

Peer-reviewed research

Market-based Estimation of Average Electricity Outage Costs in the United States

Chi Keung Woo¹, A. Tishler², Kang Hua Cao³, Han Qi⁴^a, Raymond Li⁵, Jay Zarnikau⁶

¹ Centre for Sustainable Development Studies, Hong Kong Baptist University, China, ² Collier School of Management, Tel Aviv University, Israel, ³ Department of Accountancy, Economics and Finance, Hong Kong Baptist University, China, ⁴ Shenzhen Audencia Financial Technology Institute, Shenzhen University, China, ⁵ Canberra School of Politics, Economics & Society, University of Canberra, Australia, ⁶ Department of Economics, University of Texas at Austin, USA

Keywords: Electricity outage costs, Market-based estimation, United States, JEL: D12 Q41 Q48

<https://doi.org/10.46557/001c.90927>

Energy RESEARCH LETTERS

Vol. 5, Issue 2, 2024

Electricity outage cost (*EOC*) estimates (\$ per kWh unserved) are essential input data for optimal reliability planning and efficient pricing of electricity services. Based on the 2019-2020 market data published by two US government agencies for the lower 48 states, this paper's *EOC* estimates by census region and year are median values of \$1.39 to \$2.93 per kWh unserved, well below the estimate of \$9 per kWh unserved adopted by Texas for optimal reliability planning. The policy implications of adopting our lower *EOC* estimate are (a) a reduction in an electric grid's optimal planning reserve to improve the grid's cost efficiency; and (b) a decline in the grid's marginal cost-based retail price to encourage welfare-enhancing end-use consumption.

I. Introduction

Electricity outage cost (*EOC*) estimates (\$ per kWh unserved) are essential input data for optimal reliability planning and efficient pricing of electricity services (Chao, 1983; Hobbs, 1995; Sreedharan et al., 2012; Wilkerson et al., 2014; Woo et al., 2019, 2023). Compiling reasonable estimates for electricity services' *EOC* is complicated due to the diverse *EOC* estimates reported in literature (e.g., Caves et al., 1990; D. Cheng & Vankatsesh, 2014; Mao et al., 2018; Schröder & Kuckshinrichs, 2015; Woo & Pupp, 1992). Adopting an unrealistically high *EOC* estimate causes an electric grid to overstate the optimal planning reserve and marginal-cost-based retail price.

Motivated by earlier studies and the large disparity in extant *EOC* estimates, we used market data from 2019 to 2020 published by two US government agencies to estimate average *EOCs* of the lower 48 US states. The US Energy Information Administration's (EIA) market data reflects that 2019 is the most recent pre-Covid year and 2020 is the first year of the Covid pandemic that wrecked the US economy.

Our main result in [Figure 1](#) shows the market-based *EOC* estimates by census region and year, leading to the following key findings: First, Figure 1's median estimates by cen-

sus region are \$1.39 to \$2.93 per kWh unserved, far exceeding the residential market-based estimates of \$0.12 to \$0.34 per kWh unserved (Woo et al., 2021b). However, they are less than the non-residential (commercial and industrial) market-based estimate of ~\$3.6 per kWh unserved (Woo et al., 2021a).¹ Second, Figure 1's median estimates are well below the *EOC* estimate of \$9 per kWh unserved adopted by Texas for the state's optimal reliability planning (Potomac Economics, 2019) based on the least-cost condition of $LOLE \times EOC = MGCC$, where $LOLE$ = loss-of-load expectation (hours per year) and $MGCC$ = marginal generation capacity cost (\$/kW/year) (Chao, 1983; Woo et al., 2019).²

This paper is an easy-to-use approach applicable to international regions with similar data availability. Hence, the approach is a quick reality check of the *EOC* estimates obtained through the more time-consuming approaches like survey-based contingent valuation and choice experiment (e.g., Hartman et al., 1991; Hoyos, 2010; Mitchell & Carson, 1989; Moeltner & Layton, 2002; Ozbaflı & Jenkins, 2016; Reichl et al., 2013) and market-based regression analyses of electricity consumption and backup generation ownership (e.g., Y. S. Cheng et al., 2013; Fisher-Vanden et al., 2015; Matsukawa & Fujii, 1994; Tishler, 1993).

