Unsecured	A2
PROGRESS ENERGY, INC.	
Outlook	Stable
Senior Unsecured	Baa1
PIEDMONT NATURAL GAS COMPANY, INC.	
Outlook	Stable
Senior Unsecured	A3
Commercial Paper	P-2
DUKE ENERGY OHIO, INC.	
Outlook	Stable
Issuer Rating	Baa1
First Mortgage Bonds	A2
Senior Unsecured	Baa1
DUKE ENERGY KENTUCKY, INC.	
Outlook	Stable
Senior Unsecured	Baa1

Source: Moody's Investors Service

REPORT NUMBER 1196333

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Docket No. E-7, Subs 1213 and 1214

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

Principal Authors
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Nexant, Inc.

January 2015

The work described in this report was funded by the Office of Electricity Delivery and Energy Reliability of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

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.

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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

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

[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.

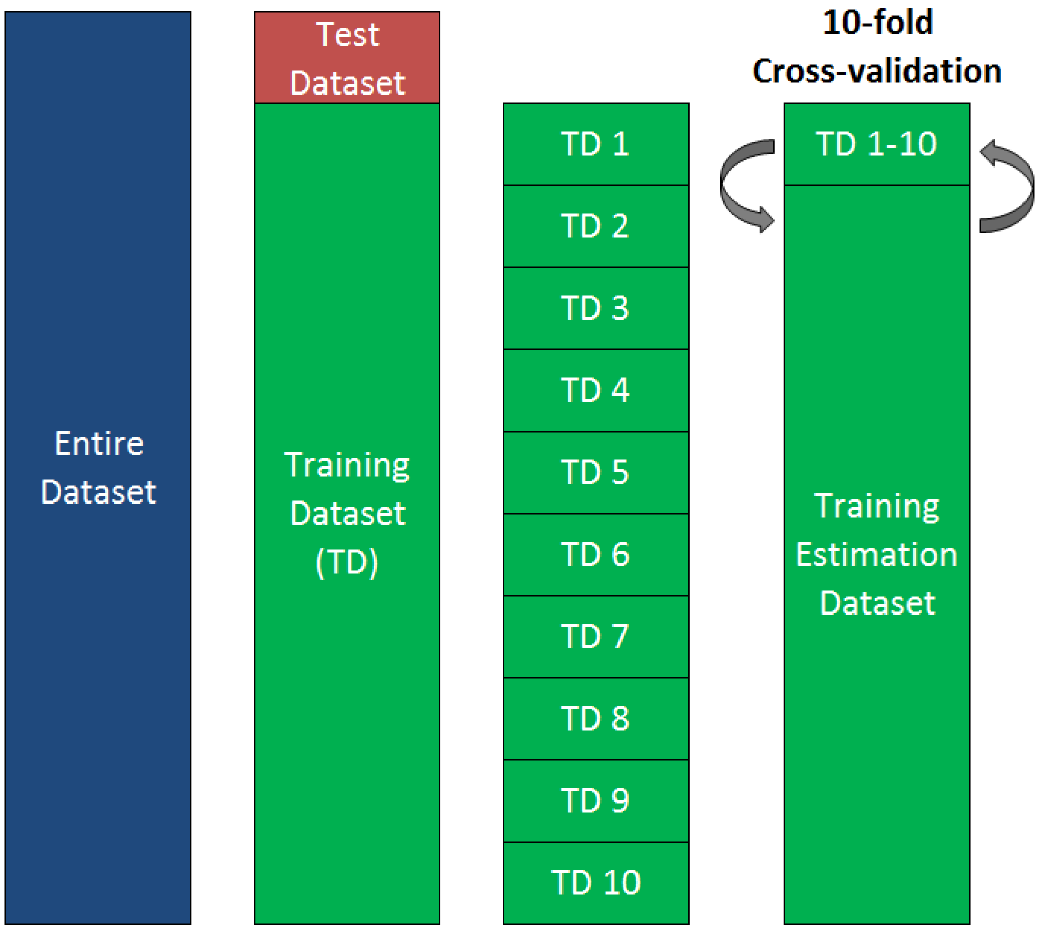
1.2 Re-estimating Econometric Models

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.

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[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:

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

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:

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

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

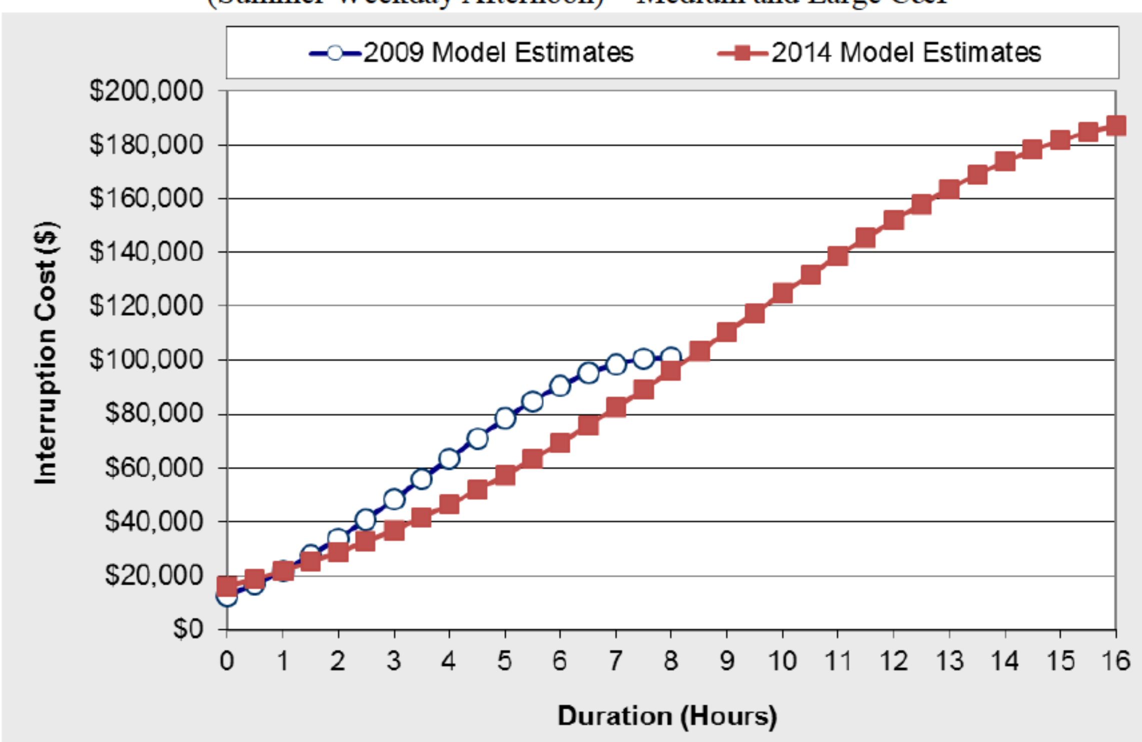
Variable	N	Average	Minimum	25th Percentile	Median	75th Percentile	Maximum
Interruption Characteristics							
duration	44,328	162	0	60	60	240	1,440
duration^2	44,328	82,724	0	3,600	3,600	57,600	2,073,600
summer	44,328	86.5%	0%	100%	100%	100%	100%
Customer Characteristics							
ln(annual MWh)	44,328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

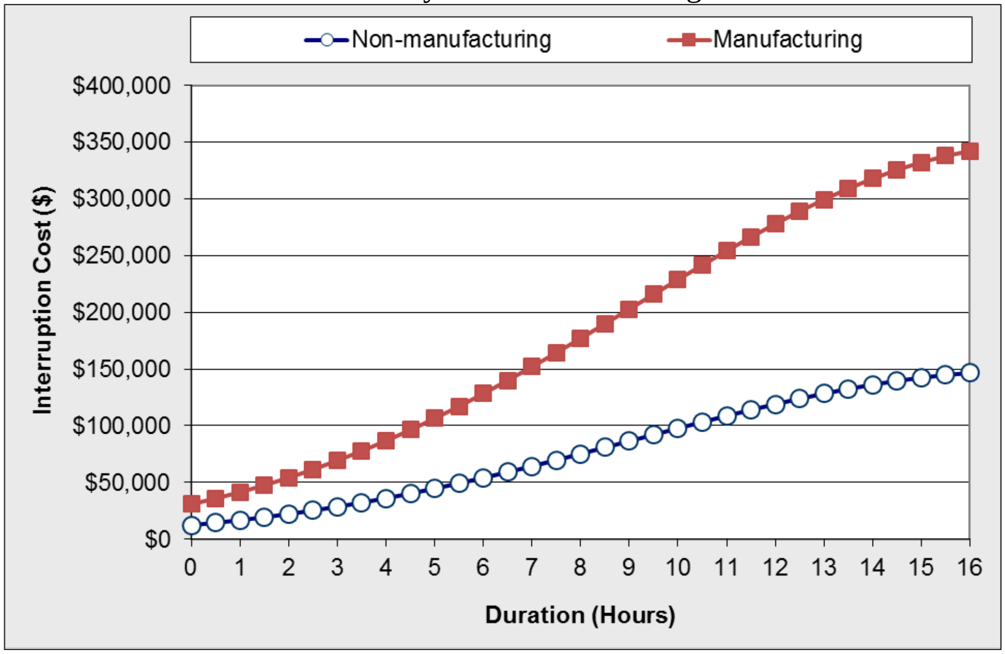
Based on the weighted-average interruption cost estimate, Table 3-8 provides cost per event (equal to the weighted-average interruption cost), cost per average kW and cost per unserved kWh for medium and large C&I customers. Cost per unserved kWh is relatively high for a momentary interruption because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

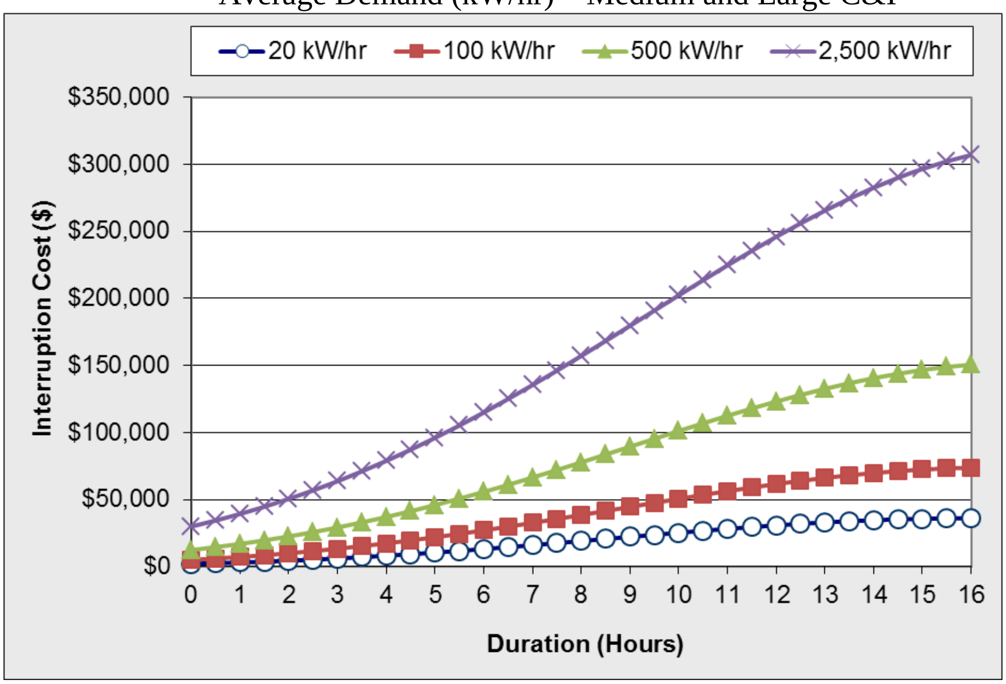
Figure 3-2 shows the medium and large C&I interruption costs in the summer for non-manufacturing and manufacturing customers. As in the 2009 model, interruption costs in the manufacturing sector are relatively high. At all durations, the estimated interruption cost for manufacturing customers is more 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.

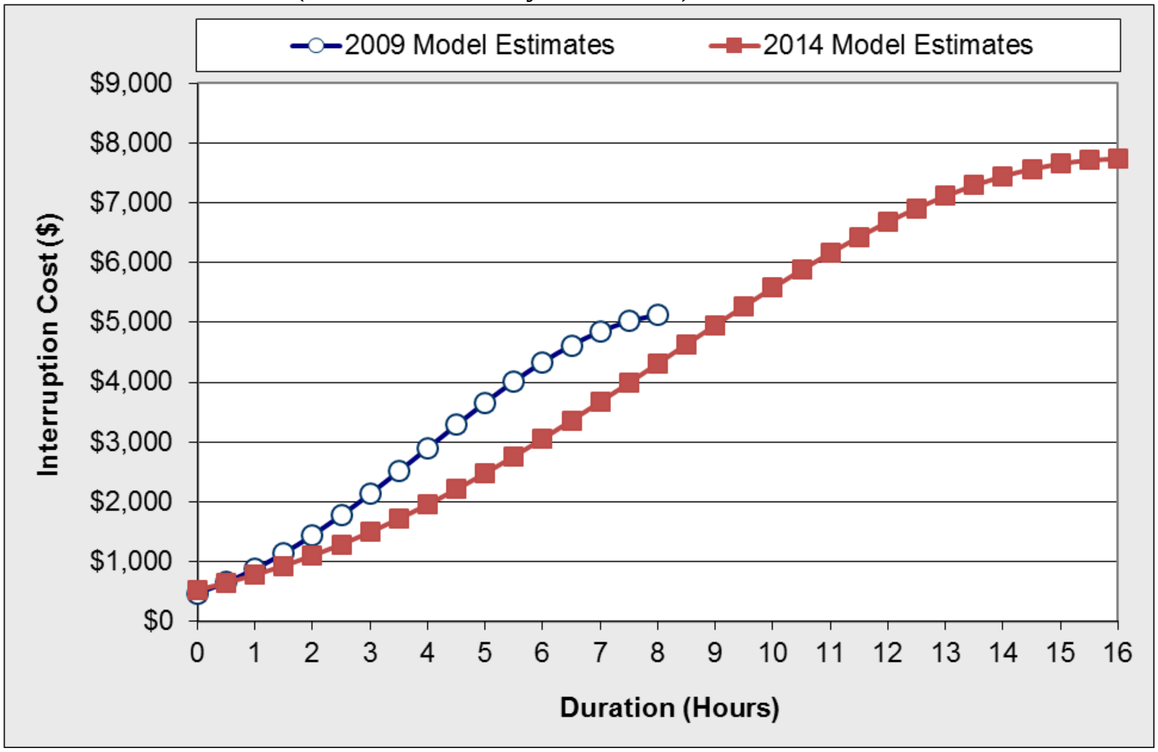
Table 4-6: Descriptive Statistics for Regression Inputs – Small C&I

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**

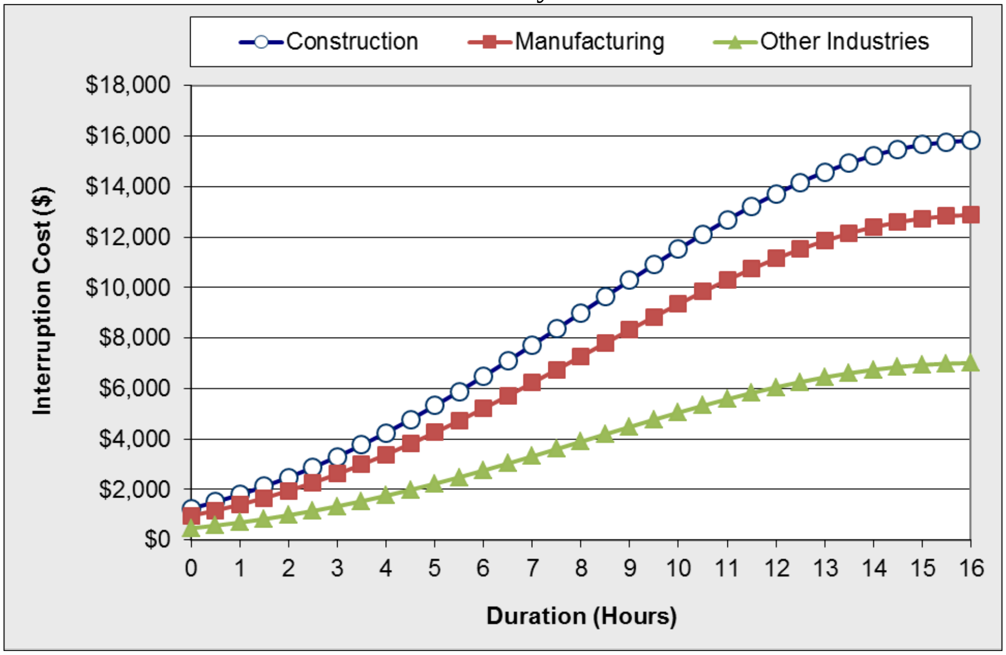
Based on the weighted-average interruption cost estimate, Table 4-8 provides cost per event (equal to the weighted-average interruption cost), cost per average kW, and cost per unserved kWh for small C&I customers. Cost per unserved kWh is relatively high for a momentary interruption because the expected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

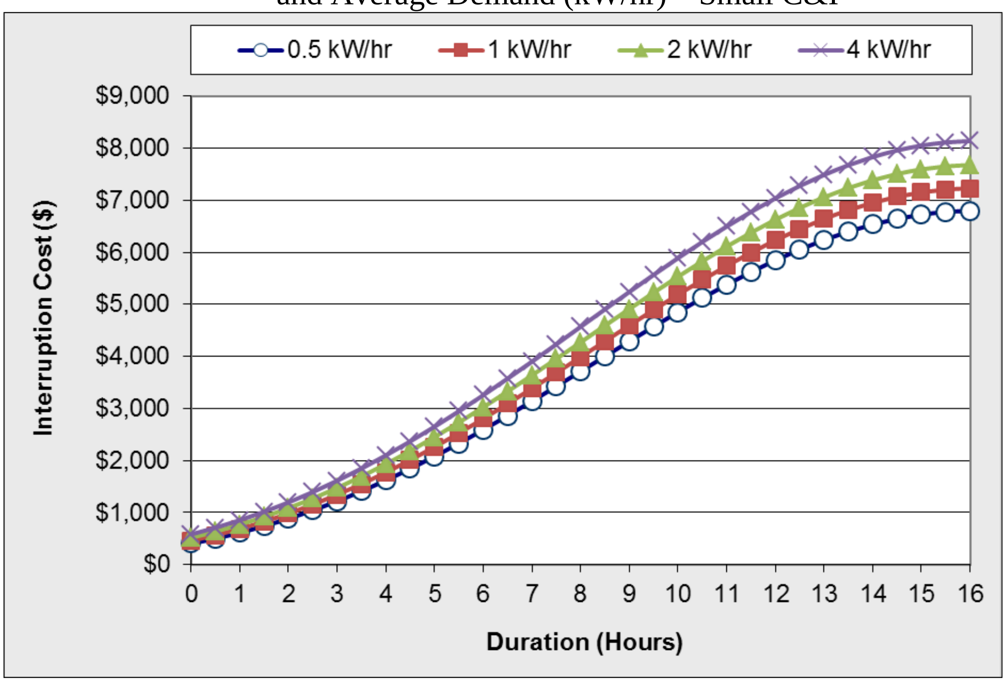
Figure 4-2 shows the small C&I interruption costs in the summer afternoon by industry. As in the 2009 model, interruption costs in the manufacturing and construction sectors are relatively high. At all durations, the estimated interruption cost for manufacturing and construction customers is around double 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.

