The Private and Social Value of Blackout Risk Reduction

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Abstract

Distributed generation (DG) provides a mechanism to generate electric energy locally rather than drawing from the power grid, which yields energy savings to DG-enabled users. This study focusses on another source of benefits, related to blackout risk reduction. When blackouts do occur, DG-enabled customers enjoy the "private benefit" of continued electric service from local generation. If DG units are deployed at scale and operated in such a way as to decrease stress on power grids during times of peak demand, all users of the grid enjoy a "social" benefit of reduced risk of blackouts occurring. Using building-integrated Combined Heat and Power (CHP) in the PJM power grid as a case study, we estimate blackout risk as a function of demand for grid-provided power and estimate the risk reduction associated with a modest deployment of CHP throughout the PJM region. Even with modest CHP deployment levels, the social benefits exceed the private benefits by an order of magnitude (~$2.5 million of private benefit versus ~$20 - $50 million of social benefit annually). Per MW of CHP, this social benefit is equivalent to prevailing prices in PJM's capacity market, suggesting the value of revisiting capacity auction rules to increase DG participation.

Keywords: Combined heat and power, Power system blackouts, Distributed generation

1. Introduction

Distributed generation (DG), including Combined heat and power (CHP), is being looked up as an alternative to the current structure of power grids with increased use of local generation near demand centers. Recent electrical blackouts caused by extreme weather events (such as Hurricane Sandy in 2013) and by the continued overloading of an aging electrical grid (the August 2003 blackout affecting much of the U.S. Midwest and Northeast) have reinforced the role that distributed power generation (DG) can play in "energy surety" or "survivability" – the ability of energy systems to continue delivery services in the face of extreme events. CHP is the onsite generation of electricity from generators (primarily fueled by natural gas) where the coproduced heat is captured and used for site specific purposes like room heating, water heating or other uses. CHP systems are highly efficient compared to conventional power generation technologies. Typical CHP systems power single-user buildings or a group of buildings in case of a shared micro-grid or district heating system. Since the same fuel source is used to generate heat and power, CHP can be beneficial economically and environmentally (Department of Energy 2016) . The onsite generator can also act as a back-up source of power during blackouts and provide continuous supply of power and heat/cooling to the site.

Facilities which had installed CHP systems were able to continue normal operations during the August 14, 2003 blackout (Carlson and Hedman 2004) and power outages caused by Hurricane Sandy (Hampson et al. 2012). Most of these facilities had invested in black start (and other services) to operate CHP independent of the grid. An interesting finding (as stated by CHP owners), which motivates our analysis, was that the ability of the CHP unit to provide continuous service in the face of a grid interruption was perceived as more valuable than the energy savings from CHP.

Several studies have examined and quantified the peak shaving benefits, savings from reduced operational costs and emission reduction benefits from CHP adoption (Maidment, Zhao, and Riffat 2001; Strachan and Farrell 2006; Ziher and Poredos 2006; Mago, Fumo, and Chamra 2009; Mago and Smith 2012; Siler-Evans, Morgan, and Azevedo 2012; Govindarajan and Blumsack 2015). This work focuses on quantifying a different set of benefits from DG, namely the reliability benefit associated with the DG unit being able to provide services in the event of a blackout on the grid.

There are two such benefits, and since the focus of our analysis is on building-integrated CHP we will refer specifically to CHP technologies in this discussion (although our method could just as easily apply to other distributed energy technologies such as batteries or micro-turbines). First, the owners of installed CHP units benefit because the CHP unit can act as a source of backup power during a blackout. We refer to this as the "private" reliability benefit since it accrues only to the CHP owner (or owners, in the case of a shared or district system). Second, with sufficiently large deployment levels CHP investments themselves may be utilized to lower the likelihood of a blackout occurring on the grid. Blackouts are more likely to be instigated during times when the electrical grid is under stress, and removing demand from the grid (onto local CHP systems) can reduce this stress. We refer to this as the "social" reliability benefit of CHP since it accrues to others besides the CHP owner (i.e., anyone on the grid that would benefit from avoiding a blackout), and the CHP owner is not assumed to be compensated by those who benefit. In other words, there is a "positive network externality" associated with blackout risk reduction via CHP installation decisions.

2. Modeling Overview

We model the private and social reliability benefits for CHP deployment by integrating four separate modelling components, with a specific application to the Mid-Atlantic United States (the region served by the PJM transmission grid operator): An econometric model of blackout risk in the PJM system; an econometric model of locational electricity prices within PJM (capturing energy cost savings from CHP); building energy models that generate electricity demands for commercial buildings with and without integrated CHP and a simulation model of building-integrated CHP operation. Each of these modelling elements is described briefly below.

(1) The econometric model for blackout risk is estimated using a rare-events logit approach, using data on reported blackouts within the PJM region and data from PJM on historical hourly system

loads. A rare-event logit model is developed that estimates the likelihood of a blackout being initiated in each hour as a function of electric loads in PJM and temporal characteristics such as seasons and time of day. (Results from the rare-events logit model with those of a conventional logit model are compared and there are few differences in estimated blackout probabilities). An econometric model for blackout duration as a function of blackout size (customers affected) and temporal variables is also estimated. We note up front that we exclude extreme weather events from the econometric blackout model, under the assumption that there is no social reliability value that CHP can provide in the face of extreme weather such as hurricanes or tornadoes. There may, however, be a private reliability benefit which we consider later in the paper.

(2) Locational electricity prices within PJM are estimated using the econometric approach developed by Sahraei-Ardakani, et al. (2015) and used in the application of CHP by Govindarajan and Blumsack (2015) (Govindarajan and Blumsack 2015), which estimates locational supply curves within regional power grids that accounts for spatial differences in fuels utilization and congestion on the electric transmission grid. This model utilizes hourly demand and pricing data from PJM, as well as fuel prices from the U.S. Energy Information Administration. This model is used to estimate energy savings from CHP and to compare the estimates with reliability benefits.

(3) CHP usage profiles are developed for specific commercial building types using the BCHP tool available from the U.S. Department of Energy (Oak Ridge National Lab 2012). Following the approach illustrated by Govindarajan and Blumsack (2015), building energy profiles were developed for three cases; Baseline case without any CHP, CHP following thermal demand and CHP following electrical demand.

(4) CHP adoption in commercial buildings in Philadelphia is simulated (in Matlab) using commercial building stock data and CHP usage profiles. The simulations assume that CHP units are deployed according to priority rankings developed by Huang et al. (1991).

The overall modelling approach is to estimate baseline hourly blackout risk and locational electricity price profiles for the PJM region. Hourly energy profiles are simulated for up to 1,000 commercial buildings (about 720 MW of CHP) in PJM with and without integrated CHP systems. As more buildings add CHP systems, these customers save on electricity purchase costs and also avoided power outage costs by operating CHP during blackouts. These two effects together constitute the private benefit of CHP adoption by commercial buildings. Removing loads from the grid and placing them on CHP also reduces the risk of blackouts, which amounts to the social value in our study. This social value of blackout risk reduction is monetized using an approach suggested by Sullivan et al. (2010).

A modest level of CHP deployment in a specific location, relative to the overall size of the PJM market as a whole, can yield blackout risk reduction benefits to the PJM system as a whole amounting to between $26,000 and $75,000 annually per MW of CHP deployed. This social reliability benefit is roughly an order of magnitude larger than the private reliability benefit that we estimate. Moreover, the estimated private reliability benefit (based on blackout costs from the existing literature) is several times smaller than the benefit associated with avoided energy purchases. These findings suggest that potential CHP adopters should not be influenced by their private reliability benefits but that a side payment or subsidy based on the social blackout risk reduction would be appropriate.

3. Blackout likelihood and expected duration modeling

While large blackouts in the U.S. power grid are relatively rare, existing analyses suggest that large blackouts have not decreased in frequency and may be increasing in frequency (Hines et al. 2009; Simonoff et al. 2007). Blackout events are instigated when there is a disturbance in the power system because of hurricanes or storms, equipment failures, targeted attack on the infrastructure or other external causes. The power grid is also vulnerable to cascading failures when disturbances initiated in a region propagate to other parts through subsequent component failures. The likelihood of smaller outage events growing into a big cascading failure sharply increases when the grid is under stress (Talukdar et al. 2003;

Dobson et al. 2007). Concurrently, historical data suggests that the odds of a blackout increases significantly during mid-afternoon hours when the grid is under stress due to peaking demand.