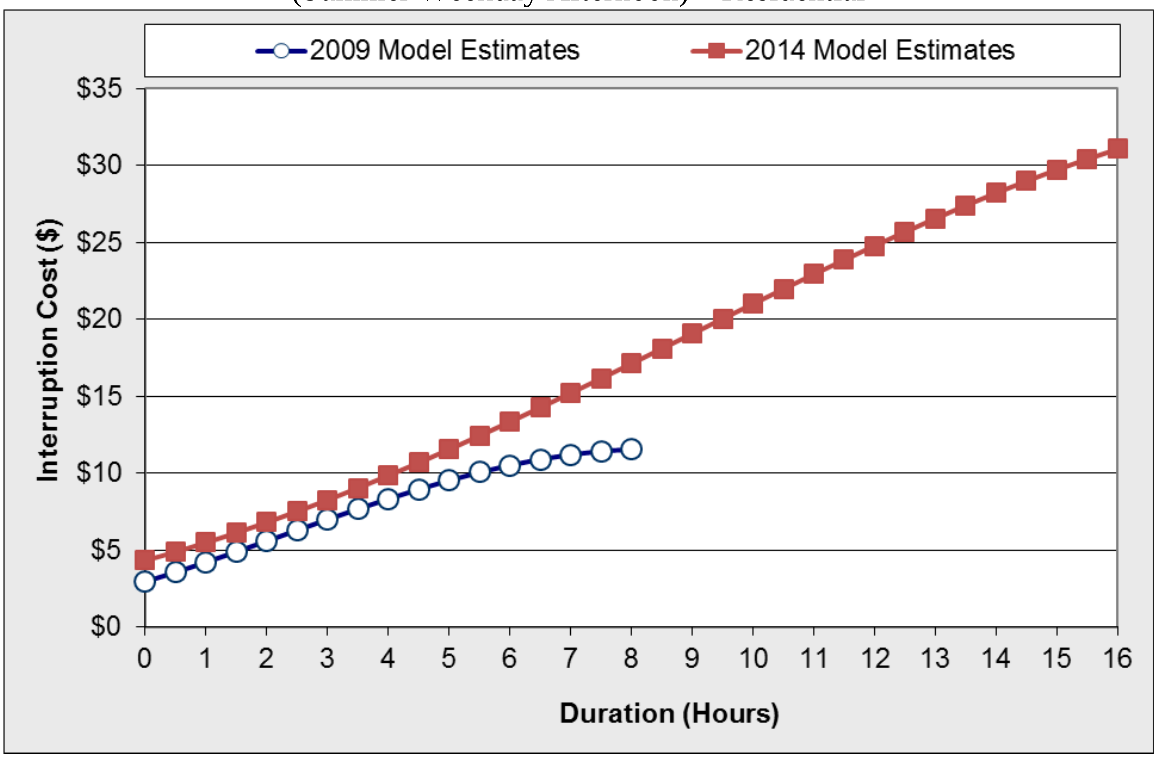
Table 5-6: Descriptive Statistics for Regression Inputs – Residential

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**

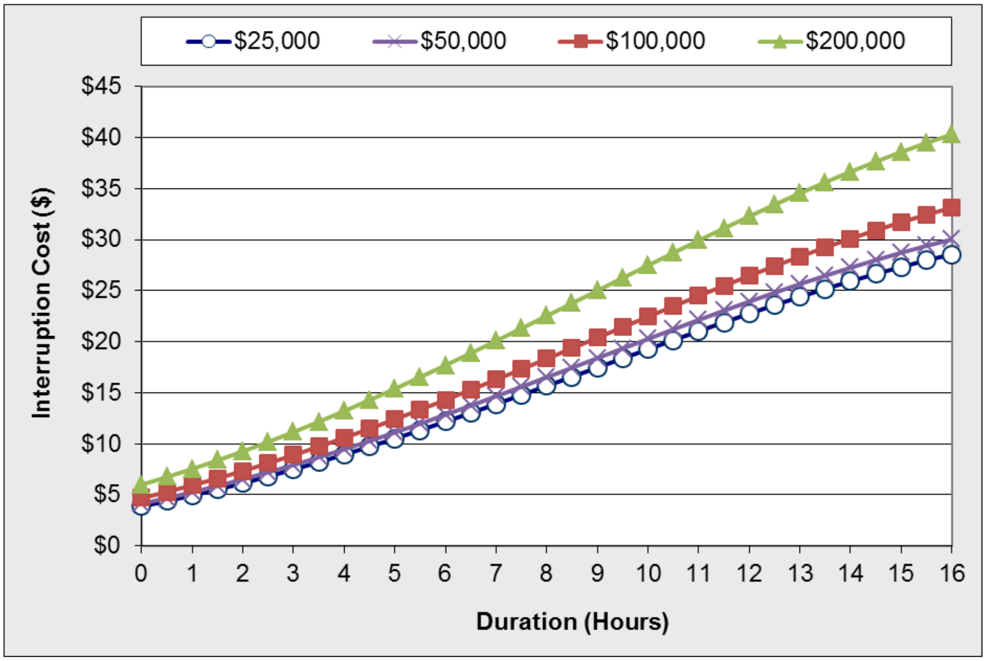
Based on the weighted-average interruption cost estimate, Table 5-8 provides cost per event (equal to the weighted-average interruption cost), cost per average kW, and cost per unserved kWh for residential customers. Cost per unserved kWh is relatively high for a momentary interruption because the expected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

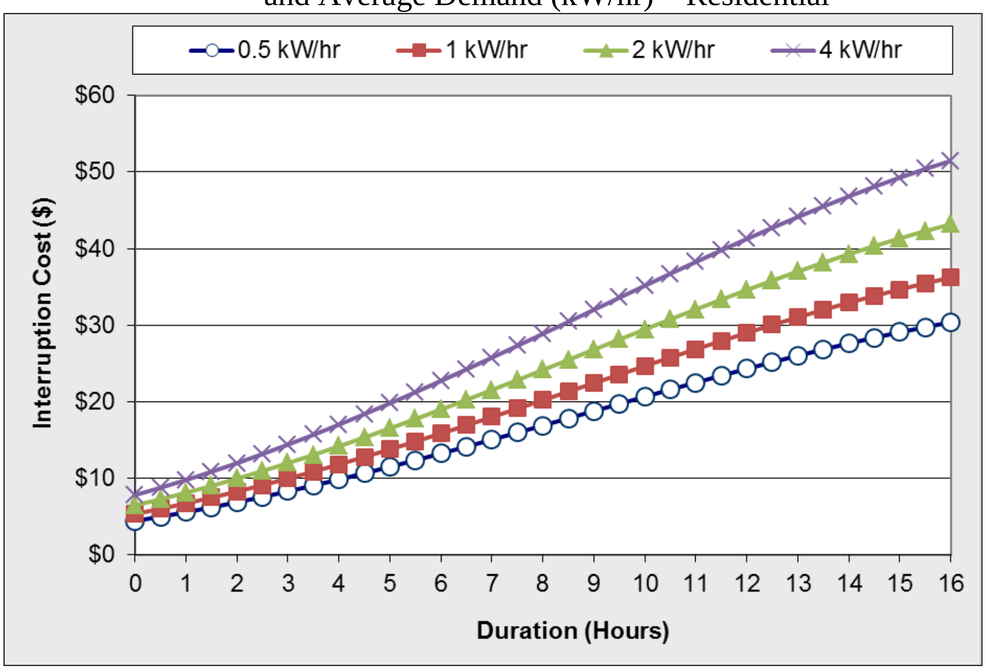
Figure 5-2 shows the residential interruption costs in the summer afternoon by levels of household income. Household income has a relatively modest impact on interruption costs. Between a household income of $50,000 and $100,000, the difference in interruption costs is only around 10% for all durations.

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.

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

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

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

North Carolina Public Staff
Data Request No. 133
DEC Docket No. E-7, Sub 1214
Item No. 133-13

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
Docket No. E-7, Subs 1213 and 1214

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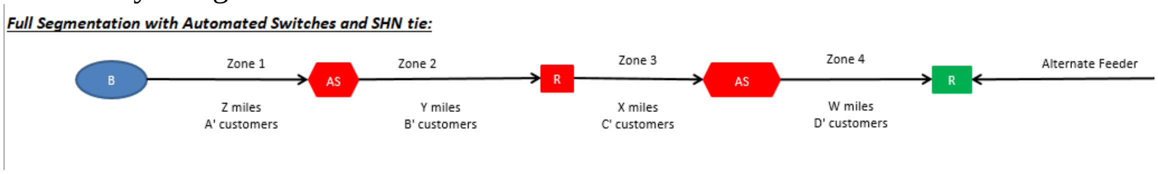
The attached response to North Carolina Public Staff Data Request No. 179-4, was provided to me by the following individual(s): Karen Ann Ralph, Lead Planning & Regulatory Support Specialist, and was provided to North Carolina Public Staff under my supervision.

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:

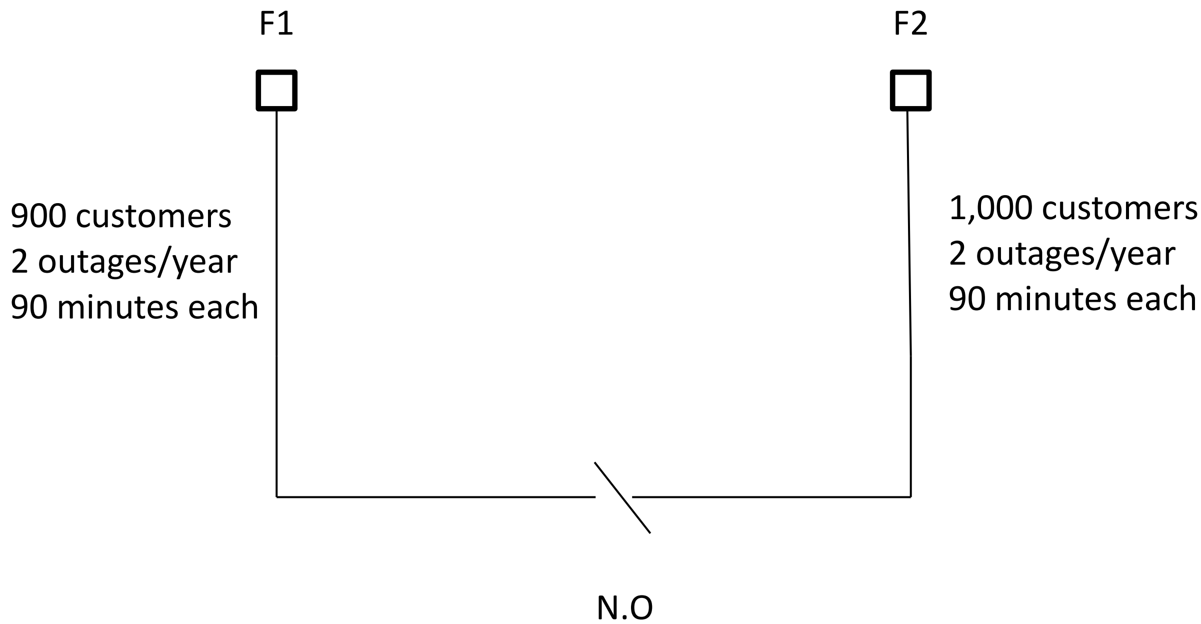
4. Assuming a fault in Zone 2 produces a fault current magnitude & duration greater than the substation breaker relay trip curve then the substation breaker would trip and reclose and as such all customers in zones 1, 2, 3, & 4 would experience a momentary interruption.
a. Assuming a fault in zone 2 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.

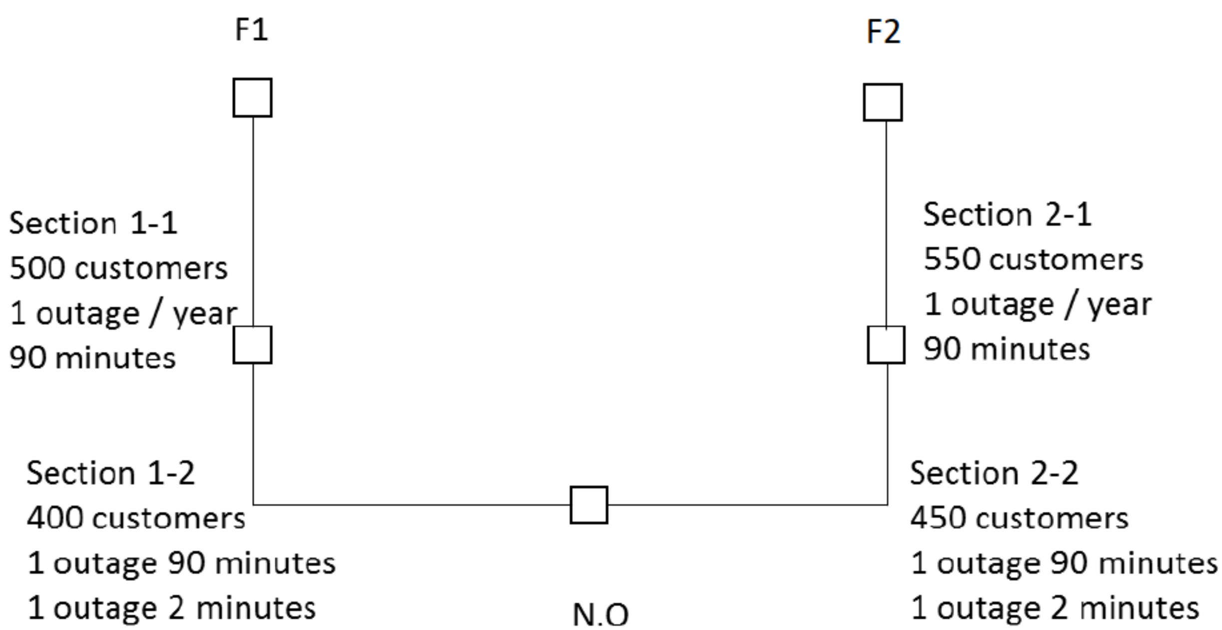
This document provides a very basic example of how to use the ICE tool to accurately calculate the reliability benefits when sustained outages are changed to momentary outages. It normally requires building at least two models and combining the results. Consider this simple example with two feeders, 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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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 Duration				
Interruption Cost	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.
[13] 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.
[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 $\gamma=0$, we obtain the usual nonlinear least squares estimator. In the case $\gamma=1$, 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 $\gamma=2$ 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 ($\gamma=2$) are in some respects a natural "baseline" specification, since if the true model is actually $C= \exp(X \cdot \beta)*u$, 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.

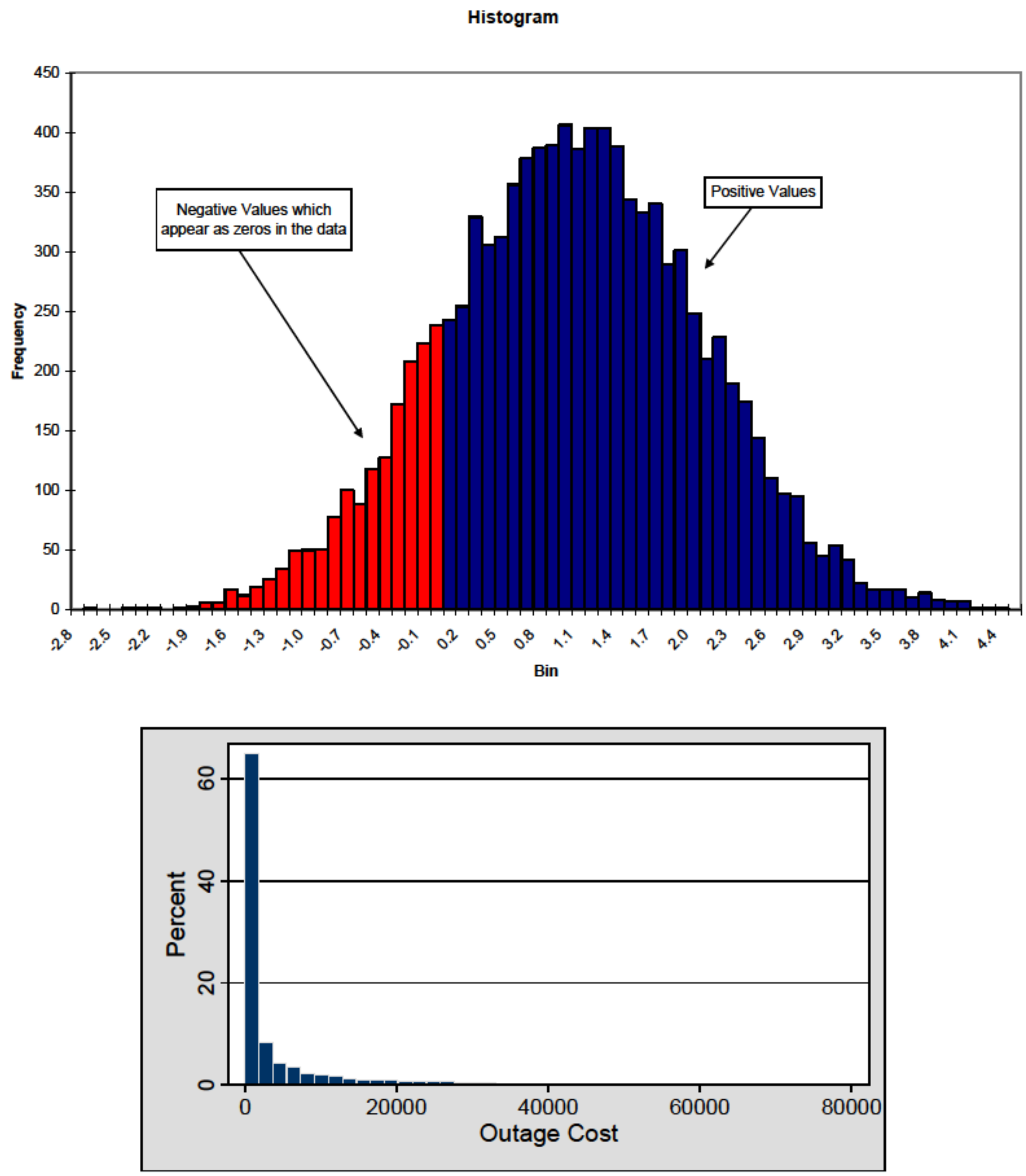

Figure 2-1. Comparison of Censored Distribution with the Actual Distribution of Interruption Costs for Medium and Large Commercial and Industrial Customers Histogram of Interruption Costs (0 to 95th Percentile)