The North American Electric Reliability Corporation (NERC) requires electric utilities to report power outage events and this data is available with the Disturbance Analysis Working Group (DAWG). More recent blackout data is reported to the U.S. Department of Energy; we focus our attention on the DAWG data for consistency of reporting practices and because the DAWG data consists of a longer time series of blackouts. Hines et al. (2009a) compiled and filtered the DAWG data for regions within the PJM electricity market. This data is used in our statistical blackout risk model. Descriptive statistics for various primary causes triggering blackouts in PJM between 1984 and 2006 are shown in Table 1. Weather is the primary cause of power outages in PJM, triggering more than one-third of events, followed by natural disasters (e.g. hurricanes and ice storms). Table 2 shows the mean duration and the frequency of blackouts initiated during various seasons and times of day in PJM. About 50 percent of the blackouts occurred during summer months with a mean duration of about 18 hours. Blackouts were more likely during afternoon hours and blackouts triggered during evening and night-time hours had longer restoration times.

Table 1. Descriptive statistics of blackouts in PJM

Primary Causes	Percentage of events	Mean duration (hours)	Mean size in MW lost	Mean size in Customers affected
Natural disaster	10	31.00	423.46	299,250
Weather	36.15	26.05	295.82	171,477
Fire	1.54	4.12	100	33,764
Intentional attack[1]	1.54	50.94	0	0
Supply shortage	3.85	8.75	151.6	465,013
Other external causes	5.38	1.54	102.57	3,500
Equipment Failure	20	3.55	142.76	16,203
Operator Error	5.38	1.98	333.57	73,925
Voltage reduction/Volunteer reduction	16.15	23.77	224.04	10,666

[1] There were no recorded size (MW or number of customers affected) for these events.

Table 2. Mean duration of blackouts initiated at different seasons and time of day

Time Variable	Mean Duration (hours)	Percentage of events
Season		
Summer	18.82	50.74
Winter	17.15	22.06
Fall/Spring	15.93	27.21
Time of day		
Morning	9.75	22.79
Noon	11.43	34.56
Evening	28.28	24.26
Night	25.19	18.38

The data may be incomplete as the utilities are not required to report small power outage events as pointed out by Hines et al. (2009). Voltage reduction/volunteer reduction events (which do not affect electricity service) and events with no recorded sizes (MW and number of customer affected) are excluded for this study. Power quality events (like voltage reduction) can affect operations in commercial buildings but those events are beyond the scope of this study.

Existing studies have analyzed the DAWG event level data on blackouts using different methods. For example, Hines et al. (2009) studies trends in blackouts in the United Sates using DAWG data. One of the key findings was that the frequency of blackouts has increased during peak demand periods (afternoon hours and summer months). Simonoff et al. (2007) used DAWG data on blackout events in North America to construct statistical models to study any trends in disturbances over time and season and to analyze the different characteristics of a power outage. The results of statistical models were used to predict expected outcomes (the size, duration etc.) of power disruptions caused by an attack on the power grid. Talukdar et al. (2003) used DAWG data to show that frequency of blackouts followed the power law for larger blackouts. Dobson et al. (2007) uses DAWG data to design probabilistic methods to examine the risk of cascading failures.

Our approach uses a rare events logit regression model to blackout likelihood as a function of total system demand for electricity in PJM and temporal characteristics. This is different from the existing studies as our approach models the likelihood of a blackout being instigated in every hour (between 1993 and 2006) using the DAWG data for regions within PJM electricity market. The authors would like to point out that the service area under PJM electricity market has changed during the time period considered for this study.

Blackouts are relatively infrequent events, which poses some challenges for the application of the logit model. When events are rare (a large number of zeros relative to ones in the dependent variable), the conventional logit probability estimates can be downward biased (King and Zeng 2001). The origin of this problem is small-sample bias in maximum likelihood estimation of the logit model. While there is no strict definition for what constitutes 'rare events,' King and Zheng (2001) define rare events data as "binary dependent variables with dozens to thousands of times fewer ones than zeros". Our blackout events data set meets this definition of rare events. This study employs the "rare events logit regression" methodology proposed in King and Zeng (2001) to address this bias. This method implements the corrections for small sample bias generating approximately unbiased and lower variance estimates of logit coefficients.

The logit regression model for hourly blackout likelihood is specified as,

$$Y_t = exp(X_t\beta + \varepsilon_t)$$

Where,

$$X_t\beta = \beta_0 + \beta_1 * Season_t + \beta_2 * Timeofday_t + \beta_3 * Weekday_t + \beta_4 * Demand_t + \beta_5 * Int_t \qquad (1)$$

The dependent variable Y_t is coded 1 if there is a blackout triggered in hour *t* or 0 otherwise. *Season* and *Timeofday* are categorical variables which explains seasonal and time of day trends in blackout likelihood. The variable *Season* is a vector consisting of summer, winter (reference variable) and fall/spring. The variable *Timeofday* is a vector consisting of morning, noon, evening and night (reference variable). *Weekday* is a dummy variable which is coded 1 if the blackout is triggered during a weekday or 0 otherwise. *Demand* is the hourly total system demand in PJM. There is also an interaction variable *Int* capturing interaction between *Timeofday* and *Demand.*

A similar approach to the one discussed in Simonoff et al. (2007) is used to model the expected duration of a blackout. Linear regression is used to model the natural logarithms of duration of a blackout given a blackout is instigated. Events with no recorded duration were excluded for this approach. The linear regression model is specified as,

$$Y_i = \beta_0 + \beta_1 * Season_i + \beta_2 * Timeofday_i + \beta_3 * Primarycause_i + \beta_4 Customers_i + \beta_5 MW_i + \varepsilon_i \quad (2)$$

The dependent variable '*Y'* is the natural logarithm of duration of a blackout, *Season* and *Timeofday* are categorical vector variables which explains seasonal and time of day trends in blackout duration. *Primarycause* is a categorical variable for various primary causes triggering blackout. *Customers* is the natural logarithms of the number of customers affected and *MW* is the natural logarithms of megawatts lost.

4. Modeling private and social benefits from CHP adoption

The private benefits to CHP owners are modeled as the avoided electricity purchase costs and the avoided customer interruption costs by operating CHP during a blackout. The private benefits (in terms of gross savings) from a single CHP unit will be,

$$Gross\ Savings, S_{i,t} = Avoided\ electricity\ costs + Avoided\ power\ outage\ costs$$

$$Gross\ Savings, S_{i,t} = \{P_{B,t} \times Q_{B,t} - P'_{i,t} \times Q'_{i,t}\} + \{C_i(c, b, f)\} \quad (3)$$

The subscript *i* indexes CHP units and *t* indexes time (on an hourly time step). For the avoided electricity purchase costs, Q_b and P_b are the baseline demand and electricity price in every hour without any CHP unit, Q' is the reduced demand with a portion of electric demand met by CHP and P' is the new electricity price. In this case, the demand satisfied by a single CHP unit is small relative to the zonal demand, and will not reduce demand sufficiently to change the zonal electricity price or the blackout probability. So the baseline price (P_b) and new electricity price (P') will be the same. For the avoided power outage costs, C_i is the power outage cost incurred by the customer (without CHP) given the customer characteristics (*c*), blackout characteristics (b) and blackout likelihood (*f*). It is assumed that CHP system has the capability to be operated throughout the duration of blackout.

A substantial number of CHP installations will, collectively, reduce the demand for electricity provided by the grid, thus reducing wholesale electricity prices. The blackout risk to CHP owners also decreases with incremental CHP adoption. Equation 3 can be rewritten as,

$$Gross\ Savings, S_{i,t} = \{P_{B,t} \times Q_{B,t} - P'_{i,t}(n) \times Q'_{i,t}\} + \{C_i(c, b, f(n))\} \quad (4)$$

where *n* represents the number of CHP units adopted. When *n* is sufficiently large, the new electricity price (P') will be lower than the baseline price (P_b) depending on the level of CHP deployment. The blackout likelihood (*f*) will also decrease depending on the number of CHP units adopted.

The positive network externality to other grid connected customers consists of the reduced power outage costs resulting because of the reduced risk. We refer to this as the social reliability benefit. Customers on the power grid that do not have CHP will enjoy the benefits of lower wholesale prices just as CHP owners do. We neglect this price benefit in our analysis for two reasons. First, for the magnitude of CHP deployment that we consider the price benefit will generally be quite small (Govindarajan and Blumsack, 2015). Second, our focus is on evaluating the positive network externalities associated with CHP deployment. While lower wholesale prices surely benefit customers without CHP, this benefit would not be considered an externality, but rather a market outcome driven by reduced demand for grid-provided power by CHP-enable customers.