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

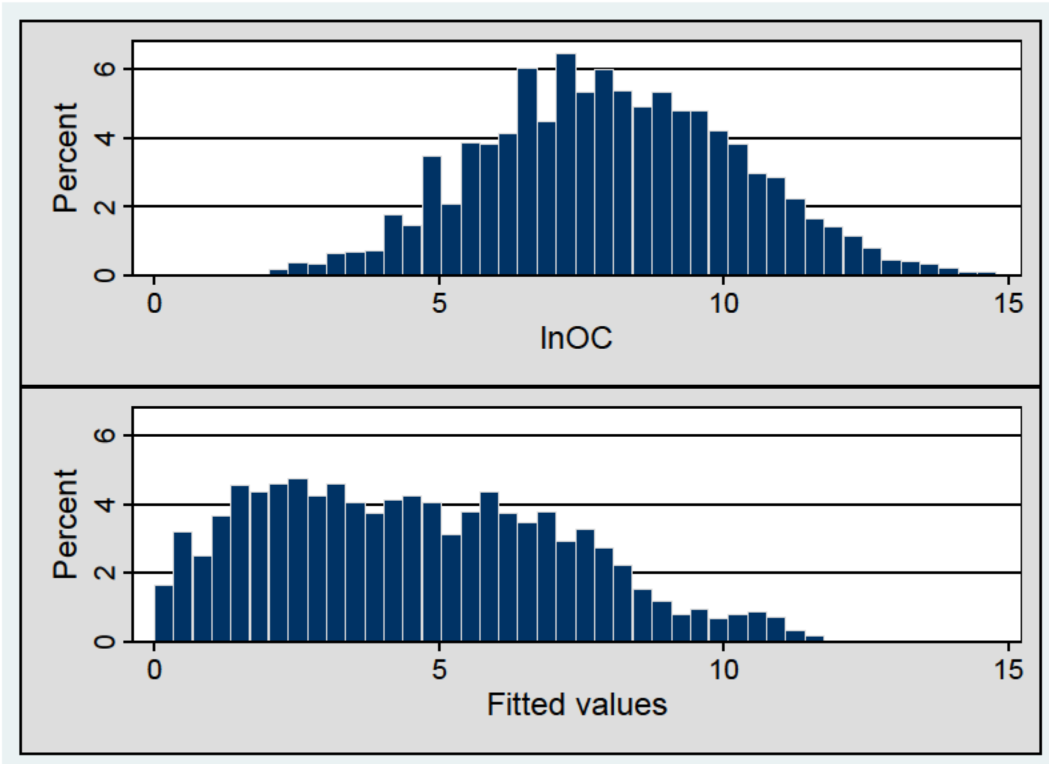

Figure 2-2. Medium and Large Commercial and Industrial Customers Histogram of Reported and Predicted Log Interruption Costs Using Tobit Specification

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:

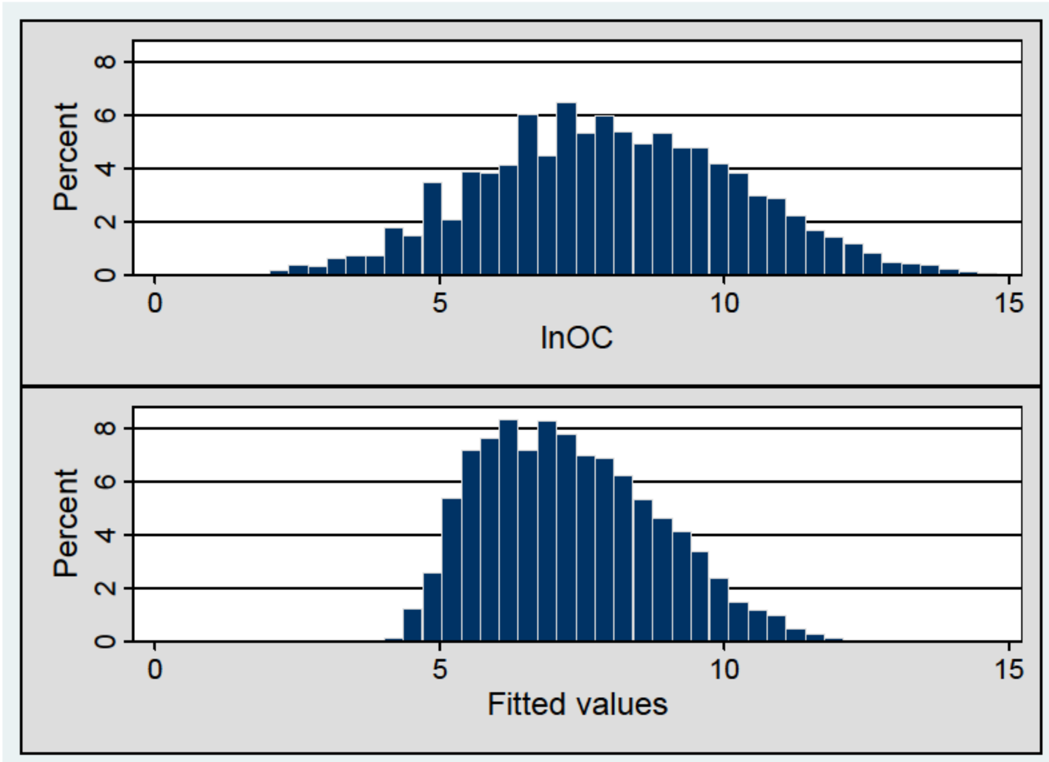

Figure 2-3. Medium and Large Commercial and Industrial Customers Histogram of Reported and Predicted Log Interruption Costs Using Heckman Specification

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.

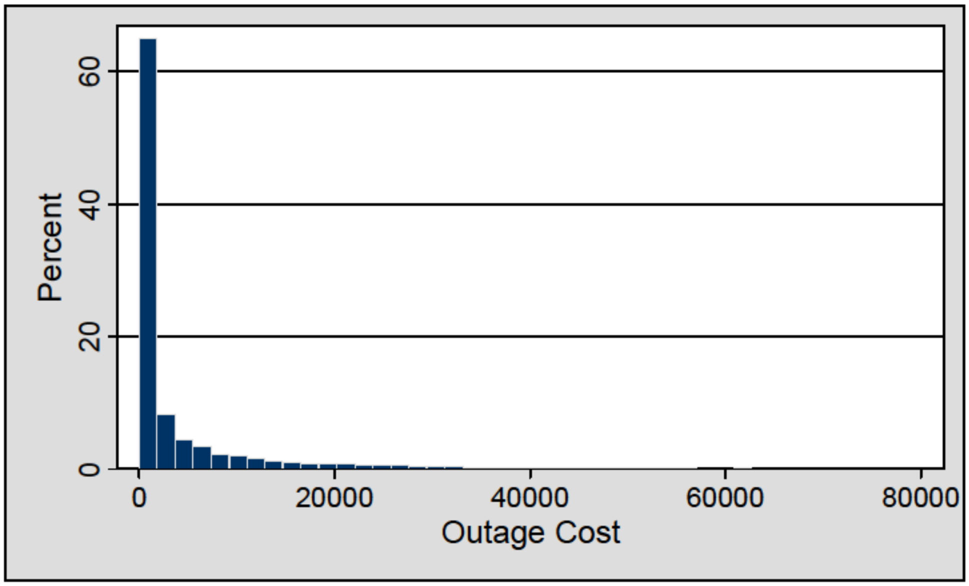

Figure 3-1. Medium and Large Commercial and Industrial Customers Histogram of Interruption Costs (0 to 95th Percentile)

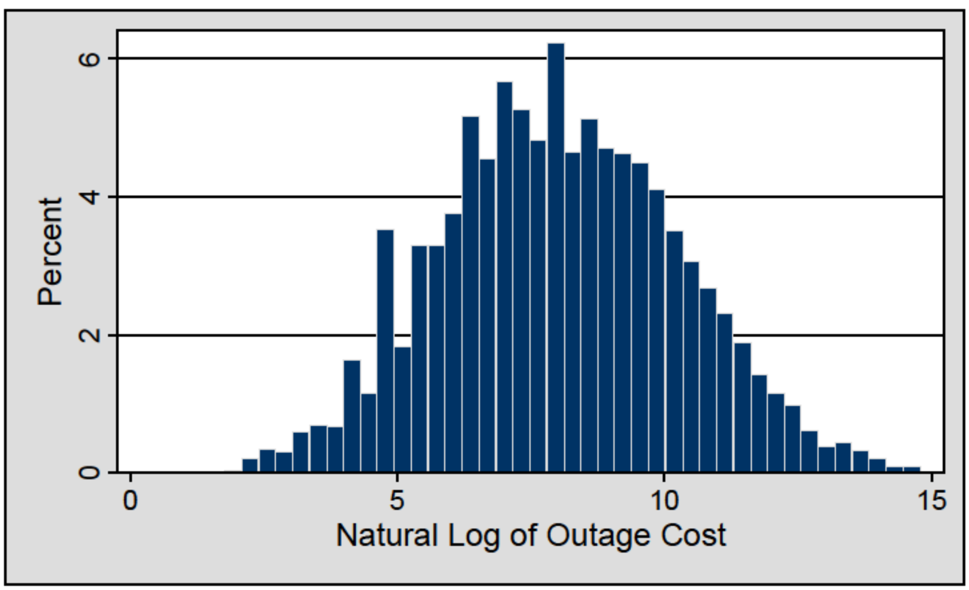

Figure 3-2. : Medium and Large Commercial and Industrial Customers Histogram of Log Interruption Costs, Positive Values Only

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.

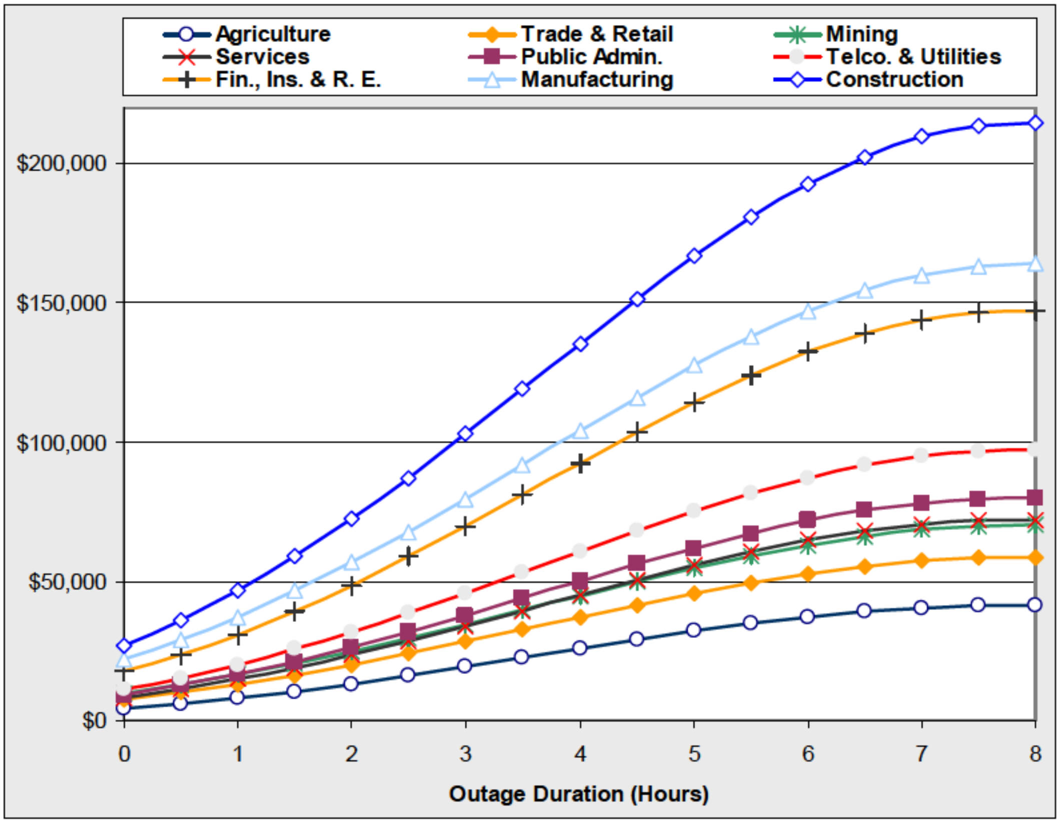

Figure 3-3. Medium and Large Commercial and Industrial Customers US 2008$ Customer Damage Functions by Industry - Summer Weekday Afternoon

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.

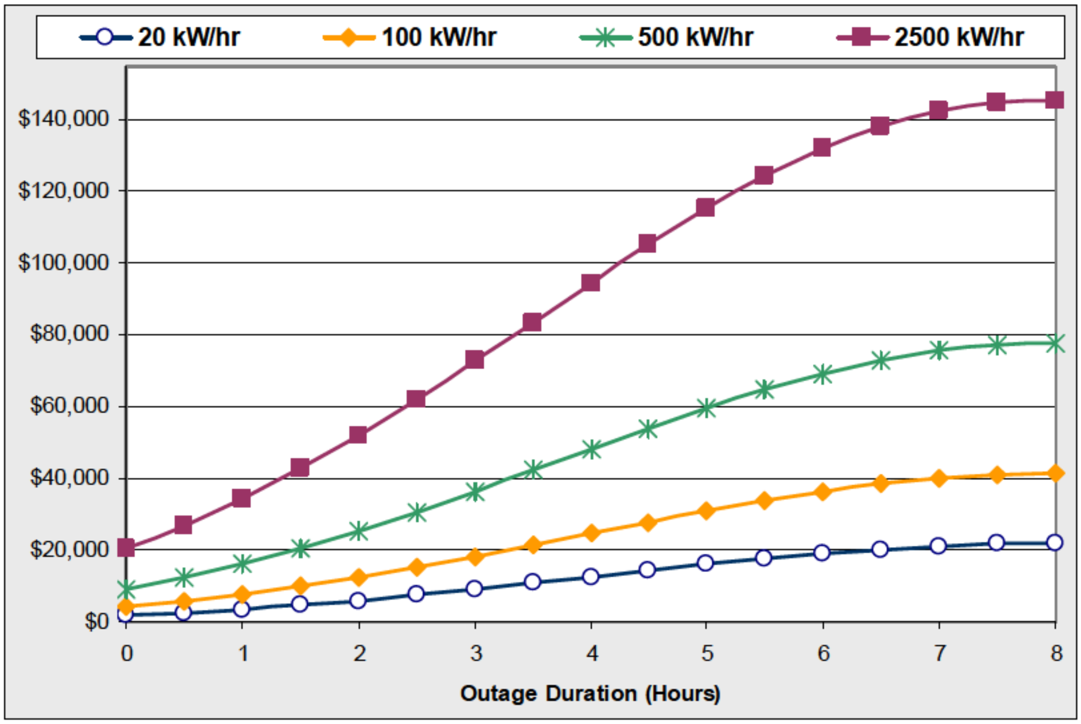

Figure 3-4. Medium and Large Commercial and Industrial Customers US 2008$ Customer Damage Functions by Average kW - Summer Weekday Afternoon

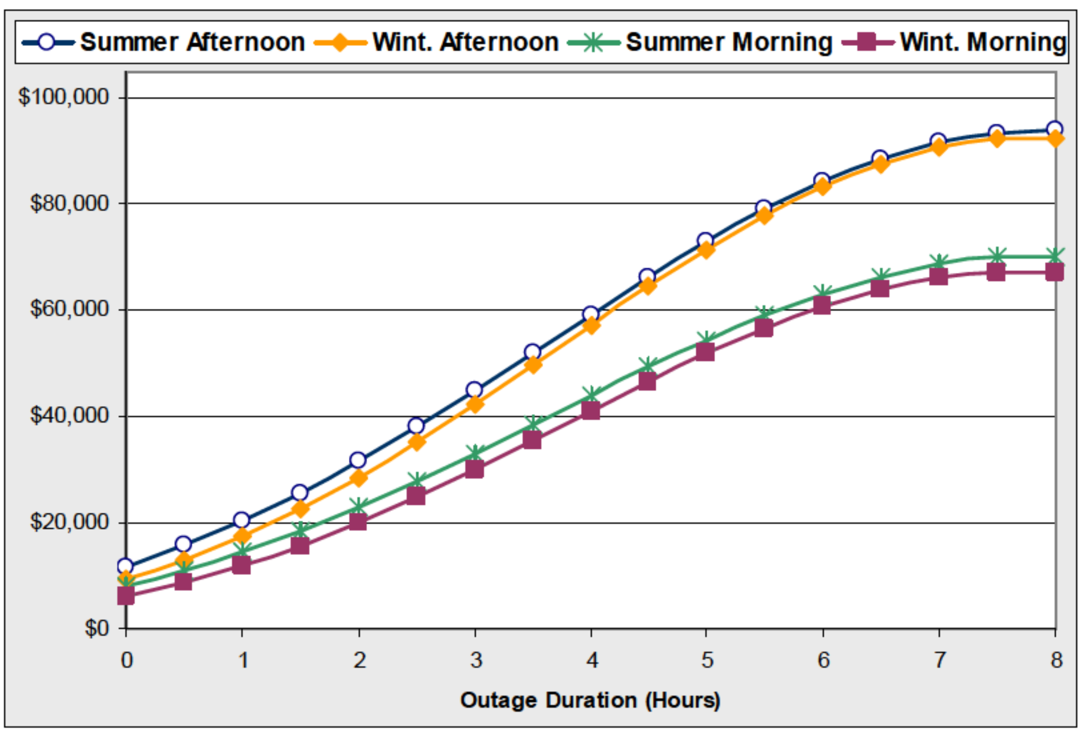

Figure 3-5. Medium and Large Commercial and Industrial Customers US 2008$ Customer Damage Functions by Season and Time of Day

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.

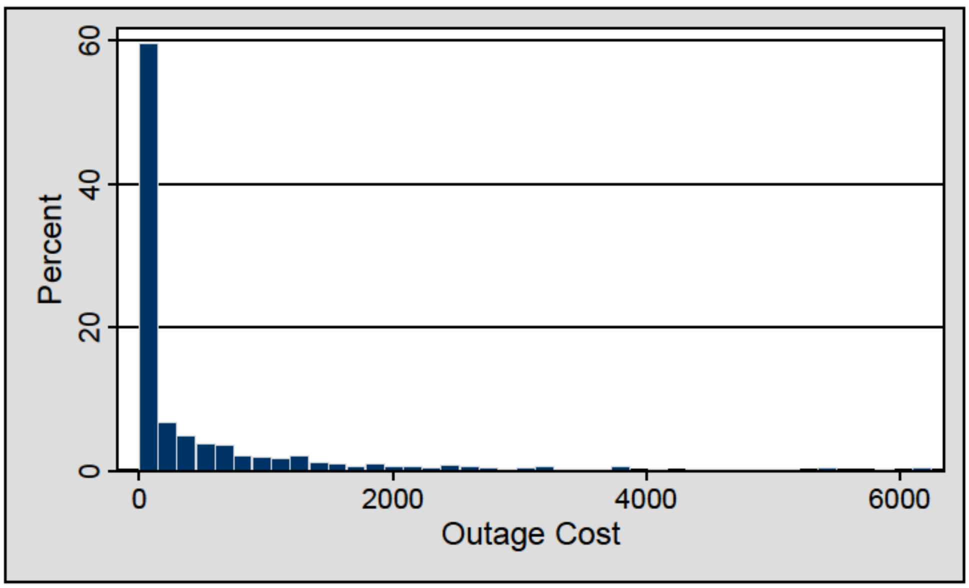

Figure 4-1. Small Commercial and Industrial Customers Histogram of Interruption Costs (0 to 95th Percentile)

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

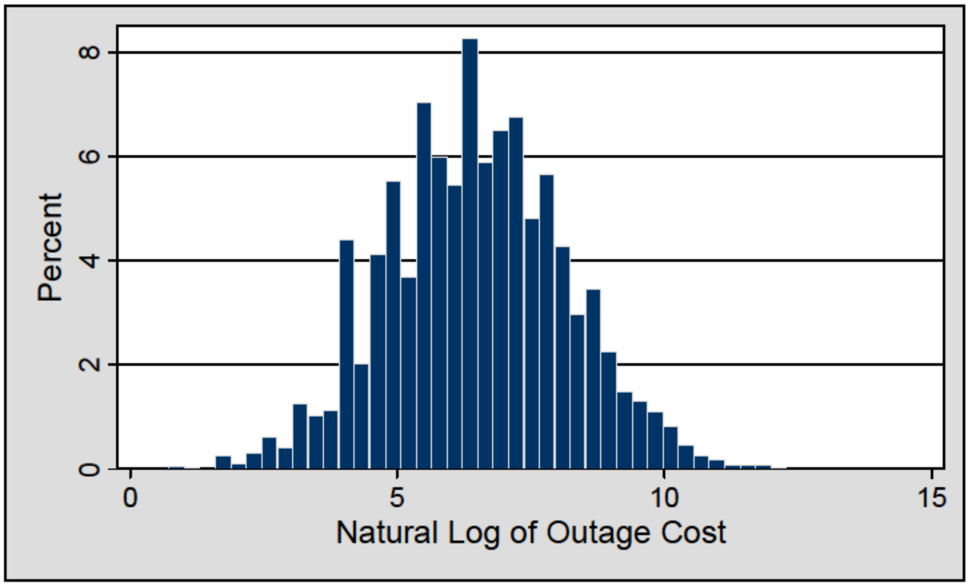

Figure 4-2. Small Commercial and Industrial Customers Histogram of Log Interruption Costs, Positive Values Only

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.

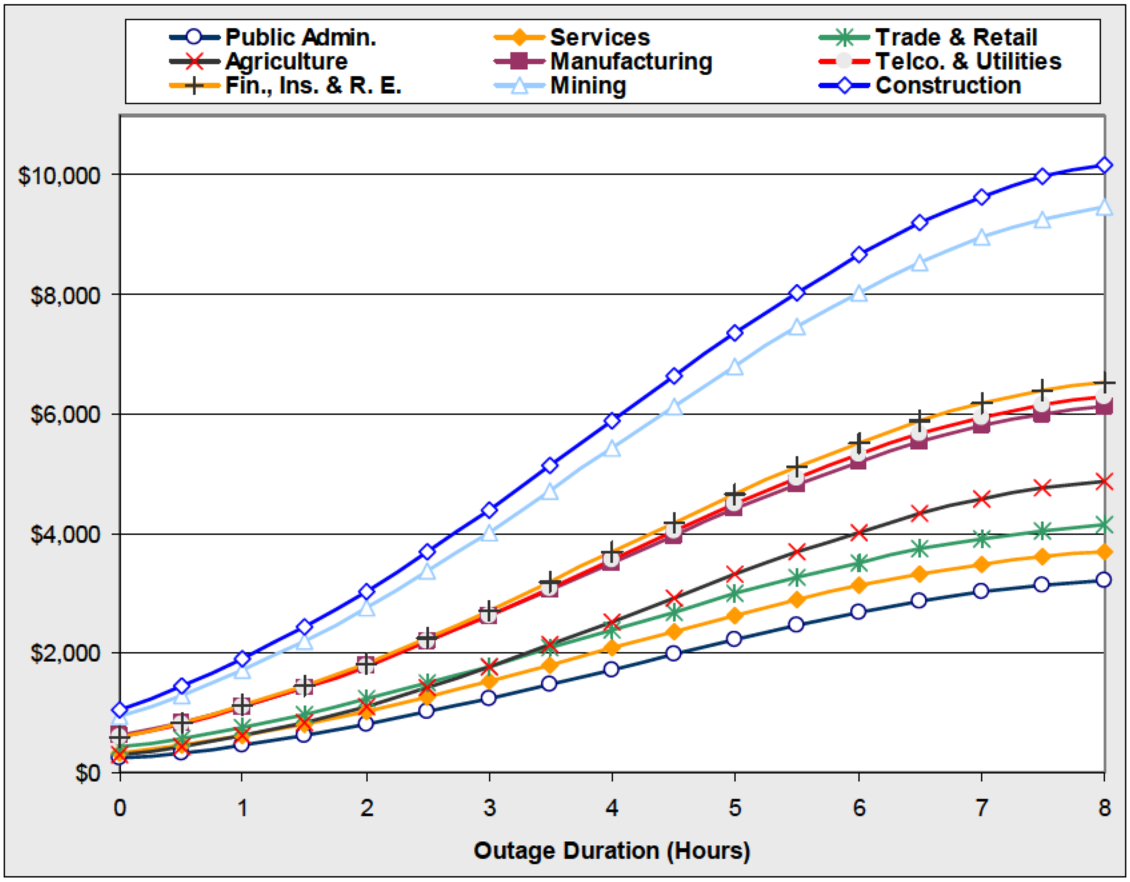

Figure 4-3. Small Commercial and Industrial Customers US 2008$ Customer Damage Functions by Industry- Summer Weekday Afternoon

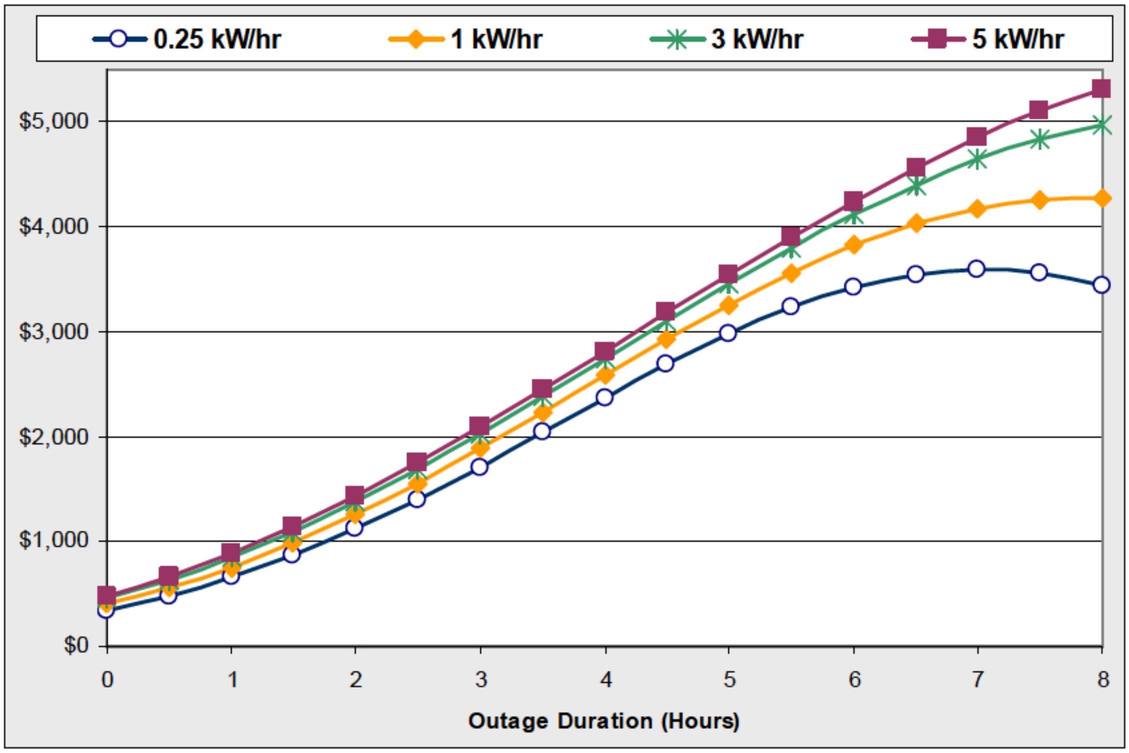

Figure 4-4. Small Commercial and Industrial Customers US 2008$ Customer Damage Functions by Average kW - Summer Weekday Afternoon

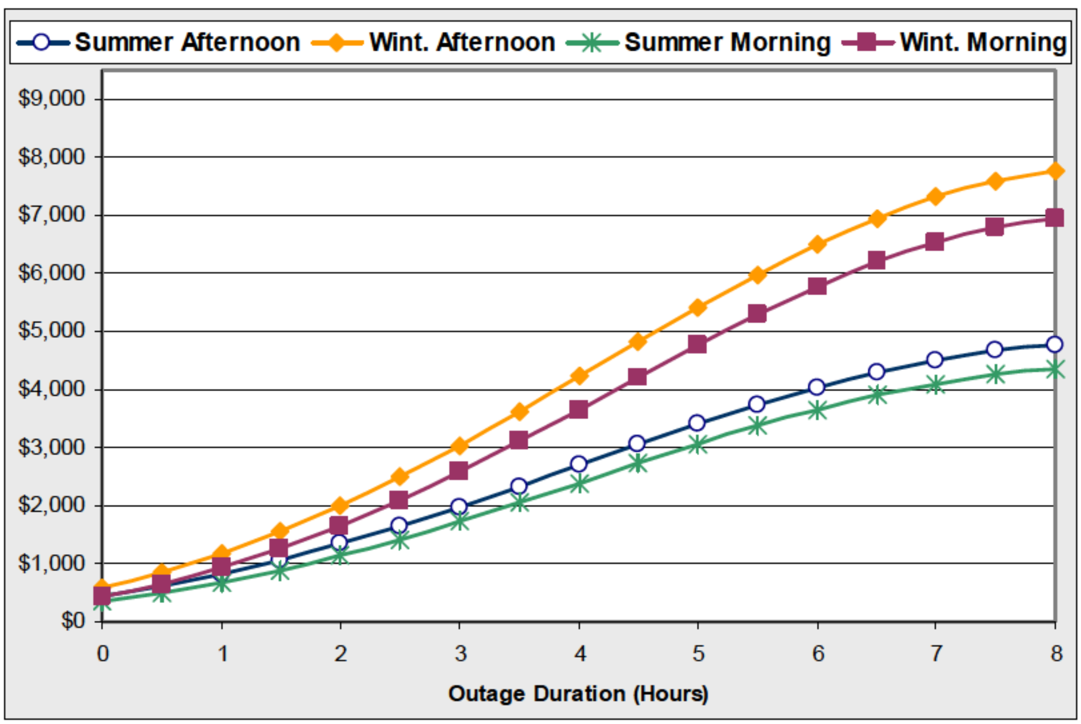

Figure 4-5. Small Commercial and Industrial Customers US 2008$ Customer Damage Functions by Season and Time of Day

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.

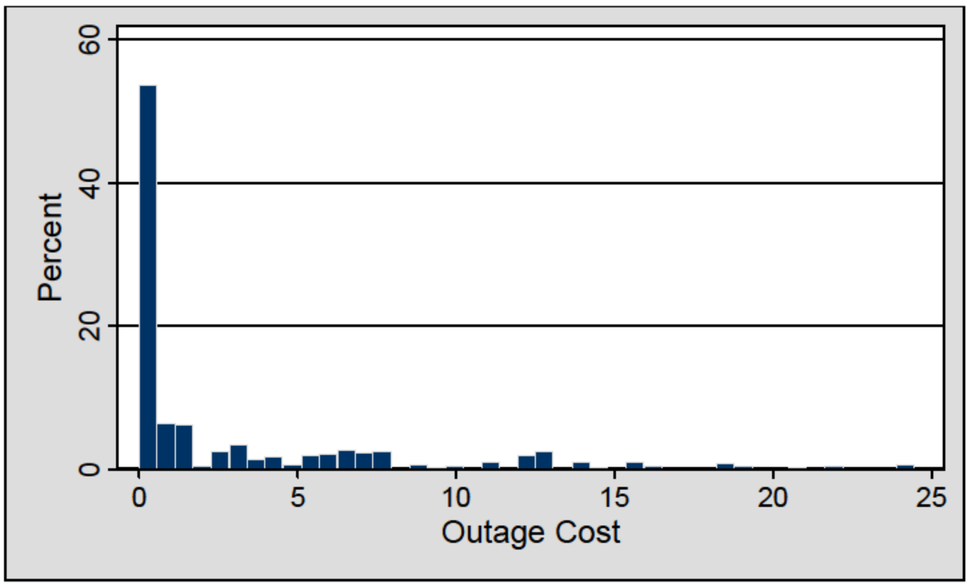

Figure 5-1. Residential Customers Histogram of Interruption Costs (0 to 95th Percentile)

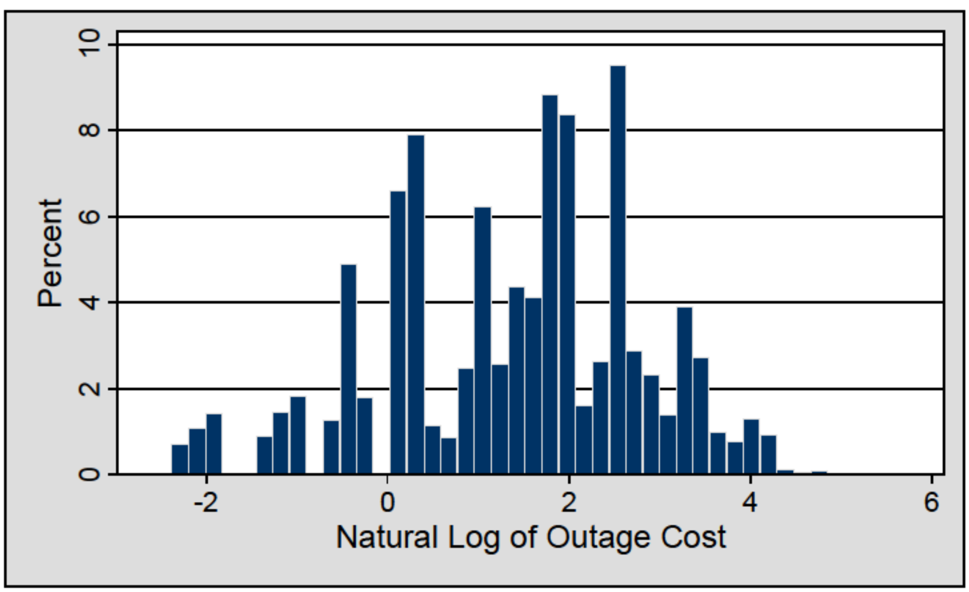

Figure 5-2. Residential Customers Histogram of Log Interruption Costs, Positive Values Only

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.

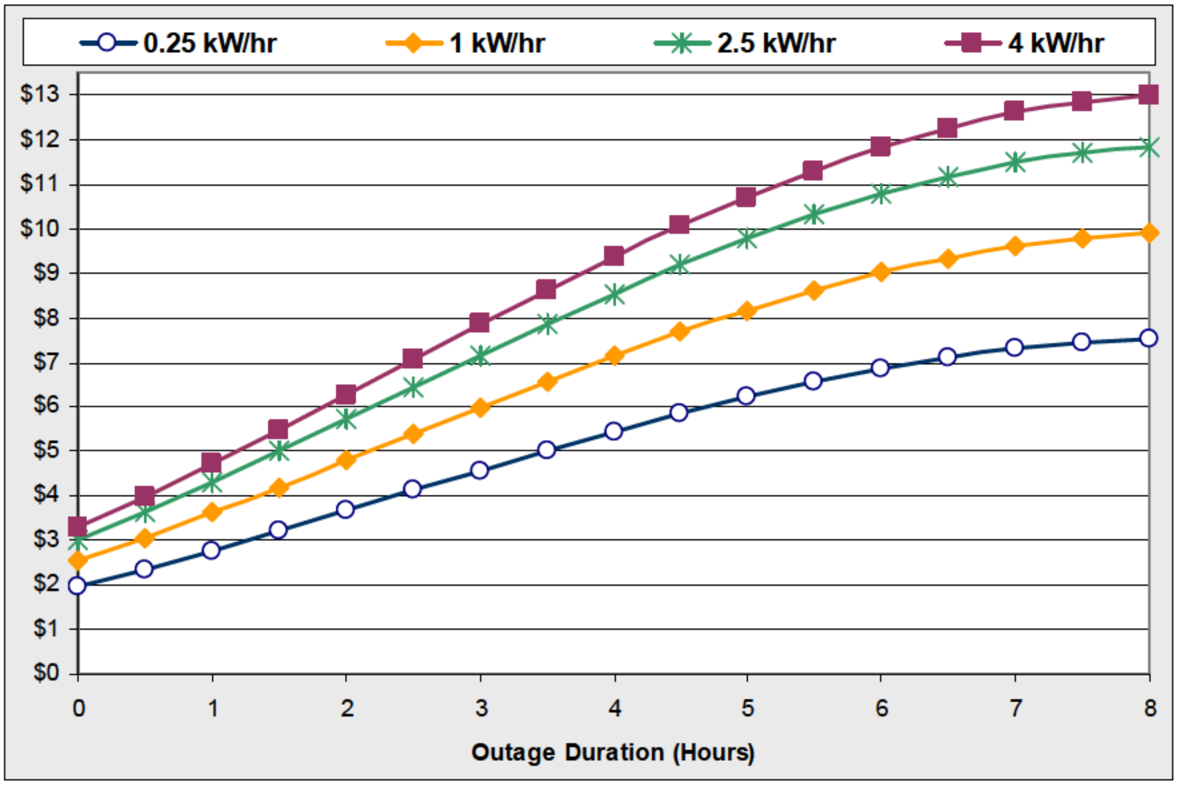

Figure 5-3. Residential Customers US 2008$ Customer Damage Functions by Average kW - Summer Weekday Afternoon

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.