The social reliability benefit is written as:

$$Social\ Benefits,\ SB_t = \Delta f_{i,t}(n) * C_i(c, b), \tag{5}$$

where $\Delta f(n)$ is the blackout risk reduction corresponding to the demand reduction from the deployment of *n* CHP units, and C_i is the sum of power outage costs experienced by electricity customers not owning CHP. The reduction in the blackout risk corresponding to the level of CHP deployment is estimated by the logit model discussed in section 2 (equation 1).

The capital cost for CHP is the upfront cost of the power generating unit and the cost of black start services to operate CHP independent of the grid. The variable cost includes fuel (assumed to be natural gas) cost for CHP system operation, the maintenance cost and additional fuel cost to operate CHP during a blackout.

$$Captail\ Costs, C_i = C_{i,pgu} + C_{i,b} \tag{6}$$

$$Variable\ Costs, VC_i = C_{i,f} + C_{i,o\&m} + C_{i,af} \tag{7}$$

$C_{i,pgu}$ is the cost of the power generating unit, $C_{i,b}$ is the cost of black start services (to operate CHP independent of grid), $C_{i,f}$ is the cost of fuel to run the CHP unit with $C_{i,o\&m}$ representing the operating and maintenance costs, and $C_{i,af}$ is the additional fuel cost to operate CHP during a blackout.

5. PJM case study

An illustrative analysis of the private and social benefits framework from the previous section focuses on the deployment of CHP among various types of commercial buildings in Philadelphia region, which lies within the PJM footprint. We draw in part on the approach described in (Govindarajan and Blumsack 2015) to simulate a large-scale adoption of CHP in commercial buildings. The approach uses building stock data and simulated energy load profiles for commercial buildings (with and without CHP) to estimate hourly CHP usage in a year. Table 3 shows the commercial buildings stock in Philadelphia region. The energy load profiles for different commercial building types were simulated using the BCHP screening tool developed by Oak Ridge National Laboratory(Oak Ridge National Lab, 2005). Simulations were done for three scenarios for each building type – baseline without CHP, CHP system following thermal loads (FTL) and CHP system following electrical load (FEL). The simulations assume that CHP units are deployed according to the priority rankings developed by Huang et al. (1991) and reproduced here as Table 3. In our modeling framework, CHP units will be installed at the most advantageous sites first (according to the priority rankings) followed by deployment at progressively less advantageous sites. All CHP units are operated during peak demand periods in the grid and there is no operation during weekends. Reflecting a limitation in the building stock data, it is assumed that building types have homogeneous thermal and electric load profiles within type and those demand profiles are well-represented by the BCHP tool. For each CHP operation strategy (FEL/FTL), the difference between the building load with and without CHP represents the hourly demand reduction in the grid. Following this, hourly demand in PJM electricity markets is reduced (using demand in 2006 as the baseline) with every CHP unit deployed. The hourly blackout probability reduction is estimated (using equation 1) with the reduction in hourly demand for each CHP operation strategy.

Table 3. Commercial buildings stock in Philadelphia. Source: Huang, et al. (1991)

Rank	**Building Type**	**Number of buildings**
1	Hospital	50
2	Hotel	74
3	Restaurant	29
4	Office	284
5	Supermarket	51
6	School	63
7	Motel	22
8	Warehouse	439

6. Results

The logit coefficients for blackout probability (equation 1) are shown in Table 4. The results suggest statistically significant seasonal and time of day effects associated with blackout likelihood. There is a positive and significant relationship between blackout likelihood and demand for electricity in PJM. A unit percent increase in demand will increase odds of a blackout by 0.0022% holding other variables constant. In other words, our model predicts that taking electricity demand off the PJM grid will reduce the likelihood of a blackout being instigated in any given hour, and this blackout reduction will be greater during summer months and afternoon hours.

We use the method illustrated in Williams (2012) to estimate average marginal effects of temporal variables (season and time of day) on blackout probability. Table 5 shows the average marginal effects of temporal variables on blackout probability. Blackouts are more likely during summer months as compared to winter months. Blackouts are more likely to be triggered during morning and afternoon hours as compared to night time. Figure 1 shows the average marginal effects of different seasons and time of day on blackout probability for various levels of demand in PJM electricity market. It can be seen that at temporal variables show higher marginal effects for higher demand levels.

As a robustness check for the rare-effects bias, we estimate equation (1) using a conventional logit approach. The results are shown in Table 4 and are similar to the rare-events logit model. This suggests that the small sample bias, pointed out by King and Zeng (2001), was not severe in the blackout data used in this study. Collier and Hoeffler (2004) used rare events logit and found that the small sample bias was not severe in their data.

Table 4. Logit regression model results: Hourly blackout likelihood in PJM

Standard errors in parentheses, *** p<0.01, ** p<0.05, *p<0.1

Variables	Logit Model	Rare Events Logit Model	Logit Model (2nd order demand)
Season			
Summer	0.541*	0.529*	0.532*
	(0.304)	(0.303)	(0.305)
Fall/Spring	0.316	0.319	0.303
	(0.321)	(0.322)	(0.321)
Time of day			
Morning	2.091**	1.854***	1.138**
	(0.903)	(0.692)	(0.514)
Afternoon	2.004***	1.944***	1.558***
	(0.685)	(0.622)	(0.423)
Evening	0.441	0.471	0.727
	(0.797)	(0.789)	(0.512)
PJM Demand	2.20×10^{-5} **	2.4×10^{-5}**	1.85×10^{-10}**
	(1.08×10^{-5})	(1.06×10^{-5})	(9.11×10^{-11})
Interaction between demand and time of day			
Interaction 1	-4.81×10^{-5}**	-0.42E-05**	-5.17×10^{-10}**
	(2.32×10^{-5})	(1.63×10^{-5})	(2.72×10^{-10})
Interaction 2	-2.27×10^{-5}*	-2.2×10^{-5}*	-2.22×10^{-10}**
	(1.41×10^{-5})	(2.24×10^{-5})	(1.21×10^{-10})
Interaction 3	5.49×10^{-6}	4.53×10^{-6}	3.56×10^{-12}
	(1.06×10^{-5})	(1.33×10^{-5})	(1.06×10^{-10})
Weekday	0.307	0.275	0.307
	(0.287)	(0.289)	(0.285)
Constant	-9.404	-9.345	-8.901
	(0.612)	(0.598)	(0.452)
Number of Observations	122,640	122,640	122,640
Log likelihood	-581.861	-	-581.723
LR $\chi^2(10)$	36.74	-	37.02
Prob > χ^2	0.0001	-	0
Pseudo R^2	0.0306	-	0.0308

Table 5. Marginal effects of temporal variables

	dy/dx	Std. Err.	z	P>z
Summer	0.00034	0.00062	1.82	0.06
Fall/Spring	0.00020	0.00021	0.91	0.36
Morning	0.00327	0.00803	2.46	0.01
Afternoon	0.00252	0.00880	3.49	0.00
Evening	0.00030	0.00063	0.47	0.63

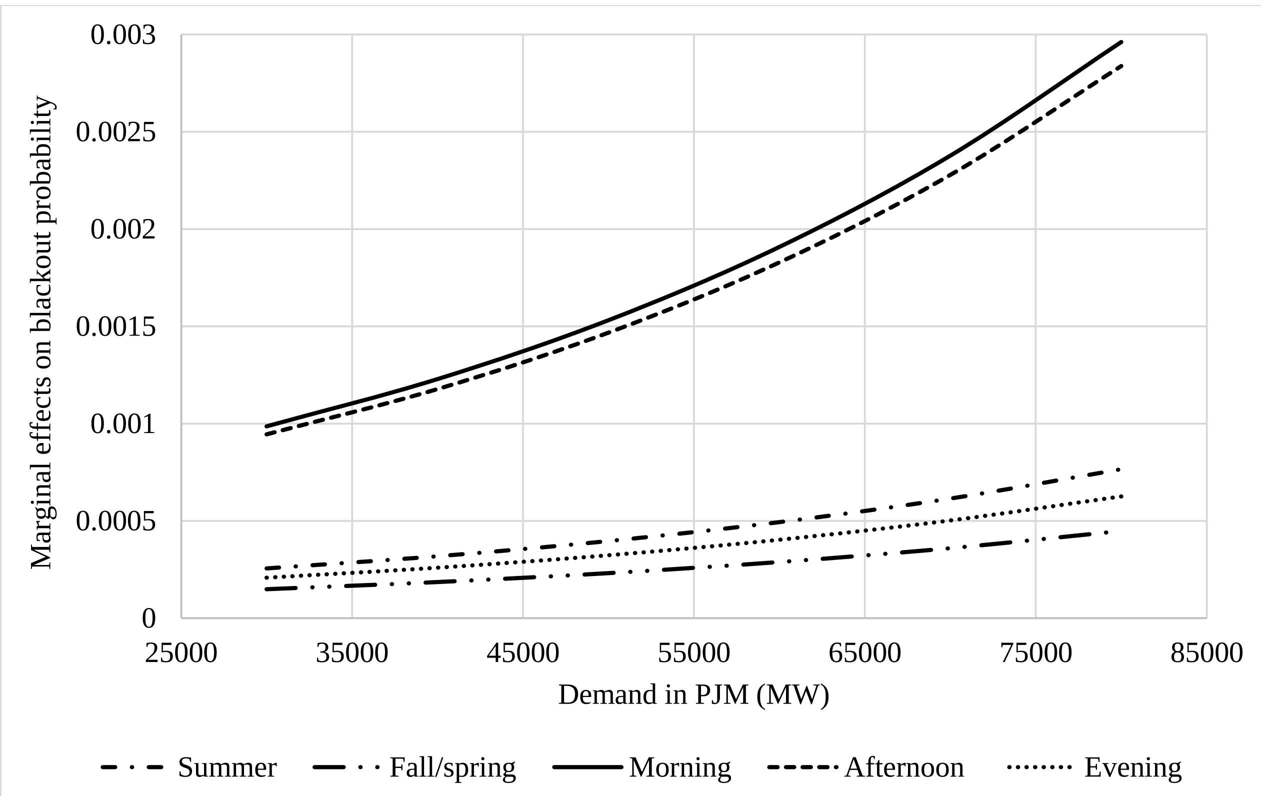

Figure 1 Marginal effects of temporal variables for different demand levels in PJM

The ANOVA table for the linear regression model for blackout duration (equation 2) is shown in Table 6. The number of customers affected and primary cause are significant predictors of blackout duration. There are no statistically significant seasonal trends and time of day trends associated with blackout duration. The inferential results are relatively unchanged as shown in Table 7. Results suggest that a 1% increase in the number of customers affected is associated with 0.62% increase in duration.

Table 6. Linear regression model results: ANOVA table

Variable	Partial SS	df	MS	F	Prob > F
Model	77.92	10	7.792	4.25	0.0007
MW lost	0.226	1	0.226	0.12	0.72
Customers affected	8.125	1	8.125	4.43	0.04
Season	0.138	2	0.068	0.04	0.96
Time of day	7.894	3	2.631	1.44	0.25
Primary Cause	15.322	3	5.107	2.79	0.05
Residual	64.135	35	1.832		

Table 7. Linear regression model results: Expected duration of a blackout in PJM

*** p<0.01, ** p<0.05, *p<0.1

Variables	Linear regression model	
	Coefficient	Standard Error
MW lost	-0.034	0.248
Customers affected	0.624**	0.262
Season		
Summer	0.263	0.611
Winter	0.220	0.669
Time of day		
Morning	0.191	0.582
Noon	1.321*	0.721
Evening	0.579	0.539
Primary cause		
Weather	1.878**	0.741
Other External causes	0.307	1.021
Equipment error	0.581	0.799
constant	-6.23	2.664
Number of observations	46	
Prob > F	0.0007	
R-squared	0.546	
Adjusted R-squared	0.4162	
Root MSE	1.357	

Adjusted means are used to explain seasonal and primary cause effects on blackout duration. Table 8 summarizes the adjusted means for primary causes for different seasons and time of day variables. Holding other variables in the model fixed, weather related blackouts exhibit longer duration across all seasons. Power outages resulting from operator error generally exhibit low restoration times. Restoration times are higher for blackouts occurring at night compared to morning and afternoon hours. These values, along with frequency of blackouts for different primary causes across seasons, are used to estimate an annual expected blackout duration.

Table 8. Adjusted means for primary causes at different seasons and time of day

Primary Cause	Season (hours)			Time of day (hours)			
	Summer	Winter	Fall/Spring	Morning	Afternoon	Evening	Night
Weather	2.08	1.73	2.79	1.27	2.32	2.48	3.24
Other External Causes	1.90	1.54	2.61	1.09	2.13	2.29	3.05
Equipment Failure	1.68	1.32	2.39	0.87	1.91	2.07	2.83
Operator Error	1.17	0.82	1.88	0.36	1.41	1.57	2.33

Based on simulated CHP deployment in the Mid-Atlantic region amounting to 1,000 single-user units for commercial buildings (more than 700 MW installed), reductions in grid-provided power are in the hundreds of Megawatts per hour (on average). The magnitude of loads taken off the grid depends on whether CHP units are operated to follow on-site electrical load (FEL mode) or on-site thermal load (FTL mode). Figure 2 shows the reduction in hourly blackout probability (averaged across a year) with incremental CHP adoption. The blackout risk reduction is higher when CHP is operated in FEL mode through larger reductions in zonal demand. Figure 3 shows the hourly blackout probability (averaged across summer months) with incremental CHP adoption. The result suggests that while the likelihood of a blackout in any given hour is small, blackouts are more likely to occur during the summer peaks as during other times of the year. While estimates in Figures 2 and 3 appear small in magnitude, they translate to more substantial numbers when translated into expected economic losses associated with blackouts.

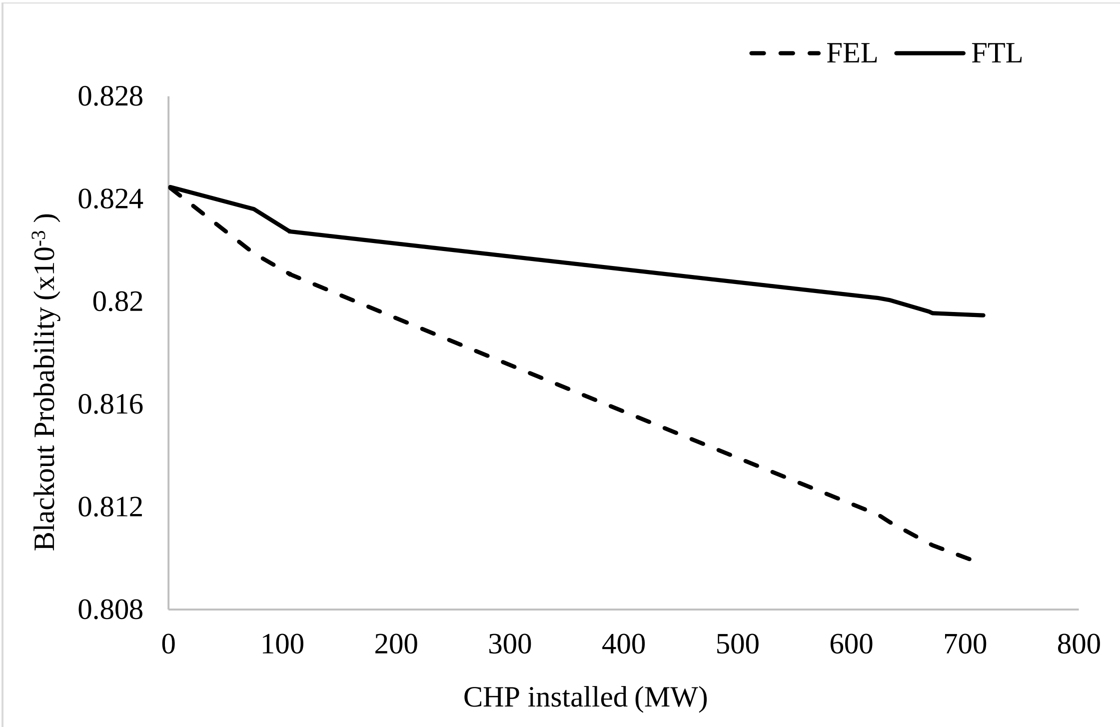

Figure 2. Hourly blackout probability (averaged over a year) with incremental CHP adoption