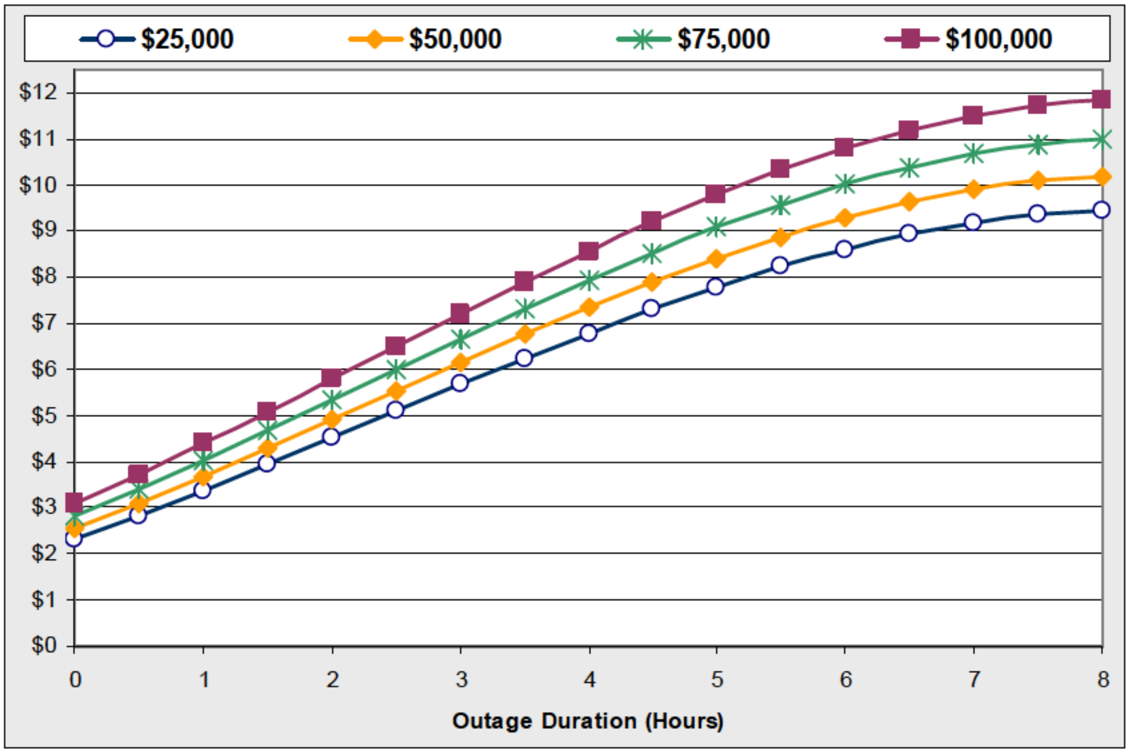

Figure 5-4. Residential Customers US 2008$ Customer Damage Functions by Household Income - Summer Weekday Afternoon

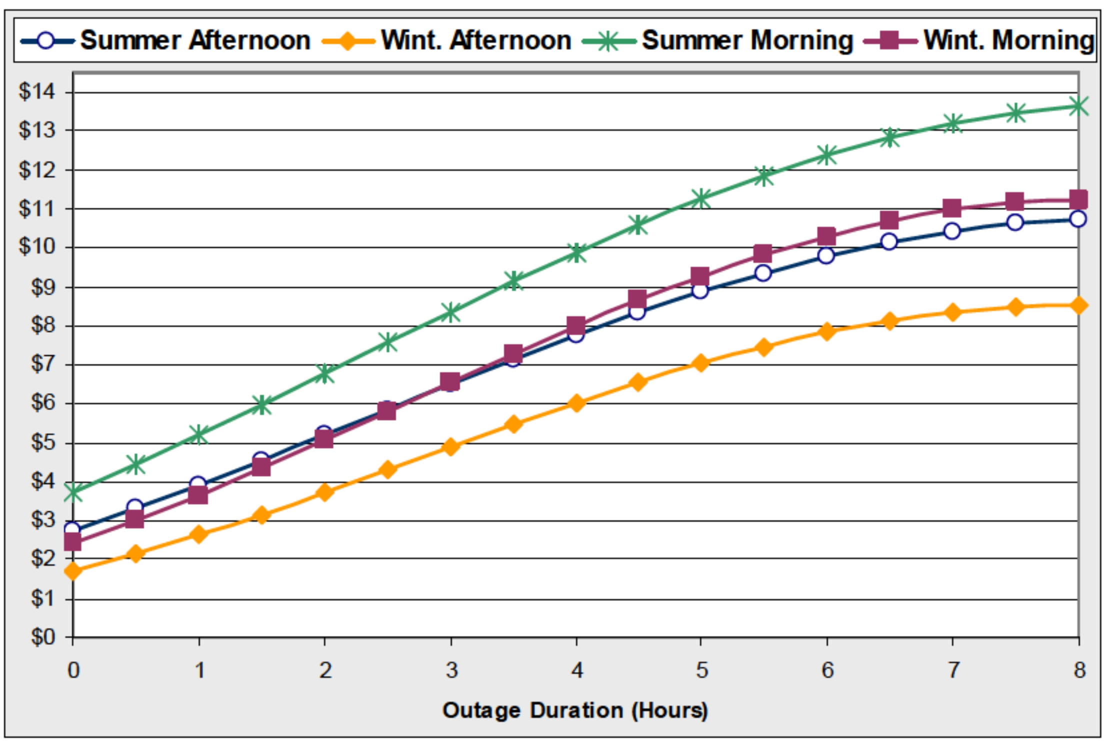

Figure 5-5. Residential Customers US 2008$ Customer Damage Functions by Season and Time of Day

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.

I/A

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 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) 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.

DUKE ENERGY CAROLINAS, LLC

Request:

Please provide a narrative that describes the integration process of supply side and demand side resources where DEC attempts to determine the optimal level of prospective DSM/EE programs. This response should include discussion on areas in the process where there is a lack of integration. This response should also include a discussion of how DEC identifies the threshold DSM/EE levels that result in changes in the resource plan, e.g. with zero DSM/EE, the resource plan results in new capacity needed in year X, with some level of DSM/EE, the need for new capacity is moved out to year X +1, with further DSM/EE, the need for new capacity is moved out to year X + 2 and so on. If DEC does not do this type of analysis, please explain how DEC determines that its total quantity of DSM/EE is optimal in the context of an *Integrated* Resource Plan that in principle is meant to balance supply- and demand-side resources such that the marginal MW of supply and demand-side resources are equal in cost.

Response:

Unlike natural gas units, solar facilities, hydro facilities or other supply-side options, DSM/EE MW impacts depend on forecasts of customer adoption for each individual DSM/EE measure and program. These long-term adoption rate estimates are shown at a technical potential, economic potential and achievable potential levels as represented in periodically updated "Market Potential Studies." Shorter term projections of EE MW impacts come from forecasted adoption rates from existing NCUC approved DSM/EE programs based on the experience of the program managers along with M&V results. It is this combination of short-term projections for existing programs and longer term achievable potential that, when combined, produce the MW and MWh reduction in the retail load forecast due to utility sponsored EE. It must be noted that achievable potential as represented in the Market Potential Study recognizes many factors outside of a traditional IRP process which focuses primarily on PVRR minimization. Factors such as appliance turn-over rates, participant cost effectiveness, general customer acceptance, free rider assumptions, efficiency standards, etc. all influence long-term projections for DSM/EE impacts. Furthermore, DSM/EE programs have separate cost-effectiveness metrics that include the utility cost test (UCT), the participant cost test (PCT) and the non-participant (or rate impact) RIM upon which programs are submitted to the NCUC for consideration. The IRP process, once completed, does inform DSM/EE cost-effectiveness for future filings by providing the EE analysis the avoided marginal energy benefits of DSM/EE consistent with the IRP planning assumptions around load, commodity prices and other input variables. Similar to historic QF pricing of capacity, historic DSM/EE utilize the current cost of a peaker for the avoided capacity component of cost effectiveness irrespective of the utility's need for capacity. All approved cost-effective programs then reduce the retail load that goes into the IRP. The balancing of EE relative to utility need for capacity, as described in Staff's question, would happen when incremental new programs are tested for cost effectiveness under the UCT. At that point, for example, if the utility did not have a need new capacity until 2022, no avoided capacity value would be ascribed in the UCT until 2022. By way of comparison, this is consistent with new solar facilities that would not have capacity value ascribed until 2022 while existing solar facilities are receiving a capacity payment based on an immediate need for capacity. It is wholly consistent to treat avoided capacity value for existing EE the same way existing QFs are treated with respect to capacity valuation, while treating incremental EE capacity value in the same manner incremental solar QF capacity value is being treated.

NC Public Staff
Docket No. E-7 Sub 1164
NC Public Staff Data Request No. 14
2018 DSM/EE Rider (Avoided Costs)
Item No. 14-4

DUKE ENERGY CAROLINAS, LLC

Request:

Please discuss the changes in the resource plan (e.g. new capacity would be needed sooner or later and avoided energy and capacity costs would go up or down) that would likely occur if all anticipated future QF contracts that are modeled in the IRP are taken out.

Response:

If all anticipated future QF contracts were removed from the DECarolinas 2016 resource plan, the need for new capacity would advance one year, from December 2022 to December 2021. Some of the future QFs already have existing LEOs before November 1, 2016. These QFs will have capacity payments that did not take into account the need for capacity in the derivation of the capacity rate.

Exhibit JRW-1

Duke Energy Carolinas, LLC
Recommended Cost of Capital

Panel A - Primary Cost of Capital Recommendation

Capital Source	Capitalization Ratios*	Cost Rate	Weighted Cost Rate
Long-Term Debt	50.00%	4.51%	2.26%
Common Equity	50.00%	9.00%	4.50%
Total Capitalization	100.00%		6.76%

* 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	47.00%	4.51%	2.12%
Common Equity	53.00%	8.40%	4.45%
Total Capitalization	100.00%		6.57%

* Capital Structure Ratios are developed in Exhibit JRW-3.

Exhibit JRW-2

Duke Energy Carolinas, 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	Market to Book Ratio
ALLETE, Inc. (NYSE-ALE)	$1,498.6	71%	0%	$3,904.4	$3,993.8	BBB+	Baa1	3.34	MN, WI	59.2%	8.2%	1.85	1.85
Alliant Energy Corporation (NYSE-LNT)	$3,534.5	85%	13%	$12,462.4	$10,172.3	A-	Baa1	3.31	WI,IA,IL,MN	44.6%	11.4%	2.13	2.13
Ameren Corporation (NYSE-AEE)	$6,291.0	85%	15%	$22,810.0	$16,366.8	BBB+	Baa1	3.64	IL,MO	46.2%	10.9%	2.11	2.11
American Electric Power Co. (NYSE-AEP)	$16,195.7	88%	0%	$55,099.1	$37,379.9	A-	Baa1	2.99	10 States	42.7%	10.3%	1.96	1.96
Avangrid (NYSE-AVG)	$6,291.0	56%	23%	$22,810.0	$16,366.8	BBB+	Baa1	3.53	NY,CT,ME	70.8%	3.9%	1.06	1.06
Avista Corp (NYSE-AVA)	$1,396.9	64%	22%	$4,648.9	$2,881.1	BBB	Baa2	2.61	WA,OR,AK,ID	45.7%	7.80%	1.62	2.91
CMS Energy Corporation (NYSE-CMS)	$6,873.0	66%	28%	$18,126.0	$13,966.2	BBB+	Baa1	2.67	MI	28.9%	14.2%	2.91	1.52
Consolidated Edison, Inc. (NYSE-ED)	$12,337.0	70%	19%	$41,749.0	$25,673.3	BBB+	A3	3.03	NY,PA	44.8%	8.6%	1.52	1.45
Dominion Energy, Inc. (NYSE-D)	$13,366.0	70%	15%	$54,560.0	$51,000.1	BBB+	NA	3.10	VA,NC,SC,OH,WV,UT	38.5%	12.31%	2.31	1.43
Duke Energy Corporation (NYSE-DUK)	$24,521.0	90%	7%	$91,694.0	$63,736.1	A-	Baa1	2.47	NC,OH,FL,SC,KY	43.1%	6.2%	1.45	1.86
Edison International (NYSE-EIX)	$12,657.0	100%	0%	$41,348.0	$18,107.4	BBB	Baa3	(0.48)	CA	45.1%	-2.4%	1.43	1.87
Entergy Corporation (NYSE-ETR)	$11,009.5	85%	1%	$31,974.4	$16,448.0	BBB+	Baa2	0.69	LA,AR,MS,TX	32.8%	10.2%	1.86	1.40
Evergy (NYSE:EVRG)	$4,275.9	100%	0%	$18,782.5	$14,840.0	A-	Baa1	3.11	KS,MO	54.2%	7.9%	1.49	2.77
Eversource Energy (NYSE-ES)	$8,448.2	79%	10%	$25,610.4	$21,470.9	A-	Baa1	3.67	CT,NH,MA	46.7%	9.2%	1.87	1.88
Exelon Corporation (NYSE-EXC)	$11,009.5	56%	5%	$31,974.4	$46,448.0	BBB+	Baa2	2.44	PA,NJ,IL,MD,DCDE	47.8%	6.4%	1.40	3.60
FirstEnergy Corporation (NYSE-FE)	$11,261.0	91%	0%	$29,911.0	$18,851.1	BBB	Baa3	2.17	OH,PA,NY,NJ,WV,MD	25.8%	25.1%	2.77	2.82
Hawaiian Electric Industries (NYSE-HE)	$2,860.8	89%	0%	$4,830.1	$4,060.1	BBB-	NA	3.87	HI	51.2%	9.6%	1.88	2.22
IDACORP, Inc. (NYSE-IDA)	$1,370.8	100%	0%	$4,395.7	$8,562.5	BBB	Baa1	3.85	ID	56.4%	9.8%	3.60	1.54
MGE Energy, Inc. (NYSE-MGEE)	$559.8	72%	28%	$1,509.4	$2,303.7	AA-	Aa2	7.69	WI	61.5%	10.6%	2.82	1.97
NextEra Energy, Inc. (NYSE-NEE)	$16,727.0	71%	0%	$70,334.0	$83,224.6	A-	Baa1	5.87	FL	49.8%	17.3%	2.22	3.04
NorthWestern Corporation (NYSE-NWE)	$1,192.0	77%	23%	$4,521.3	$2,991.2	BBB	NA	2.94	MT,SD,NE	47.8%	10.5%	1.54	1.92
OGE Energy Corp. (NYSE-OGE)	$2,270.3	100%	0%	$8,643.8	$7,899.1	BBB+	Baa1	4.19	OK,AR	56.0%	10.8%	1.97	1.71
Pinnacle West Capital Corp. (NYSE-PNW)	$3,691.2	95%	0%	$14,029.6	$16,260.8	A-	A3	4.04	AZ	50.6%	10.1%	3.04	1.75
Portland General Electric Company (NYSE-POR)	$1,991.0	100%	0%	$6,887.0	$4,287.2	BBB+	A3	2.85	OR	50.3%	8.6%	1.71	1.63
PNM Resources, Inc. (NYSE-PNM)	$1,436.6	100%	0%	$5,234.6	$3,360.4	BBB+	Baa3	1.73	NM,TX	37.6%	5.8%	1.92	1.67
PPL Corporation (NYSE-PPL)	$7,785.0	94%	4%	$34,458.0	$20,457.2	A-	Baa2	3.37	PA,KY	34.6%	16.3%	1.75	2.30
Sempra Energy (NYSE-SRE)	$1,991.0	56%	44%	$6,887.0	$31,467.5	BBB+	Baa1	2.02	CA,TX	43.1%	6.5%	1.63	2.13
Southern Company (NYSE-SO)	$23,495.0	65%	14%	$80,797.0	$48,493.6	A-	Baa2	2.49	GA,FL,NJ,IL,VA,TN,MS	38.3%	8.4%	1.67	2.02
WEC Energy Group (NYSE-WEC)	$7,679.5	58%	42%	$22,000.9	$22,541.0	A-	Baa1	3.76	WI,IL,MN,MI	45.3%	3.3%	2.30	1.88
Xcel Energy Inc. (NYSE-XEL)	$11,537.0	84%	15%	$36,944.0	$25,972.7	A-	Baa1	3.21	MN,WI,ND,SD,MI	41.5%	10.7%	2.13	
Mean	$7,851.8	81%	11%	$26,964.6	$21,986.1	BBB+	Baa1	3.14		46.0%	9.6%	2.00	
Median	$6,582.0	85%	6%	$22,405.5	$16,407.4	BBB+	Baa1	3.10		45.5%	9.7%	1.87	

Data Source Company 2018 SEC 10-K filings; *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	Market to Book Ratio
ALLETE, Inc. (NYSE-ALE)	$1,498.6	71%	0%	$3,904.4	$3,993.8	BBB+	Baa1	3.34	MN, WI	59.2%	8.2%	1.85	1.85
Alliant Energy Corporation (NYSE-LNT)	$3,534.5	85%	13%	$12,462.4	$10,172.3	A-	Baa1	3.31	WI,IA,IL,MN	44.6%	11.4%	2.13	2.13
Ameren Corporation (NYSE-AEE)	$6,291.0	85%	15%	$22,810.0	$16,366.8	BBB+	Baa1	3.64	IL,MO	46.2%	10.9%	2.11	2.11
American Electric Power Co. (NYSE-AEP)	$16,195.7	88%	0%	$55,099.1	$37,379.9	A-	NA	2.99	10 States	42.7%	10.3%	1.96	1.96
Avangrid (NYSE-AVG)	$6,291.0	56%	23%	$22,810.0	$16,366.8	BBB+	Baa1	3.53	NY,CT,ME	70.8%	3.9%	1.06	1.06
CMS Energy Corporation (NYSE-CMS)	$6,873.0	66%	28%	$18,126.0	$13,966.2	BBB+	NA	2.67	MI	28.9%	14.2%	2.91	1.52
DTE Energy Company (NYSE-DTE)	$14,212.0	37%	39%	$21,650.0	$20,066.4	BBB+	Baa1	3.15	MI	42.9%	10.8%	1.87	
Evergy (NYSE:EVRG)	$4,275.9	100%	0%	$18,782.5	$14,840.0	A-	Baa1	3.11	KS,MO	54.2%	7.9%	1.49	2.77
Hawaiian Electric Industries (NYSE-HE)	$2,860.8	89%	0%	$4,830.1	$4,060.1	BBB-	NA	3.87	HI	51.2%	9.6%	1.88	2.22
NextEra Energy, Inc. (NYSE-NEE)	$16,727.0	71%	0%	$70,334.0	$83,224.6	A-	Baa1	5.87	FL	49.8%	17.3%	2.22	3.04
NorthWestern Corporation (NYSE-NWE)	$1,192.0	77%	23%	$4,521.3	$2,991.2	BBB	NA	2.94	MT,SD,NE	47.8%	10.5%	1.54	1.92
OGE Energy Corp. (NYSE-OGE)	$2,270.3	100%	0%	$8,643.8	$7,899.1	BBB+	NA	4.19	OK,AR	56.0%	10.8%	1.97	1.71
Otter Tail Corporation (NDQ-OTTR)	$916.4	49%	0%	$1,581.1	$1,975.3	BBB	Baa2	4.19	OK,AR	54.5%	11.6%	2.71	
Pinnacle West Capital Corp. (NYSE-PNW)	$3,691.2	95%	0%	$14,029.6	$16,260.8	A-	A3	4.04	AZ	50.6%	10.1%	3.04	1.75
Portland General Electric Company (NYSE-POR)	$1,991.0	100%	0%	$6,887.0	$4,287.2	BBB+	A3	2.85	OR	50.3%	8.6%	1.71	1.63
PNM Resources, Inc. (NYSE-PNM)	$1,436.6	100%	0%	$5,234.6	$3,360.4	BBB+	Baa3	1.73	NM,TX	37.6%	5.8%	1.92	1.67
Southern Company (NYSE-SO)	$23,495.0	65%	14%	$80,797.0	$48,493.6	A-	NA	2.49	GA,FL,NJ,IL,VA,TN,MS	38.3%	8.4%	1.67	1.95
WEC Energy Group (NYSE-WEC)	$7,679.5	58%	42%	$22,000.9	$22,541.0	A-	Baa1	3.76	WI,IL,MN,MI	45.3%	3.3%	2.30	1.88
Xcel Energy Inc. (NYSE-XEL)	$11,537.0	84%	15%	$36,944.0	$25,972.7	A-	Baa1	3.21	MN,WI,ND,SD,MI	41.5%	10.7%	2.13	
Mean	$6,998.4	78%	11%	$22,707.8	$18,643.1	BBB+	Baa1	3.42		48.0%	9.7%	2.03	
Median	$4,275.9	84%	0%	$18,126.0	$14,840.0	BBB+	Baa1	3.31		47.8%	10.3%	1.96	

Data Source Company 2018 SEC 10-K filings; *Value Line Investment Survey* , 2019.