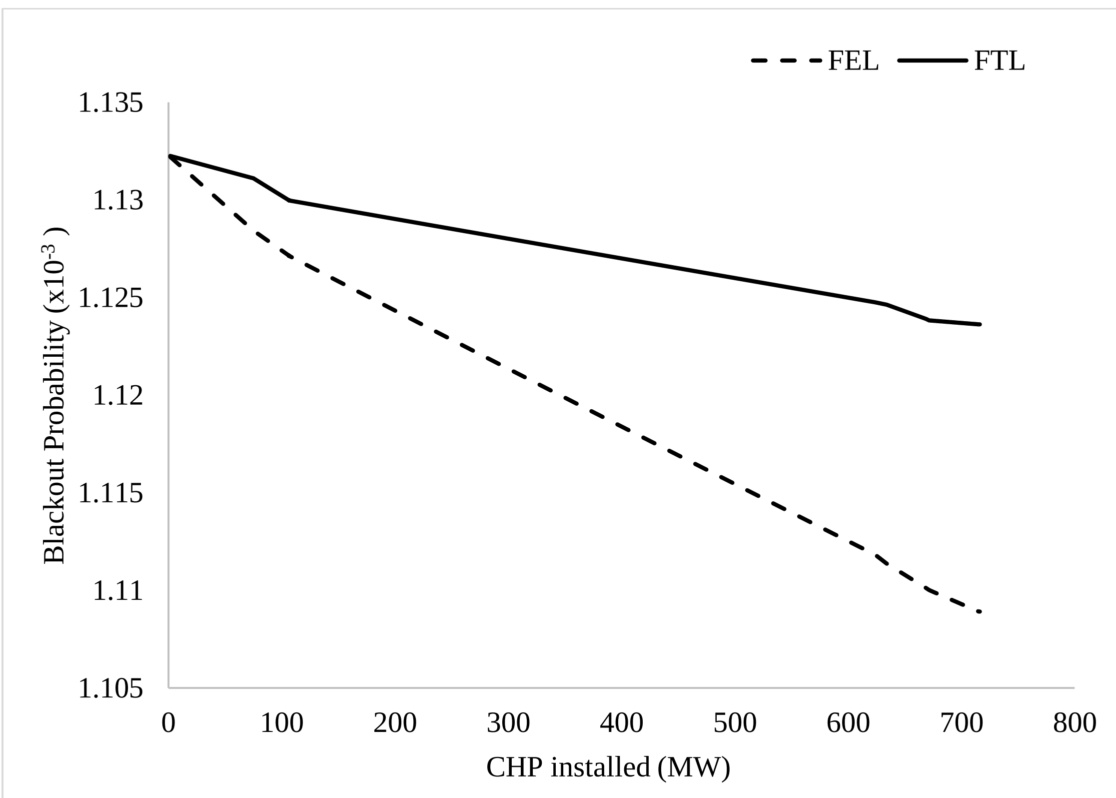

Figure 3. Hourly blackout probability (averaged over summer months) with incremental CHP deployment

We draw upon an approach described by Sullivan et al. (2010) to estimate power outage costs incurred by commercial buildings given the duration of blackout. The approach uses expected outage conditions (duration, time of occurrence etc.) and customer characteristics (building type, annual MWh etc.) as inputs to estimate the level of outage costs for different commercial building types. The results from the linear regression model (the expected duration of blackouts for different seasons and primary causes) and customer characteristics (from BCHP tool outputs for building demand profiles) are used as inputs to model described in Sullivan et al (2010) to estimate annual power outage costs for different commercial building types. Figure 4 shows annual power outage costs for different commercial building types in the Philadelphia region. The power outage costs may reach into the thousands of dollars per event (excluding extreme weather events). The severity of the impact of blackouts is reflected in these power outage costs estimates. Hospitals have the highest power outage costs as the impact of blackouts are severe affecting the welfare of patients.

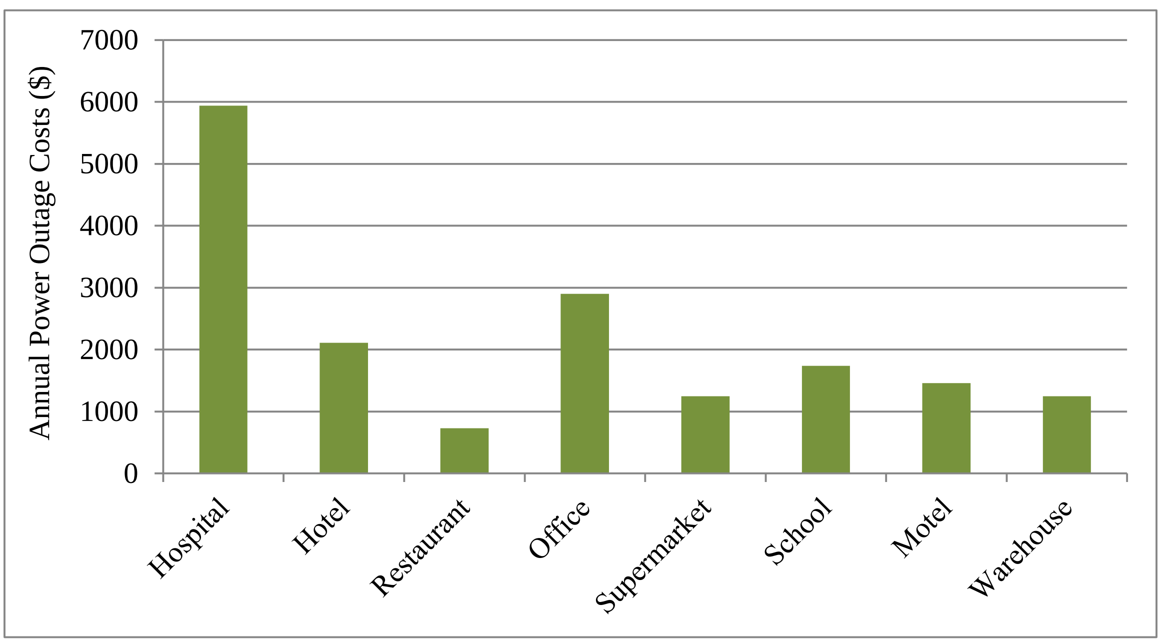

Figure 4. Annual power outage costs for commercial buildings in Philadelphia, combining the blackout risk logit model and Sullivan et al (2010)

The results of our analysis of private benefits accruing to CHP owners are shown in Figure 5. Recall that the private reliability benefits to CHP owners reflect the avoided power outage costs where building sites could use the local electricity generated from CHP and sustain critical operations during a blackout. Figure 5 shows these total private benefits in the 1,000 commercial buildings that we modeled in the PJM region (about 720 MW of CHP). The primary axis (on the left) shows the avoided power outage costs to CHP owners accounting for the additional fuel costs to operate CHP during power outages. The secondary axis (on the right) shows the net energy savings from avoided electricity purchases (net savings would be the difference between the gross savings and the cost of natural gas to fuel the CHP unit, plus other operational / maintenance costs). These estimates accounts for blackout risk reduction and electricity price reduction from incremental CHP adoption (as formulated in Equation 4).

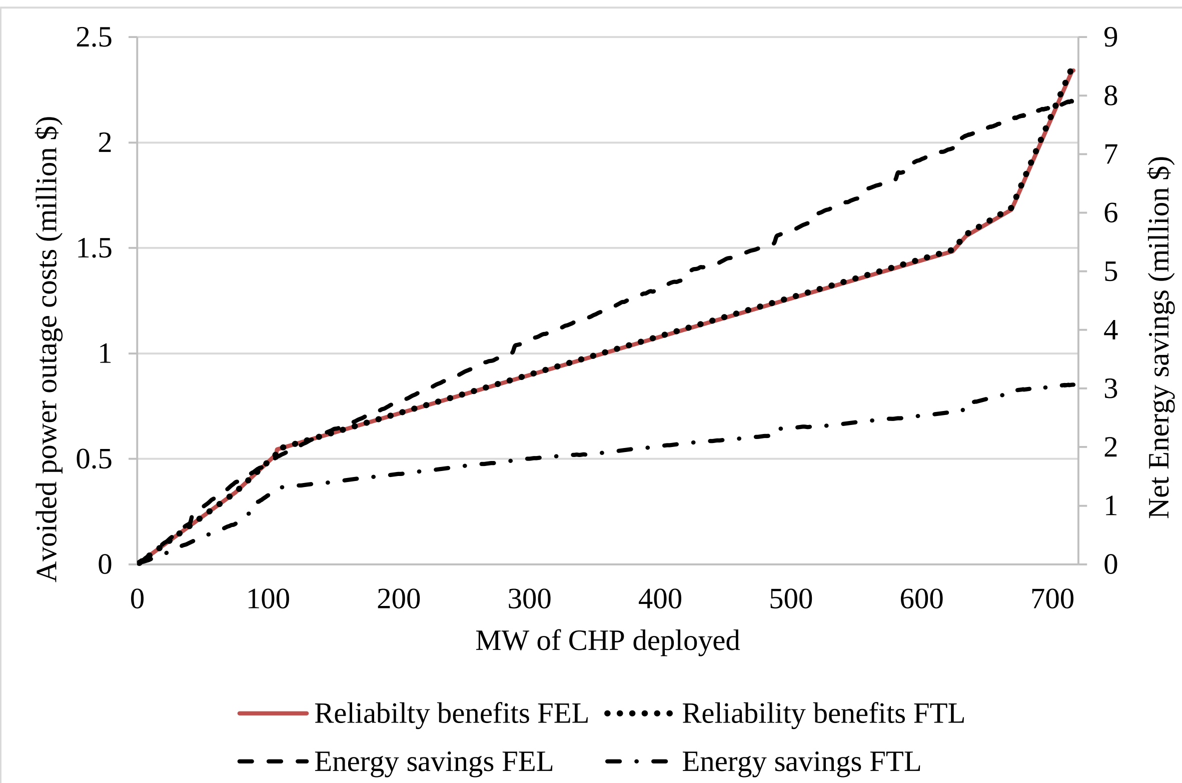

Figure 5. Private reliability and energy-savings benefits from CHP adoption

The estimates of energy savings outweigh the avoided power outage costs for both CHP operation modes (FEL and FTL). The avoided annual power outage costs are higher in case of CHP-FEL as compared to CHP-FTL with incremental CHP adoption. Though the difference is not large, it arises because the CHP-FEL mode involves larger reductions in demand for grid-provided electricity thus resulting in larger blackout risk reduction. This difference can be seen clearly in Figure 6 which shows the monetized risk reduction to CHP owners from incremental CHP adoption. The reduction in outage costs associated with risk reduction (i.e., a lower likelihood of blackouts, as distinct from the ability for CHP units to continue providing services during blackouts) is up to two orders of magnitude smaller than energy savings during times when no blackouts occur.

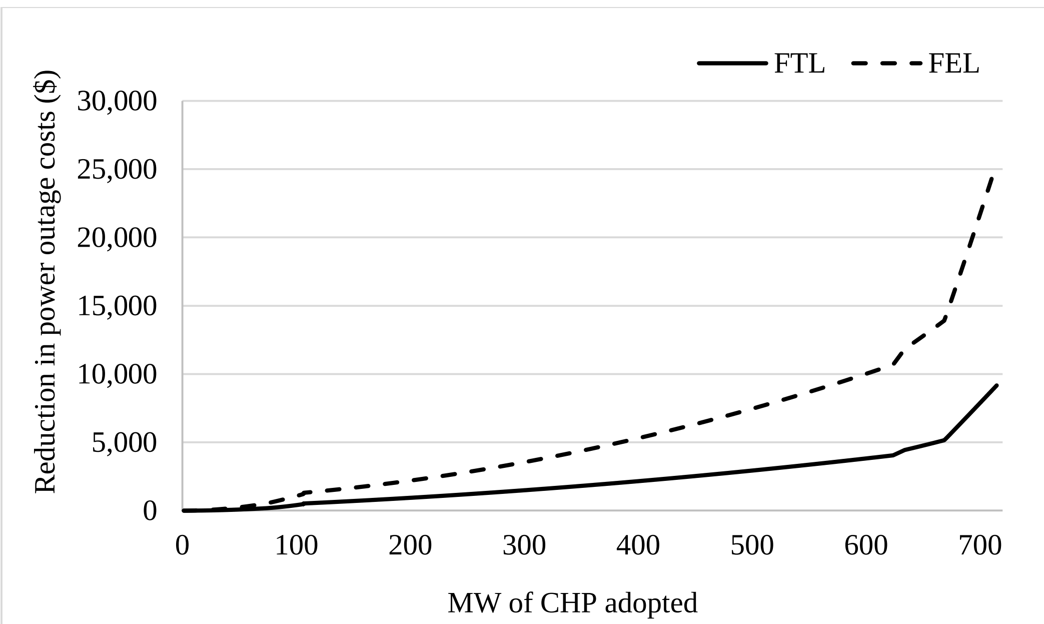

Figure 6. Monetized risk reduction to CHP owners from CHP adoption

We now turn to assessing the social benefit of blackout risk reduction via CHP in our PJM case study. Recall that the social reliability value represents the benefit associated with a lower risk of blackouts, accruing to electricity customers not adopting CHP. We utilize our blackout likelihood model (equation 5) and our model of hourly electricity load in the PJM system with and without CHP to estimate this risk reduction. Figure 7 shows the reduction in power outage costs to other grid connected customers in PJM as incremental CHP adoption increases. We note that CHP units operated in FEL mode yield several times higher benefits compared to operating in FTL mode. Since operating in FEL mode maximizes the electrical load taken off the grid, this result is sensible. The social benefits amount up to $75,000 per MW of CHP deployed when 720 MW of CHP is operated in FEL mode. The social benefits are lower, amounting to roughly $26,000 per MW when an equal amount of CHP capacity is operated in FTL mode. An increase in 1 MW of CHP capacity in the PJM region, operated in FEL mode, corresponds to an incremental social benefit of roughly $1,000 per MW of CHP. The incremental social benefit when CHP is operated in FTL mode is more than an order of magnitude lower, at roughly $30 per MW of CHP.

Moreover, we find that in our PJM case study the monetized risk reduction is higher to the PJM grid as a whole as compared to CHP owners (as shown in Figure 6 & 7). These findings suggest that most of the value associated with increased CHP adoption in our case study accrues to parties other than the owners of the CHP units (and given the size of the PJM system relative to our assumed CHP deployment level, the number of customers without CHP far exceeds the number with CHP). Because of the public good nature of electric reliability, a side payment or subsidy to CHP owners that operate their capacity in a way that maximizes the social blackout risk reduction benefit could be considered appropriate.

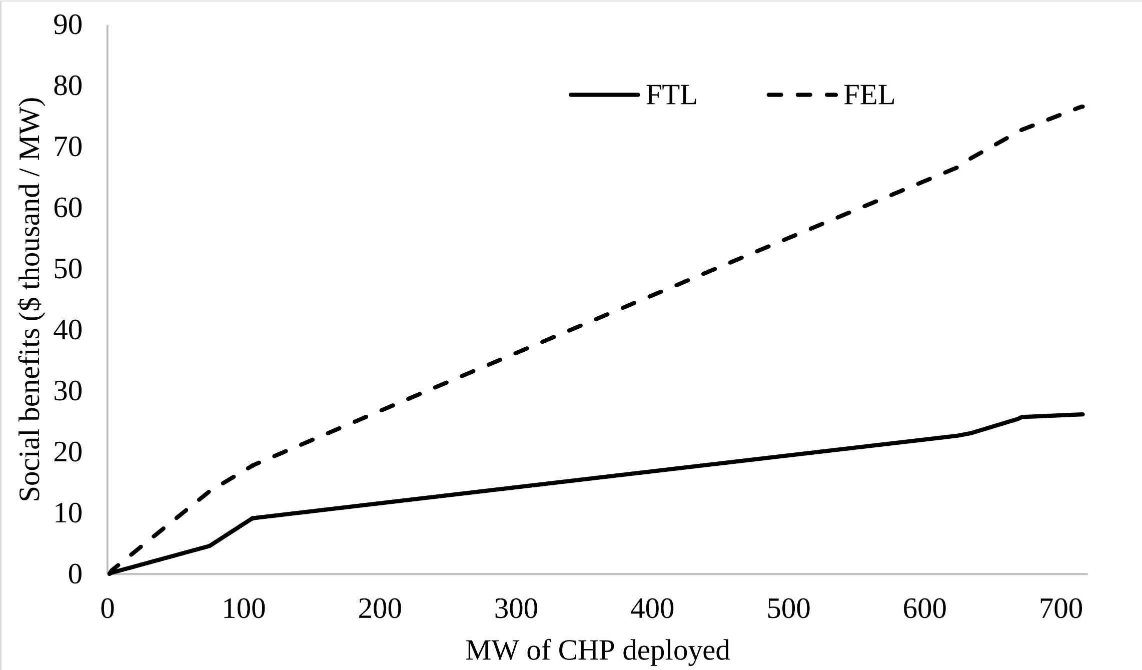

Figure 7. Monetized risk reduction to the grid with incremental CHP adoption

CHP operated in FTL mode has been found to be more economical for the CHP owner, in terms of energy savings, as compared to FEL mode (Govindarajan and Blumsack 2015). Meanwhile, our analysis of blackout risk reduction suggests that CHP units operated in FEL mode can reduce the stress on the grid to a greater extent as compared to operating in FTL mode, with up to four times the social reliability benefits. There is thus some tension between operating CHP units to maximize energy savings or other private benefits to CHP owners and operating those same units to maximize benefits to the grid as a whole. A solution that partially resolves this tension would be for CHP owners to operate units in FTL mode except during hours when the blackout risk was relatively high. Using a combination of FTL and FEL in this way will have a higher operational costs than operating only in FTL mode, but would also yield higher system-wide benefits than solely operating in FTL mode. The system benefits from a hybrid operating strategy would depend on the blackout probability threshold i.e., the blackout risk above which CHP units will be switched from FTL to FEL mode.