Exhibit JRW-2

Duke Energy Carolinas, LLC
***Value Line* Risk Metrics**

Panel A
Electric Proxy Group

Company	Beta	Financial Strength	Safety	Earnings Predictability	Stock Price Stability
ALLETE, Inc. (NYSE-ALE)	0.65	A	2	85	95
Alliant Energy Corporation (NYSE-LNT)	0.60	A	2	90	95
Ameren Corporation (NYSE-AEE)	0.55	A	2	85	95
American Electric Power Co. (NYSE-AEP)	0.55	A+	1	85	100
Avangrid (NYSE-AVG)	0.40	B++	2	NMF	95
Avista Corp (NYSE-AVA)	0.60	A	2	65	90
CMS Energy Corporation (NYSE-CMS)	0.50	B++	2	85	100
Consolidated Edison, Inc. (NYSE-ED)	0.45	A+	1	100	100
Dominion Energy Inc. (NYSE-D)	0.55	B++	2	60	100
Duke Energy Corporation (NYSE-DUK)	0.50	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 (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	60	95
FirstEnergy Corporation (NYSE-FE)	0.65	B++	2	40	90
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)	0.55	A	1	95	85
NextEra Energy, Inc. (NYSE-NEE)	0.55	A+	1	70	100
NorthWestern Corporation (NYSE-NWE)	0.60	B++	2	85	100
OGE Energy Corp. (NYSE-OGE)	0.75	A	2	80	95
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)	0.70	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)	0.50	A+	1	90	95
Xcel Energy Inc. (NYSE-XEL)	0.50	A+	1	100	100
Mean	0.57	A	1.8	77	96

Data Source: *Value Line Investment Survey* , 2019

Panel B
Hevert Proxy Group

Company	Beta	Financial Strength	Safety	Earnings Predictability	Stock Price Stability
ALLETE, Inc. (NYSE-ALE)	0.65	A	2	85	95
Alliant Energy Corporation (NYSE-LNT)	0.60	A	2	90	95
Ameren Corporation (NYSE-AEE)	0.55	A	2	85	95
American Electric Power Co. (NYSE-AEP)	0.55	A+	1	85	100
Avangrid (NYSE-AVG)	0.40	B++	2	NMF	95
CMS Energy Corporation (NYSE-CMS)	0.50	B++	2	85	100
DTE Energy Company (NYSE-DTE)	0.55	B++	2	85	100
Evergy (NYSE:EVRG)	NMF	B++	2	NMF	NMF
Hawaiian Electric Industries (NYSE-HE)	0.55	A	2	60	100
NextEra Energy, Inc. (NYSE-NEE)	0.55	A+	1	70	100
NorthWestern Corporation (NYSE-NWE)	0.60	B++	2	85	100
OGE Energy Corp. (NYSE-OGE)	0.80	A	2	80	95
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)	0.50	A+	1	90	95
Xcel Energy Inc. (NYSE-XEL)	0.50	A+	1	100	100
Mean	0.56	A	1.8	83	97

Data Source: *Value Line Investment Survey* , 2019

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 Carolinas, LLC
Capital Structure Ratios and Debt Cost Rate

Panel A - DEC's Proposed Capital Structure and Debt Cost Rates

	Percent of Total	Cost
Long-Term Debt	47.00%	4.51%
Common Equity	53.00%	
Total Capital	100.00%	

Panel B - Duke Energy Carolinas, LLC and Duke Energy Corporation Capital Structure Ratios

Duke Energy Carolinas, LLC	Ratios
Short-Term Debt	4.2%
Long-Term Debt	44.6%
Common Equity	51.2%
Total Capital	100.0%

Duke Energy Corporation	Ratios
Short-Term Debt	6.0%
Long-Term Debt	50.6%
Common Equity	43.4%
Total Capital	100.0%

Panel C - Staff's Capital Structure Ratios and Debt Cost Rates

	DEC Proposed	Adjustment	Staff Proposed	Cost
Long-Term Debt	47.00%	1.063830	50.00%	4.51%
Common Equity	53.00%	0.943396	50.00%	
Total Capital	100.00%		100.00%	

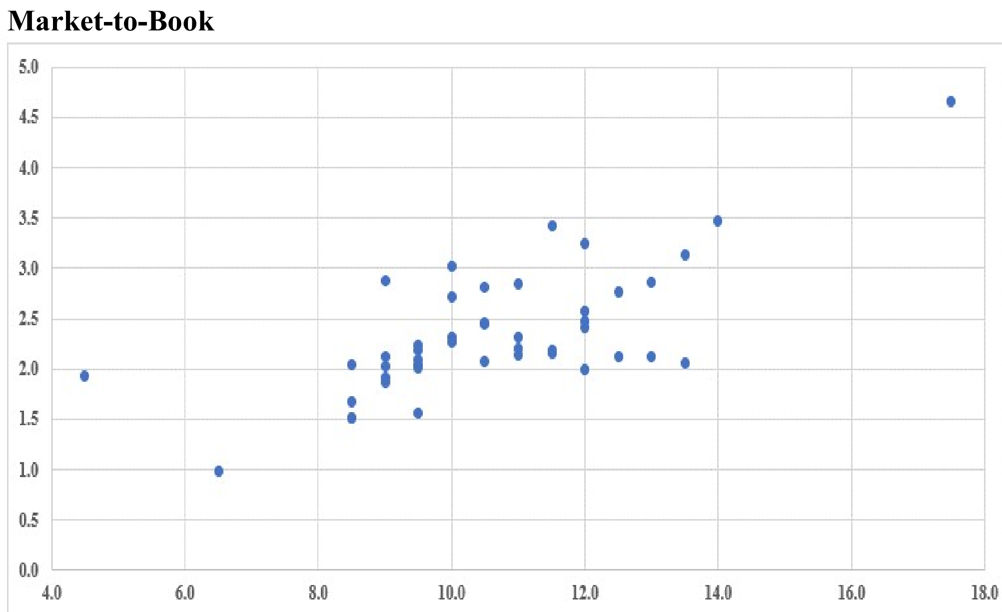
DOCKET NO. E-7, SUB 1214
Exhibit JRW-3
Capital Structure Ratios and Debt Cost Rate
Page 2 of 2

Duke Energy Carolinas, LLC and Duke Energy Corporation Capital Structure Ratios
Quarterly - 2017-2019

	2017 FQ4	*2018 FQ1*	*2018 FQ2*	*2018 FQ3*	*2018 FQ4*	*2019 FQ1*	*2019 FQ2*	*2019 FQ3*	
Duke Energy Carolinas, LLC	12/31/2017	3/31/2018	6/30/2018	9/30/2018	12/31/2018	3/31/2019	6/30/2019	9/30/2019	Average
Short-Term Debt	6.1%	3.8%	5.5%	5.8%	1.9%	3.2%	5.2%	2.1%	4.2%
Long-Term Debt	41.3%	44.6%	44.1%	43.5%	47.4%	46.0%	43.5%	46.1%	44.6%
Common Equity	52.7%	51.6%	50.4%	50.8%	50.7%	50.8%	51.3%	51.8%	51.2%
Total Capital	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	2017 FQ4	*2018 FQ1*	*2018 FQ2*	*2018 FQ3*	*2018 FQ4*	*2019 FQ1*	*2019 FQ2*	*2019 FQ3*	
Duke Energy Corporation	12/31/2017	3/31/2018	6/30/2018	9/30/2018	12/31/2018	3/31/2019	6/30/2019	9/30/2019	Average
Short-Term Debt	5.6%	7.1%	6.3%	6.4%	6.6%	5.2%	6.1%	5.1%	6.0%
Long-Term Debt	51.0%	50.2%	50.6%	50.6%	49.9%	51.1%	50.8%	50.5%	50.6%
Common Equity	43.4%	42.8%	43.1%	43.1%	43.5%	43.7%	43.1%	44.4%	43.4%
Total Capital	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Source: S&P Global Market Intelligence

Exhibit JRW-4
Electric Utilities and Gas Distribution Companies



Expected Return on Equity
R-Square = .50, N=43

Source: *Value Line Investment Survey* , 2019.

DOCKET NO. E-7, SUB 1214
Exhibit JRW-5
Public Utility Capital Cost Indicators

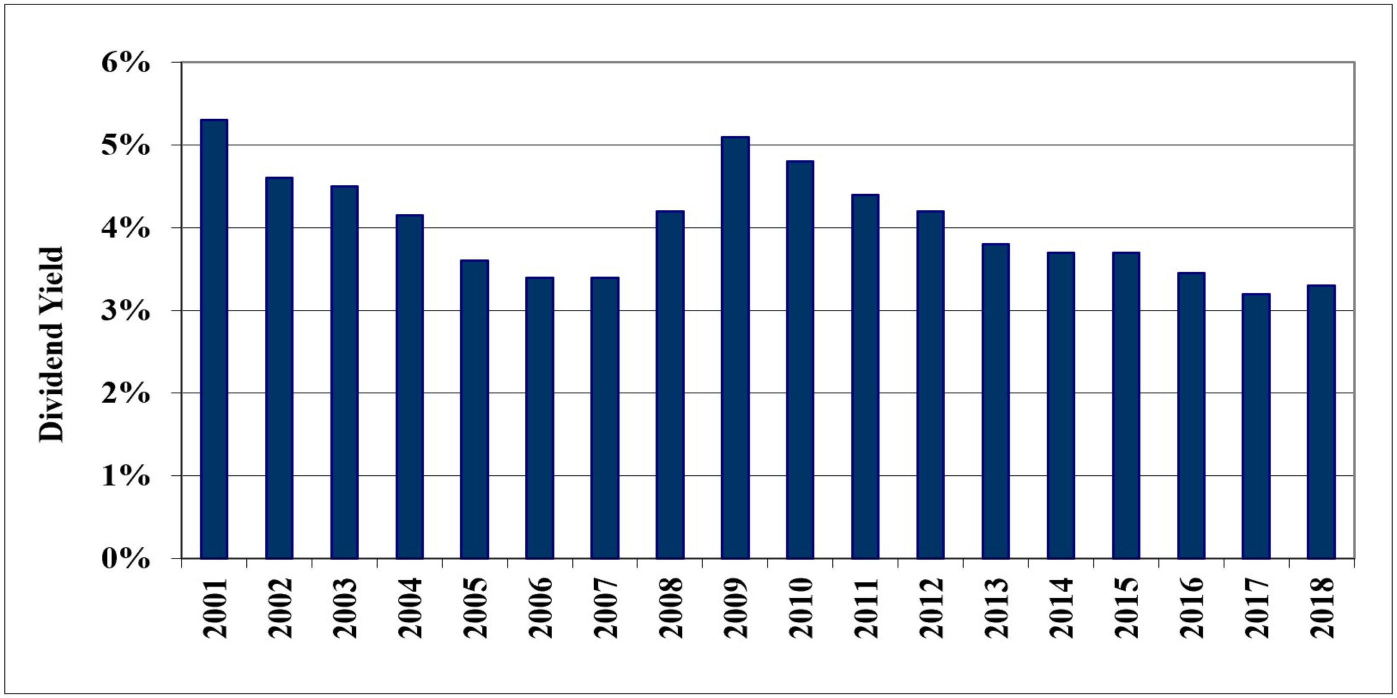
Exhibit JRW-5
Long-Term 'A' Rated Public Utility Bonds

Data Source: Mergent Bond Record

DOCKET NO. E-7, SUB 1214
Exhibit JRW-5
Public Utility Capital Cost Indicators
Page 2 of 4

Exhibit JRW-5

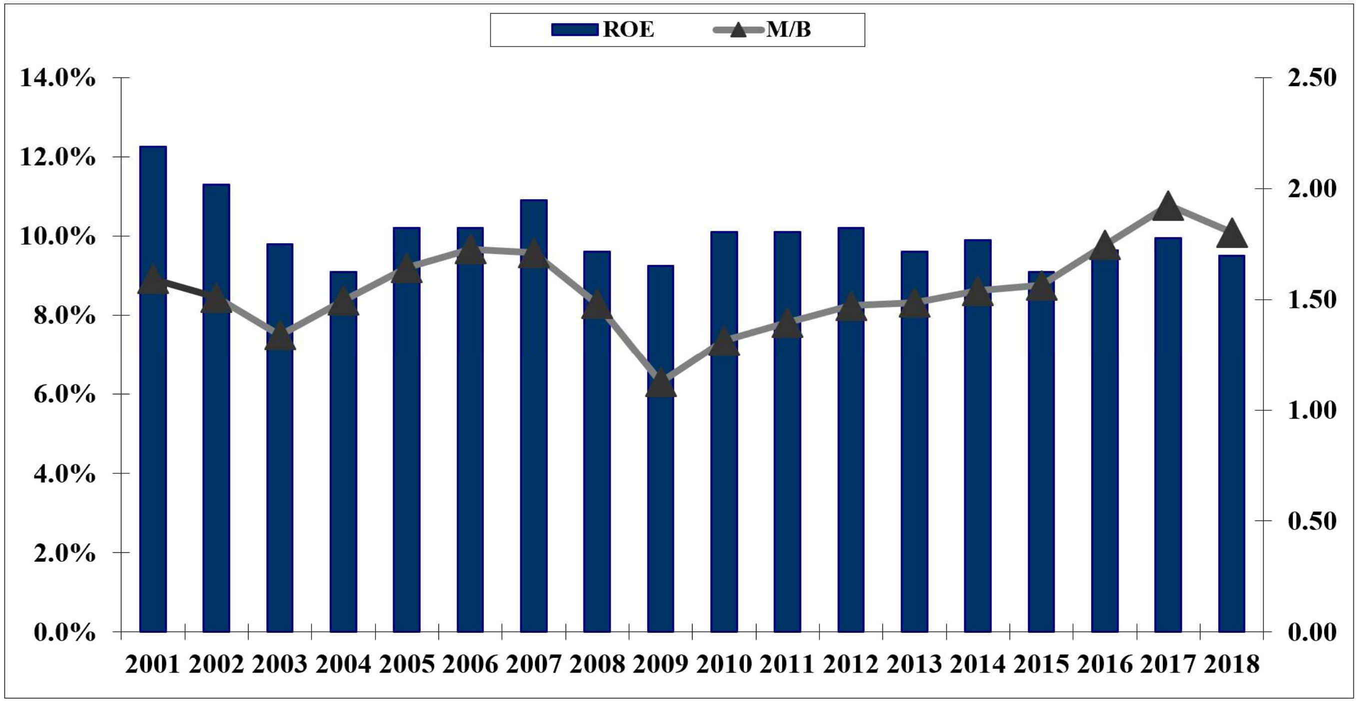
Electric Utility Average Dividend Yield



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

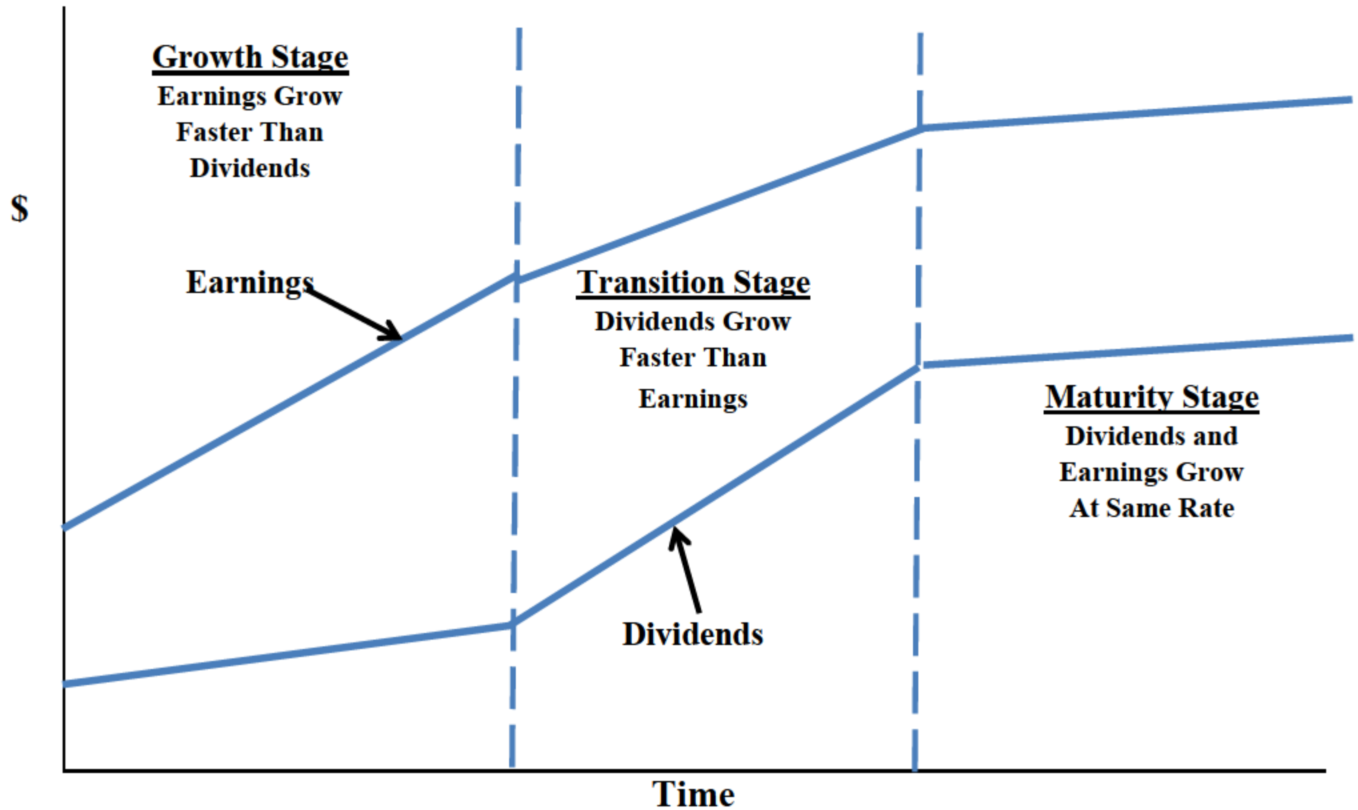


Exhibit JRW-7

Duke Energy Carolinas, LLC
Discounted Cash Flow Analysis

Panel A
Electric Proxy Group

Dividend Yield*	3.15%
Adjustment Factor	1.025
Adjusted Dividend Yield	3.23%
Growth Rate**	5.00%
Equity Cost Rate	8.25%