To assess the private and social benefits and costs from such a hybrid operational strategy, we use the BCHP tool described earlier to generate hourly energy demand profiles with a combination of FEL and FTL operation modes for commercial buildings. Our simulations assume that the operational mode will switch from FTL to FEL when the blackout probability in PJM reaches a defined threshold (so at the threshold level or higher, all CHP owners will switch from FTL to FEL mode). We assume that this threshold is the same for all CHP units, the blackout probability is identically estimated for all CHP units using our blackout probability model (equation 5), and perform a sensitivity analysis on the blackout probability threshold. We also assume that there is no cost involved in switching from FTL to FEL mode, other than change in fuel and variable O&M costs. Hourly energy demand profiles were simulated for a range of blackout probability thresholds. Figure 8 shows the additional monetized blackout risk reduction (averaged across all types of commercial buildings) by switching to FEL mode during periods of high blackout risk. The x-axis shows various levels of blackout probability threshold, i.e., the maximum blackout probability at which the CHP owners will switch from FTL to FEL mode. The additional costs and benefits decrease as the blackout probability threshold approaches peak blackout probability (~0.0024) observed in PJM during the time horizon of our case study. This is because of the number of hours where CHP units switch from FEL to FTL decreases.

At lower threshold levels (more-frequent switching between FTL and FEL), the additional operational costs to CHP owners from switching to FEL mode outweigh the social benefits. But, at higher thresholds (greater than ~ 0.0014, meaning less-frequent switching between FEL and FTL) the social benefits offset the additional operational costs. At all threshold levels, the additional operational costs are higher than the private benefits to CHP owners. There is thus no private incentive (in terms of energy savings or the private benefit from blackout risk reduction) to CHP owners in commercial buildings to switch from FTL to FEL to reduce blackout risk. Based on the social blackout risk reduction, switching to FEL during high blackout risk periods can be a viable option and an incentive to bear the additional operational costs to CHP owners would be appropriate.

The benefits and costs associated with operating building-integrated CHP units to reduce blackout risk vary widely by the commercial building environment in which CHP is installed. To illustrate a range of costs and benefits based on the type of commercial building considered, Figure 9 and 10 show the benefits and costs of switching from FTL to FEL in hospitals (Figure 9) and warehouses (Figure 10). Hospitals yield higher social and private monetized risk reduction as compared to the average value across all buildings, and exhibit a similar blackout probability threshold where the social benefits of switching from FTL to FEL mode outweigh the operational costs as compared to the set of modeled commercial buildings as a whole (Figure 8). The social reliability benefits are much lower in warehouses, and operational costs from switching to FEL are higher than the benefits at all threshold levels. The results suggest that switching the operational mode from FTL to FEL may not be beneficial for all building types.

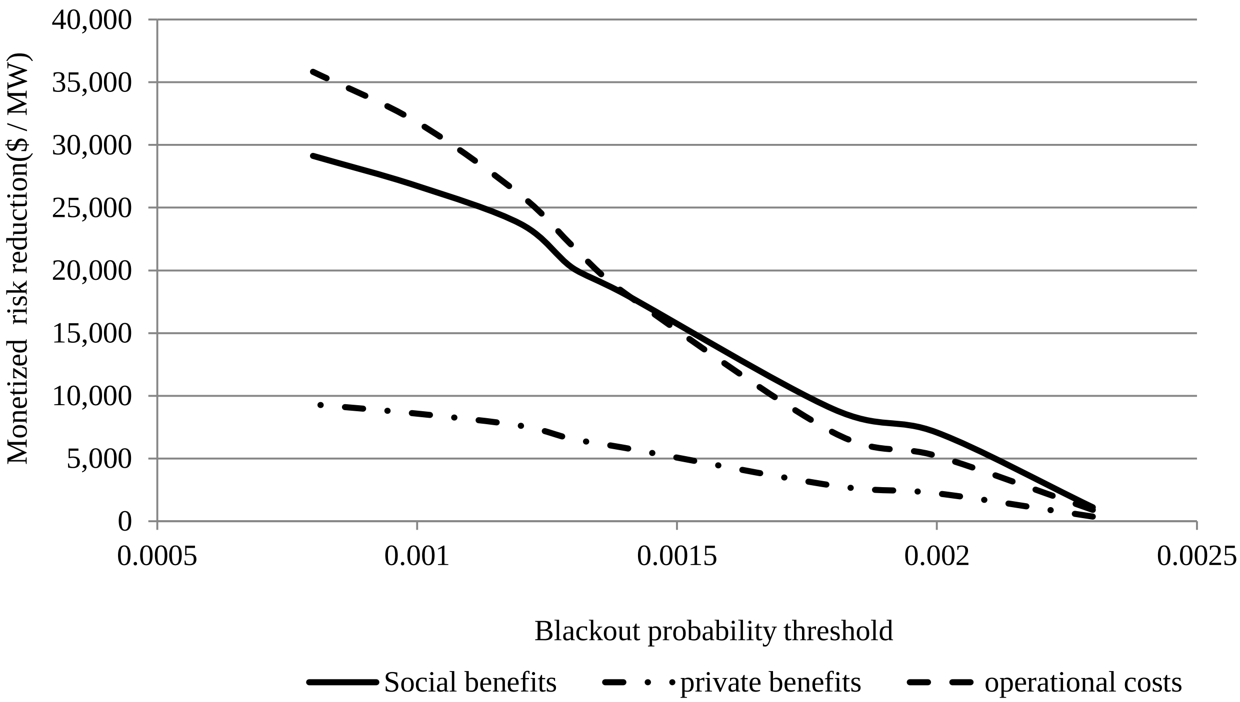

Figure 8. Monetized blackout risk reduction by switching from FTL to FEL averaged across all commercial buildings. Note that a lower threshold blackout probability implies more-frequent switching from FTL to FEL mode.

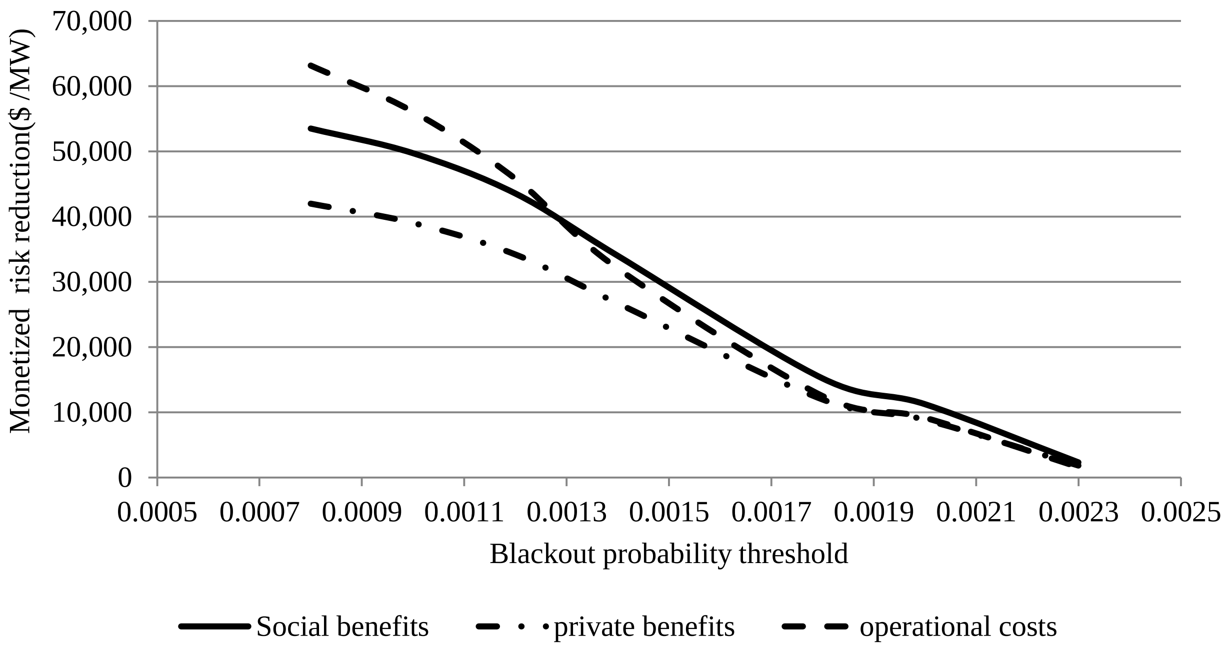

Figure 9. Monetized blackout risk reduction by switching from FTL to FEL in hospitals