* 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 Carolinas, 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)	$2.35	2.9%	2.8%	2.8%
Alliant Energy Corporation (NYSE-LNT)	$1.42	2.6%	2.7%	2.8%
Ameren Corporation (NYSE-AEE)	$1.98	2.6%	2.6%	2.6%
American Electric Power Co. (NYSE-AEP)	$2.80	3.0%	3.0%	3.1%
Avangrid (NYSE-AVG)	$1.76	3.5%	3.5%	3.5%
Avista Corporation (NYSE-AVA)	$1.55	3.3%	3.3%	3.4%
CMS Energy Corporation (NYSE-CMS)	$1.53	2.5%	2.5%	2.5%
Consolidated Edison, Inc. (NYSE-ED)	$2.96	3.4%	3.3%	3.3%
Dominion Resources, Inc. (NYSE-D)	$3.67	4.5%	4.5%	4.7%
Duke Energy Corporation (NYSE-DUK)	$3.78	4.2%	4.1%	4.2%
Edison International (NYSE-EIX)	$2.55	3.5%	3.6%	3.7%
Entergy Corporation (NYSE-ETR)	$3.72	3.1%	3.2%	3.4%
Evergy, Inc. (NYSE-EVRG)	$2.02	3.2%	3.2%	3.2%
Eversource Energy (NYSE-ES)	$2.14	2.6%	2.6%	2.7%
Exelon Corp. (NYSE-EXC)	$1.45	3.2%	3.2%	3.1%
FirstEnergy Corporation (ASE-FE)	$1.56	3.2%	3.3%	3.4%
Hawaiian Electric Inductries (NYSE-HE)	$1.28	2.8%	2.9%	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	2.1%	2.1%	2.3%
NorthWestern Corporation (NYSE-NWE)	$2.30	3.2%	3.2%	3.2%
OGE Energy Corp. (NYSE-OGE)	$1.55	3.6%	3.6%	3.6%
Pinnacle West Capital Corp. (NYSE-PNW)	$3.13	3.6%	3.4%	3.4%
Portland General Electric Company (NYSE-POR)	$1.54	2.8%	2.8%	2.8%
PNM Resources, Inc. (NYSE-PNM)	$1.23	2.5%	2.4%	2.5%
PPL Corporation (NYSE-PPL)	$1.65	4.7%	5.0%	5.2%
SEMPRA Energy (NYSE-SRE)	$3.87	2.6%	2.6%	2.7%
Southern Company (NYSE-SO)	$2.48	4.0%	4.0%	4.2%
WEC Energy Group (NYSE-WEC)	$2.53	2.8%	2.8%	2.9%
Xcel Energy Inc. (NYSE-XEL)	$1.62	2.6%	2.6%	2.6%
Mean		3.1%	3.1%	3.2%
Median		3.1%	3.1%	3.1%

Data Sources: http://quote yahoo com, January, 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)	$2.35	2.9%	2.8%	2.8%
Alliant Energy Corporation (NYSE-LNT)	$1.42	2.6%	2.7%	2.8%
Ameren Corporation (NYSE-AEE)	$1.98	2.6%	2.6%	2.6%
American Electric Power Co. (NYSE-AEP)	$2.80	3.0%	3.0%	3.1%
Avangrid (NYSE-AVG)	$1.76	3.5%	3.5%	3.5%
CMS Energy Corporation (NYSE-CMS)	$1.53	2.5%	2.5%	2.5%
DTE Energy Company (NYSE-DTE)	$4.05	3.2%	3.2%	3.2%
Evergy, Inc. (NYSE-EVRG)	$2.02	3.2%	3.2%	3.2%
Hawaiian Electric Inductries (NYSE-HE)	$1.28	2.8%	2.9%	2.9%
NextEra Energy Inc. (NYSE-NEE)	$5.00	2.1%	2.1%	2.3%
NorthWestern Corporation (NYSE-NWE)	$2.30	3.2%	3.2%	3.2%
OGE Energy Corp. (NYSE-OGE)	$1.55	3.6%	3.6%	3.6%
Otter Tail Corporation (NDQ-OTTR)	$1.40	2.8%	2.7%	2.7%
Pinnacle West Capital Corp. (NYSE-PNW)	$3.13	3.6%	3.4%	3.4%
Portland General Electric Company (NYSE-POR)	$1.54	2.8%	2.8%	2.8%
PNM Resources, Inc. (NYSE-PNM)	$1.23	2.5%	2.4%	2.5%
Southern Company (NYSE-SO)	$2.48	4.0%	4.0%	4.2%
WEC Energy Group (NYSE-WEC)	$2.53	2.8%	2.8%	2.9%
Xcel Energy Inc. (NYSE-XEL)	$1.62	2.6%	2.6%	2.6%
Mean		3.0%	2.9%	3.0%
Median		2.8%	2.8%	2.9%

Data Sources: http://quote yahoo com, January, 2020

Exhibit JRW-7

Duke Energy Carolinas, 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)	1.0	3.0	5.5	4.0	3.0	5.5
Alliant Energy Corporation (NYSE-LNT)	4.5	7.5	4.0	4.5	7.0	4.5
Ameren Corporation (NYSE-AEE)	0.5	-3.5	-0.5	4.5	2.5	0.5
American Electric Power Co. (NYSE-AEP)	3.0	4.5	4.0	5.0	5.0	3.5
Avangrid (NYSE-AVG)						
Avista Corp (NYSE-AVA)	5.5	8.5	4.0	5.0	4.5	4.5
CMS Energy Corporation (NYSE-CMS)	10.0	21.5	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	3.0	1.0	-0.5	1.0	-2.5
Evergy (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	3.0	5.5	3.5	4.0	6.0
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)	4.0	6.5	7.5	1.0	9.5	6.0
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	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	3.4	5.4	3.9	3.0	5.2	3.3
Median	4.0	4.5	4.0	4.0	5.0	4.5
Data Source: *Value Line Investment Survey.*	Average of Median Figures =			4.3		

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)	1.0	3.0	5.5	4.0	3.0	5.5
Alliant Energy Corporation (NYSE-LNT)	4.5	7.5	4.0	4.5	7.0	4.5
Ameren Corporation (NYSE-AEE)	0.5	-3.5	-0.5	4.5	2.5	0.5
American Electric Power Co. (NYSE-AEP)	3.0	4.5	4.0	5.0	5.0	3.5
Avangrid (NYSE-AVG)						
CMS Energy Corporation (NYSE-CMS)	10.0	21.5	4.5	7.0	7.0	5.5
DTE Energy Company (NYSE-DTE)	8.0	4.5	4.0	8.0	6.5	4.5
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)	4.0	6.5	7.5	1.0	9.5	6.0
Otter Tail Corporation (NDQ-OTTR)	2.0	1.0		14.0	1.5	3.5
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	5.0	5.8	4.5	5.5	6.2	4.8
Median	4.5	4.5	4.0	5.0	6.3	4.5
Data Source: *Value Line Investment Survey.*	Average of Median Figures =			4.8		

Exhibit JRW-7

Duke Energy Carolinas, 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			*Value Line* Sustainable Growth		
	Earnings	Dividends	Book Value	Return on Equity	Retention Rate	Internal Growth
ALLETE, Inc. (NYSE-ALE)	5.0	5.0	3.0	9.0%	34.0%	3.1%
Alliant Energy Corporation (NYSE-LNT)	6.5	5.5	7.5	10.0%	38.0%	3.8%
Ameren Corporation (NYSE-AEE)	6.5	4.5	5.5	10.5%	44.0%	4.6%
American Electric Power Co. (NYSE-AEP)	4.0	5.5	4.5	10.5%	32.0%	3.4%
Avangrid (NYSE-AVG)	8.5	3.0	1.0	5.5%	30.0%	1.7%
Avista Corp (NYSE-AVA)	3.5	3.5	3.5	8.0%	32.0%	2.6%
CMS Energy Corporation (NYSE-CMS)	7.0	7.0	7.0	13.5%	38.0%	5.1%
Consolidated Edison, Inc. (NYSE-ED)	3.0	3.5	3.5	8.5%	33.0%	2.8%
Dominion Energy Inc. (NYSE-D)	6.5	5.0	7.0	13.0%	21.0%	2.7%
Duke Energy Corporation (NYSE-DUK)	6.0	2.5	2.5	8.5%	30.0%	2.6%
Edison International (NYSE-EIX)	NMF	4.5	5.5	11.0%	41.0%	4.5%
Entergy Corporation (NYSE-ETR)	2.0	3.5	4.5	11.5%	36.0%	4.1%
Evergy (NYSE-EVRG)	NMF	NMF	NMF	8.5%	35.0%	3.0%
Eversource Energy (NYSE-ES)	5.5	5.5	4.5	9.0%	38.0%	3.4%
Exelon Corporation (NYSE-EXC)	9.0	5.5	5.0	9.0%	52.0%	4.7%
FirstEnergy Corporation (NYSE-FE)	6.5	3.5	7.0	16.0%	36.0%	5.8%
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)	6.0	5.0	5.0	10.5%	46.0%	4.8%
Nextera Energy, Inc. (NYSE-NEE)	10.5	10.0	7.5	12.5%	40.0%	5.0%
NorthWestern Corporation (NYSE-NWE)	2.0	4.5	3.5	9.0%	31.0%	2.8%
OGE Energy Corp. (NYSE-OGE)	6.5	6.5	4.0	11.5%	33.0%	3.8%
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)	1.5	2.0	5.5	13.0%	36.0%	4.7%
Sempra Energy (NYSE-SRE)	11.0	8.0	6.5	11.5%	42.0%	4.8%
Southern Company (NYSE-SO)	3.5	3.0	3.5	12.5%	27.0%	3.4%
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	5.1	4.7	10.4%	35.7%	3.7%
Median	5.8	5.0	4.5	10.3%	35.5%	3.6%
Average of Median Figures =		5.1			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			*Value Line* Sustainable Growth		
	Earnings	Dividends	Book Value	Return on Equity	Retention Rate	Internal Growth
ALLETE, Inc. (NYSE-ALE)	5.0	5.0	3.0	9.0%	34.0%	3.1%
Alliant Energy Corporation (NYSE-LNT)	6.5	5.5	7.5	10.0%	38.0%	3.8%
Ameren Corporation (NYSE-AEE)	6.5	4.5	5.5	10.5%	44.0%	4.6%
American Electric Power Co. (NYSE-AEP)	4.0	5.5	4.5	10.5%	32.0%	3.4%
Avangrid (NYSE-AVG)	8.5	3.0	1.0	5.5%	30.0%	1.7%
CMS Energy Corporation (NYSE-CMS)	7.0	7.0	7.0	13.5%	38.0%	5.1%
DTE Energy Company (NYSE-DTE)	4.5	7.0	6.0	9.5%	33.0%	3.1%
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)	10.5	10.0	7.5	12.5%	40.0%	5.0%
NorthWestern Corporation (NYSE-NWE)	2.0	4.5	3.5	9.0%	31.0%	2.8%
OGE Energy Corp. (NYSE-OGE)	6.5	6.5	4.0	11.5%	33.0%	3.8%
Otter Tail Corporation (NDQ-OTTR)	5.0	4.0	4.5	11.0%	34.0%	3.7%
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)	3.5	3.0	3.5	12.5%	27.0%	3.4%
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	5.6	4.5	10.2%	34.6%	3.5%
Median	5.3	5.8	4.3	10.0%	34.0%	3.4%
Average of Median Figures =		5.1			Median =	3.4%

*** '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 Carolinas, 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-AVG)	3.5%	3.4%	3.4%
Avista Corp (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 (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%
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	4.1%	5.4%	4.9%
Median	4.4%	5.4%	4.7%

Data Sources: www reuters com, www zacks com, http://quote yahoo com, January, 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%

Exhibit JRW-7

Duke Energy Carolinas, 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	4.3%	4.8%
Projected *Value Line* Growth in EPS, DPS, and BVPS	5.1%	5.1%
Sustainable Growth ROE * Retention Rate	3.6%	3.4%
Projected EPS Growth from Yahoo, Zacks, and Reuters - Mean/Median	4.9%/4.7%	5.4%/5.4%

Exhibit JRW-8

Duke Energy Carolinas, LLC
Capital Asset Pricing Model

Panel A
Electric Proxy Group

Risk-Free Interest Rate	**3.75%**
Beta*	**0.55**
Ex Ante Equity Risk Premium**	**5.75%**
CAPM Cost of Equity	**6.9%**

* See page 3 of Exhibit JRW-8

** See pages 5 and 6 of Exhibit JRW-8

Panel B
Hevert Proxy Group

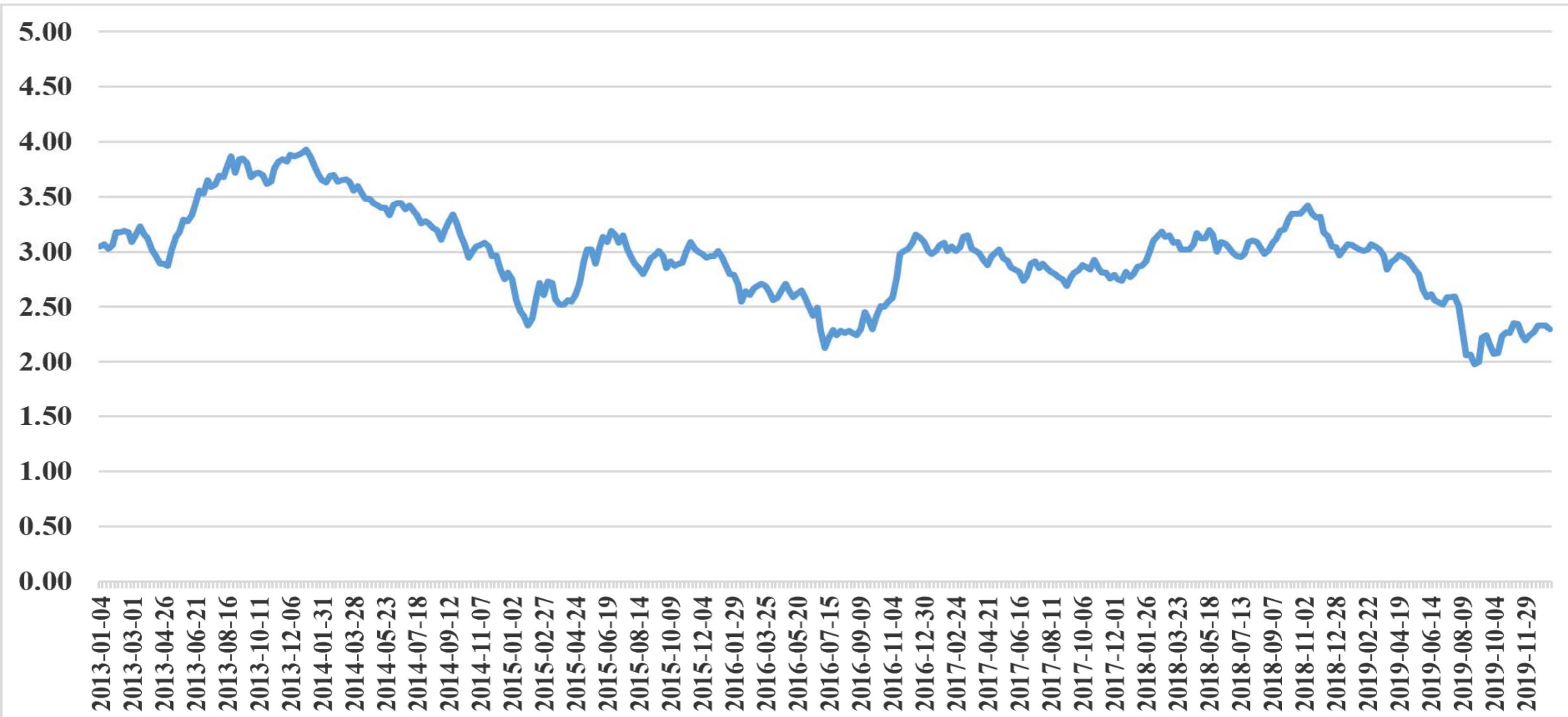
Risk-Free Interest Rate	**3.75%**
Beta*	**0.55**
Ex Ante Equity Risk Premium**	**5.75%**
CAPM Cost of Equity	**6.9%**

* 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.

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CAPM Study
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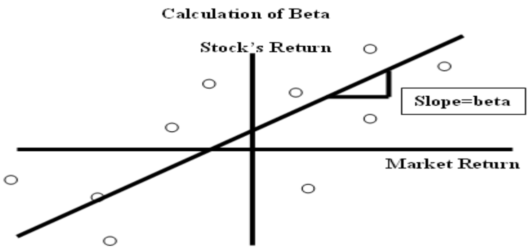

Panel A
Electric Proxy Group

Company Name	Beta
ALLETE, Inc. (NYSE-ALE)	0.65
Alliant Energy Corporation (NYSE-LNT)	0.60
Ameren Corporation (NYSE-AEE)	0.55
American Electric Power Co. (NYSE-AEP)	0.55
Avangrid (NYSE-AVG)	0.40
Avista Corp (NYSE-AVA)	0.60
CMS Energy Corporation (NYSE-CMS)	0.50
Consolidated Edison, Inc. (NYSE-ED)	0.45
Dominion Energy Inc. (NYSE-D)	0.55
Duke Energy Corporation (NYSE-DUK)	0.50
Edison International (NYSE-EIX)	0.55
Entergy Corporation (NYSE-ETR)	0.60
Evergy (NYSE:EVRG)	NMF
Eversource Energy (NYSE-ES)	0.55
Exelon Corporation (NYSE-EXC)	0.65
FirstEnergy Corporation (NYSE-FE)	0.65
Hawaiian Electric Industries (NYSE-HE)	0.55
IDACORP, Inc. (NYSE-IDA)	0.55
MGE Energy, Inc. (NYSE-MGEE)	0.55
NextEra Energy, Inc. (NYSE-NEE)	0.55
NorthWestern Corporation (NYSE-NWE)	0.60
OGE Energy Corp. (NYSE-OGE)	0.75
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)	0.70
Sempra Energy (NYSE-SRE)	0.70
Southern Company (NYSE-SO)	0.50
WEC Energy Group (NYSE-WEC)	0.50
Xcel Energy Inc. (NYSE-XEL)	0.50
Mean	0.58
Median	0.55

Data Source *Value Line Investment Survey* , 2019.

Panel B
Hevert Proxy Group

Company	Beta
ALLETE, Inc. (NYSE-ALE)	0.65
Alliant Energy Corporation (NYSE-LNT)	0.60
Ameren Corporation (NYSE-AEE)	0.55
American Electric Power Co. (NYSE-AEP)	0.55
Avangrid (NYSE-AVG)	0.40
CMS Energy Corporation (NYSE-CMS)	0.50
DTE Energy Company (NYSE-DTE)	0.55
Evergy (NYSE:EVRG)	NMF
Hawaiian Electric Industries (NYSE-HE)	0.55
NextEra Energy, Inc. (NYSE-NEE)	0.55
NorthWestern Corporation (NYSE-NWE)	0.60
OGE Energy Corp. (NYSE-OGE)	0.80
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)	0.50
Xcel Energy Inc. (NYSE-XEL)	0.50
Mean	0.56
Median	0.55

Data Source *Value Line Investment Survey* , 2019.

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 Repo	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	Geometric				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 Compai	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%**

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Exhibit JRW-8
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Duff & Phelps Risk-Free Interest Rates and Equity Risk Premium Estimates

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 31, 2018 – UNTIL FURTHER NOTICE	**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.