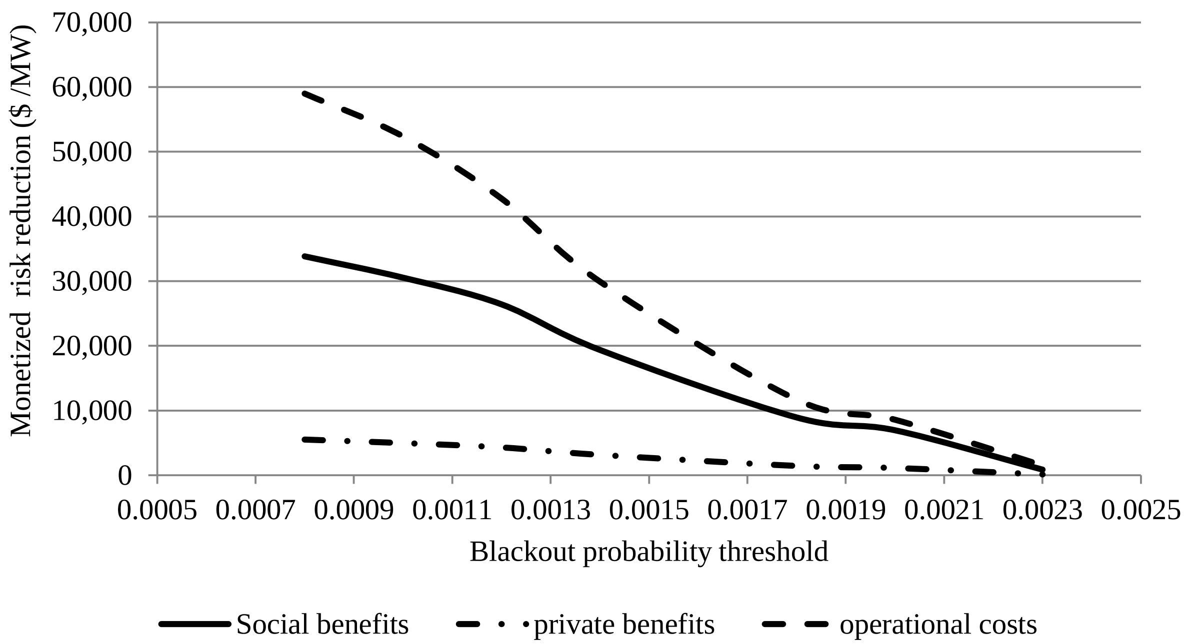

Figure 10. Monetized blackout risk reduction by switching from FTL to FEL in warehouses

7. Policy Implications

Our case study of building-integrated CHP adoption in the PJM region suggests that the social benefits from blackout risk reduction greatly outweigh the private benefits accruing to CHP owners. Moreover, we observe a great deal of variation in blackout risk reduction benefits based on building type. These two results likely generalize to other behind-the-meter generation technologies besides CHP (e.g. building-scale batteries or micro-size gen-sets). Perhaps more specific to CHP adoption relative to other distributed energy generation or storage technologies, we find that for some building types the increased costs associated with switching between FTL and FEL operations outweigh the social benefits of blackout risk reduction.

The results lead us to some policy implications on CHP adoption and its operation schedule. Firstly, the decision by building owners adopt CHP primarily depends on cost effective energy services provided by CHP. The results of this study suggest that energy-savings benefit is generally larger than the private reliability benefit, although we recognize that the perceived value of reliability among CHP owners may be quite high immediately following large blackouts, as illustrated in Hampson, et al. (2012). The positive network externality to other grid connected customers from blackout risk reduction is, however, more substantial. The existing literature has discussed policy measures to support CHP adoption (for example feed-in tariff, pricing CO_2 emissions and options suggested by Siler-Evans et al, 2012). Our analysis suggests some justification for an additional policy measure to provide CHP owners with payments for the blackout risk reduction, which could happen through expanded participation in demand response programs such as those run by PJM. The capacity prices in PJM the last several years have ranged from $27,000/MW-year to $62,000/MW-year, based on capacity prices published by PJM. These payments are comparable with the social value of blackout risk reduction ($26,000-$75,000 per MW of CHP) we estimate in this study. Any such subsidy or payment mechanism, however, may need to be subject to a type of net benefits test because of the heterogeneous nature of blackout risk reduction benefits from different building types. Secondly, the results suggest that CHP owners have little private incentive to operate in a way that maximizes blackout risk reduction for the grid as a whole. Electric utilities or independent system operators such as PJM can collaborate with CHP owners to design an operation schedule which will benefit both the owners in terms of energy cost savings and the grid with blackout risk reduction. Electric utilities can also incentivize CHP adoption to meet state level energy efficiency goals (an example from the PJM region is Pennsylvania's Act 129, which sets annual and peak demand reduction targets for all of the state's utilities (Sahraei-Ardakani et al. 2012)) and some part of this requirement can be achieved by CHP operation during high demand hours which also leads to blackout risk reduction.

Conclusion

With sufficient deployment scale and proper operational protocols (i.e., operating CHP to follow electrical loads during peak demand periods), even modest levels of CHP deployment in regional electric grids can yield substantial reliability-related benefits. Using historical data on blackout frequencies, durations and scope (number of customers affected) from the PJM electricity market, blackout risk is quantified as a function of system-wide electricity demand. Unsurprisingly, risk is highest during the winter and summer peaks, with summer blackout risk being somewhat larger than winter blackout risk.

CHP units operated to ameliorate peak demand can benefit electricity consumers in two ways. First, CHP-enabled customers can continue to receive electricity service even when power-grid interruptions occur, as long as fuel supplies are not interrupted. This "private reliability benefit" would amount to between $2 and $2.5 million per year with a deployment level of 1,000 CHP units throughout the Mid-Atlantic region. The average private benefit would thus amount to $2,000 to $2,500 per year. The private reliability benefit, however, is smaller than the energy-savings benefit by a factor of 1.5 to 4.

The second mode of reliability benefit from CHP deployment accrues to the grid as a whole through the reduction of stress and thus blackout risk. There is a social value associated where customers who don't deploy CHP will be benefited from reduced risk of a blackout. We estimate that the annual social benefits of blackout risk reduction amount to $75,000 per MW of CHP when CHP is operated in a way to follow electrical load during peak periods. The estimated annual social benefits are lower -

$26,000 per MW of CHP when CHP is operated to follow thermal load. It may be a viable option to switch from FEL to FTL operation mode during periods of high blackout risk in PJM in certain building types (like hospitals).

The results suggest that payments to CHP owners/operators for these reliability benefits would be economically justified, but our analysis does have some drawbacks. First, our blackout risk model is relevant only to blackouts that are not caused extreme events such as hurricanes or ice storms. CHP could provide a social reliability benefit in these circumstances in a type of micro-grid configuration, but our model is not able to capture this type of benefit. Second, the logit model can be used to estimate the impacts of relatively small changes in risk, but not large changes. In the scope of the PJM electricity market, with generating capacity of nearly 200 GW and peak demands of around 180 GW, we believe that simulating the removal of less than 0.5% of that demand is appropriate for the logit model. Removal of larger levels of demand, perhaps 10%, would be less appropriate. Our model thus has some limitations in terms of its ability to estimate blackout risk reduction with very large CHP deployments.

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