Source: https://www.duffandphelps.com/-/media/assets/pdfs/publications/valuation/coc/erp-risk-free-rates-jan-2008-present.ashx?la=en

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Exhibit JRW-8
CAPM Study
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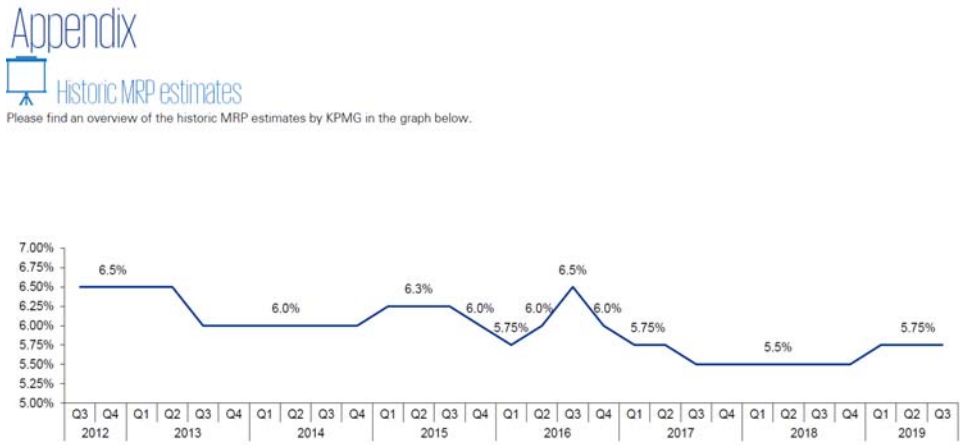
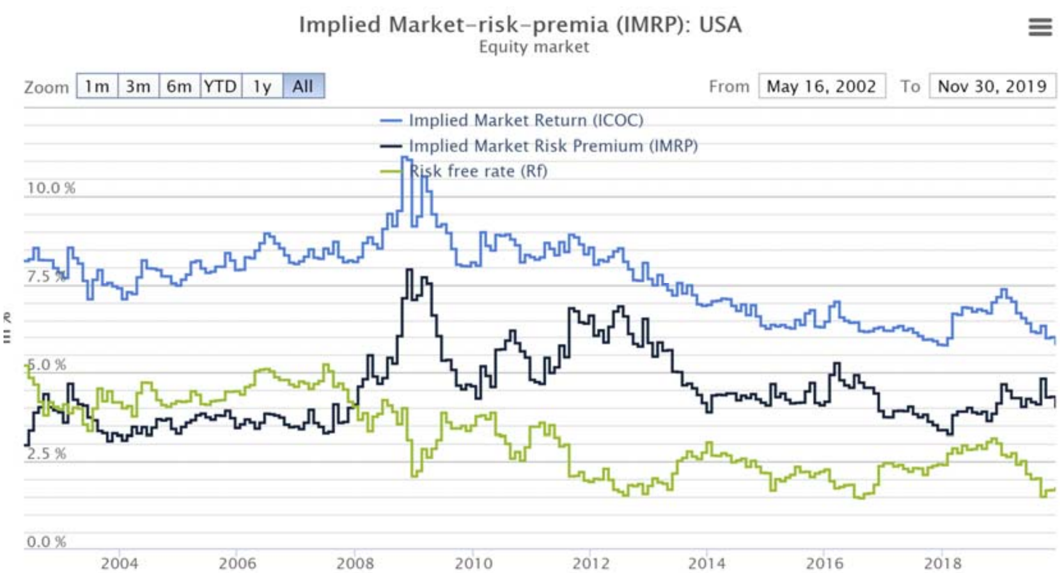
Panel A
KPMG Equity Risk Premium Recommendation



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
30-Nov-19



Market
Return
5 78%
Risk
Premium
4 00%

Risk-Free
Rate
1.78%

Source: http://www market-risk-premia com/us html

Capital Source	Capitalization Ratios*	Cost Rate	Weighted Cost Rate
Long-Term Debt	47.00%	4.51%	2.12%
Common Equity	53.00%	10.50%	5.57%
Total Capitalization	100.00%		7.68%

DOCKET NO. E-7, SUB 1214
Exhibit JRW-9
Duke Energy Carolinas, LLC ROE Results

Panel A
Mr. Hevert's DCF Results

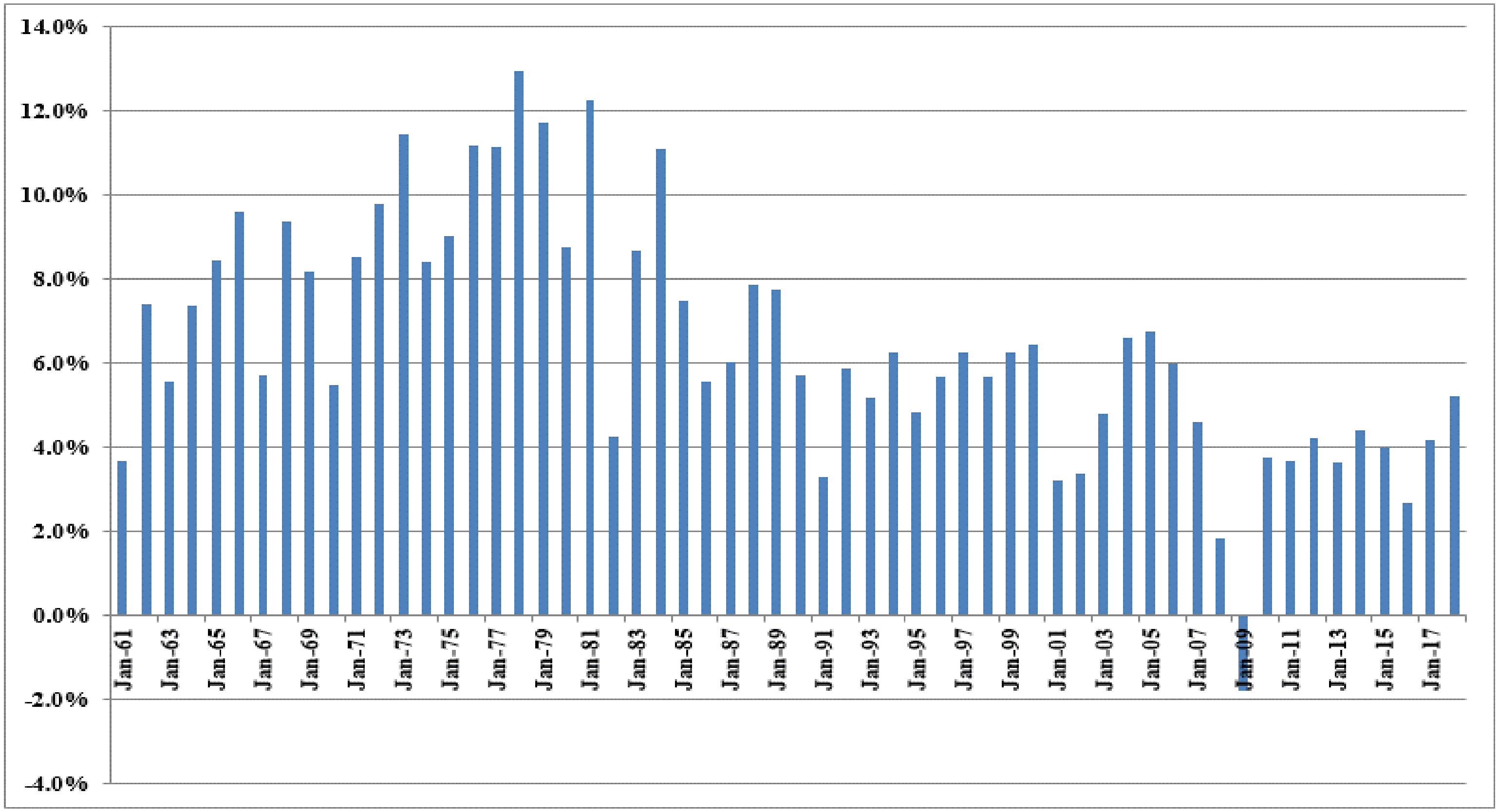
	Mean	**Mean High**
30-Day Average	8.86%	9.73%
90-Day Average	8.95%	9.82%
180-Day Average	9.09%	9.96%

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 (2.63%)	8.73%	8.68%
Near Term Projected 30-Year Treasury (2.70%)	8.80%	8.75%
Average Value Line Beta Coefficient		
Current 30-Year Treasury (2.63%)	9.74%	9.69%
Near Term Projected 30-Year Treasury (2.70%)	9.81%	9.75%
Empirical CAPM	**Bloomberg Derived Market Risk Premium**	**Value Line Derived Market Risk Premium**
Average Bloomberg Beta Coefficient		
Current 30-Year Treasury (2.63%)	10.27%	10.21%
Near Term Projected 30-Year Treasury (2.70%)	10.34%	10.28%
Average Value Line Beta Coefficient		
Current 30-Year Treasury (2.63%)	11.03%	10.96%
Near Term Projected 30-Year Treasury (2.70%)	11.10%	11.03%
Bond Yield Plus Risk Premium Approach		
Current 30-Year Treasury (2.63%)	9.90%	
Near Term Projected 30-Year Treasury (2.70%)	9.90%	
Long-Term Projected 30-Year Treasury (3.70%)	10.06%	

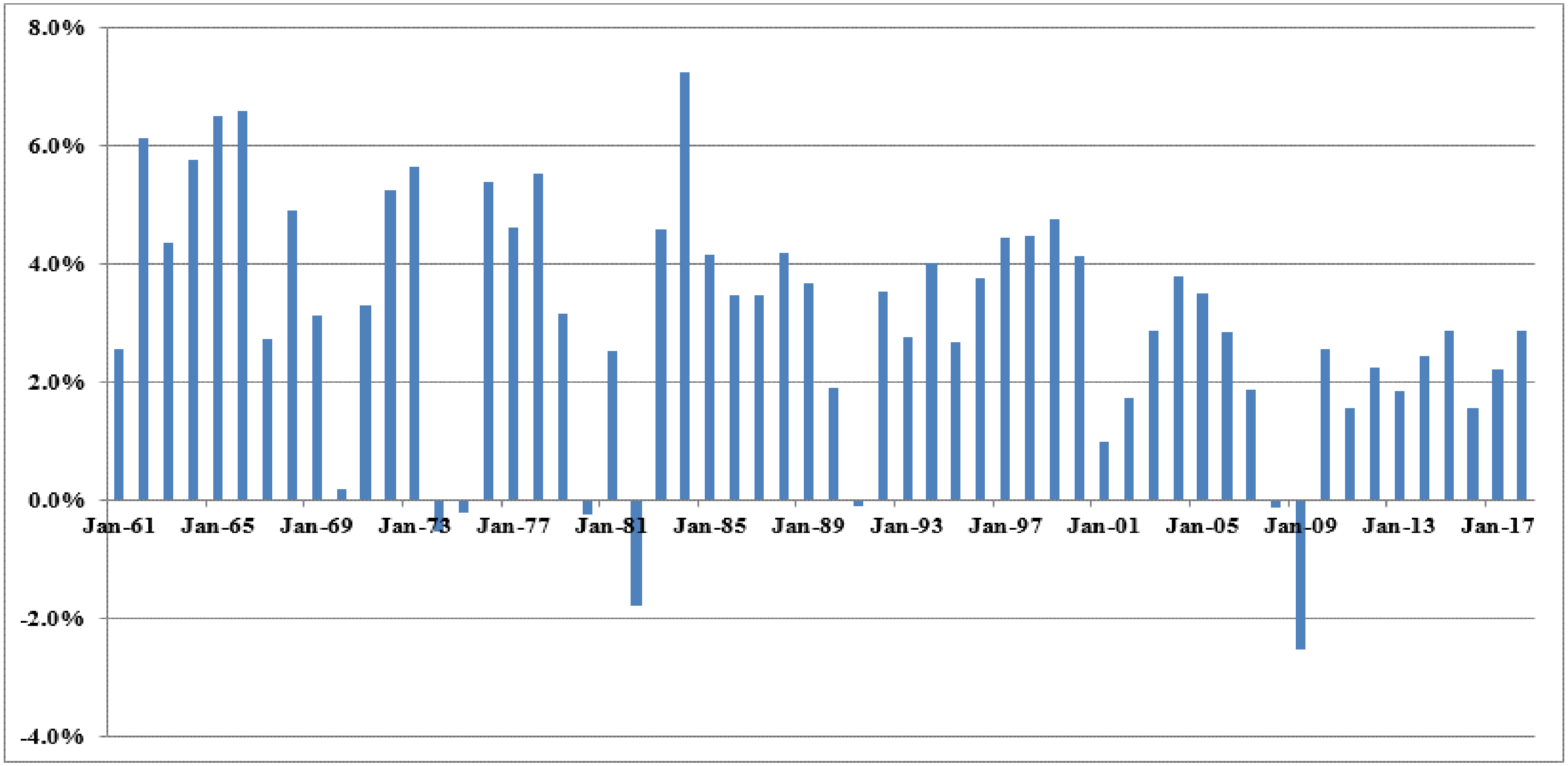
DOCKET NO. E-7, SUB 1214
Exhibit JRW-10
Annual Nominal GDP Growth Rates

Nominal GDP Growth Rates
Annual Growth Rates - 1961-2018



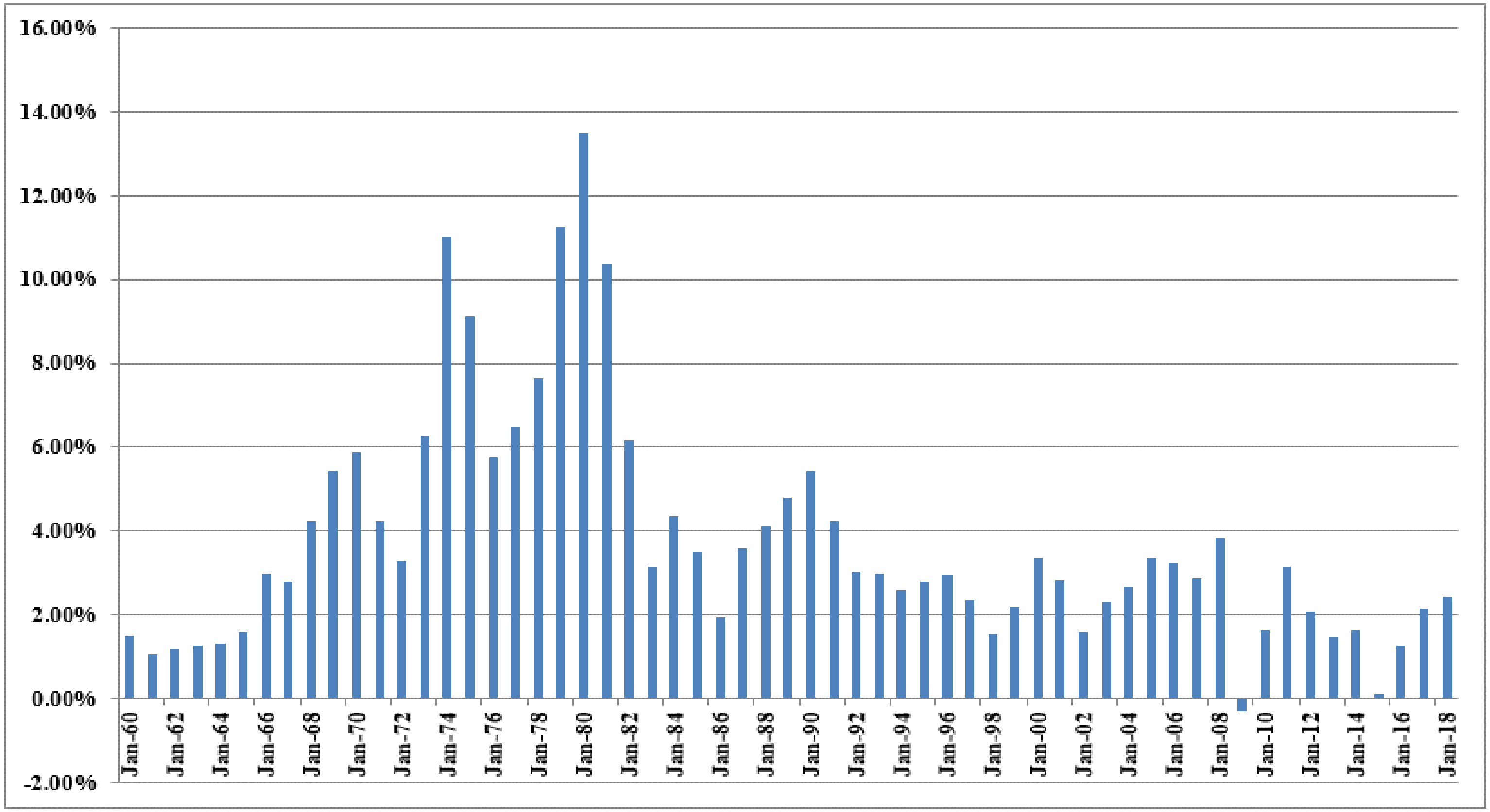
Data Sources: GDPA -https://fred.stlouisfed.org/series/GDPA

**Annual Real GDP Growth Rates
1961-2018**



Data Sources: GDPC1 - https://fred.stlouisfed.org/series/GDPCA

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

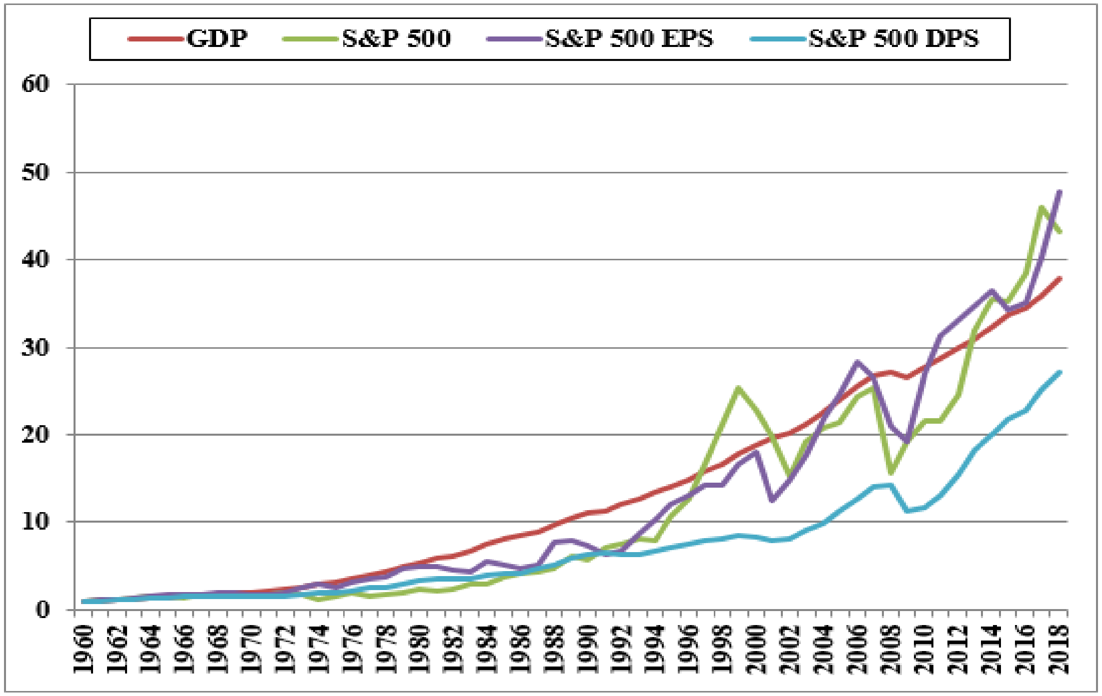
Panel B
Projected GDP Growth Rates

	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