^a Corresponding author email: steffan@szu.edu.cn

¹ Woo et al.'s (2021b) non-residential estimate was based on an overstated wage of \$75 per hour, about three times the correctly stated wage of \$27/hour. Using the correct wage of \$27/hour, the non-residential *EOC* estimate should have been ~3.6 per kWh unserved.

² Since the optimal $LOLE$ equals $MGCC / EOC$, a decrease in *EOC* implies an increase in the optimal $LOLE$ and a reduction in an electric grid's planning reserve.

Table 1. The Descriptive Statistics for $\{P_j\}$, $\{X_j\}$ and A .

| Variable | Mean | Standard deviation | Coefficient of variation | Minimum | Maximum |
|---|----------|--------------------|--------------------------|---------|----------|
| P_1 = Electricity price (\$/kWh) | 0.11 | 0.03 | 0.28 | 0.08 | 0.19 |
| P_2 = Natural gas price (\$/Mcf) | 3.75 | 0.99 | 0.26 | 2.37 | 7.22 |
| P_3 = Fuel oil price (\$/gallon) | 2.58 | 0.30 | 0.12 | 2.15 | 3.70 |
| P_4 = Propane price (\$/gallon) | 2.19 | 0.61 | 0.28 | 1.16 | 4.36 |
| P_5 = Hourly wage (\$/hour) | 26.63 | 2.96 | 0.11 | 21.45 | 34.53 |
| X_1 = Electricity usage (kWh) | 7.79E+10 | 7.50E+10 | 0.96 | 5.33E+9 | 4.29E+11 |
| X_2 = Natural gas usage (Mcf) | 5.84E+8 | 6.84E+8 | 1.17 | 1.30E+7 | 4.16E+9 |
| X_3 = Fuel oil usage (gallons) | 1.26E+9 | 1.19E+9 | 0.94 | 1.04E+8 | 8.41E+9 |
| X_4 = Propane usage (gallons) | 2.69E+8 | 4.07E+8 | 1.51 | 2.71E+7 | 2.78E+9 |
| X_5 = Labor usage (hours) | 5.48E+9 | 5.83E+9 | 1.06 | 4.97E+8 | 3.17E+10 |
| A = Total amount of electricity available (kWh) | 8.69E+10 | 7.88E+10 | 0.91 | 5.33E+9 | 4.59E+11 |

Descriptive statistics of annual data for the lower 48 states available from the EIA and BLS; sample period = 2019-2020; sample size = 96 observations

The Section II contains the methodology and data, Section III presents the results and the Section IV concludes the paper.

II. Methodology and Data

A. Short-run EOC formula

Our short-run EOC formula is an adaptation of Woo et al.'s (2021a, 2021b) methodology. Consider a state's cost function for aggregate production:

$$C = C(Y, P_1, \dots, P_J, \mathbf{K}, A) = \sum_j P_j X_j \quad (1)$$

where Y = aggregate output index; P_j = price of input X_j with $j = 1$ for electricity, 2 for natural gas, 3 for fuel oil, 4 for propane, 5 for labor; \mathbf{K} = vector of fixed inputs (e.g., capital and land); and A = total amount of electricity available.

Including an additional input, such as material (e.g., plastic or steel), does not change the EOC formula presented below when the usage of material is strictly proportional to Y (Woo et al., 2021a). This is because the material content of Y in the short-run should not depend on the usage of X_1 to X_5 .

We used $\max(G, X_1)$ to measure A , where G = annual total generation \times (1 – average line loss of 5%). Overlooked by the above cited EOC studies, this measurement of A reflects interstate electricity trading under wholesale market competition in the US (Cao et al., 2021). If a state is an exporter, $G > X_1$, and G measures a state's total amount of electricity available. If the state is an importer, $G < X_1$, and its electricity import is $(X_1 - G) > 0$, implying that X_1 proxies the state's total amount of electricity available.

Invoking the Envelope Theorem (Takayama, 1985), the effect of ΔA on C is represented as follows:

$$\Delta C = \sum_j P_j \partial X_j / \partial A \Delta A \quad (2)$$

Let $\varepsilon_j = (\partial X_j / \partial A) (A / X_j)$ denote the elasticity of X_j with respect to A , which allows us to rewrite equation (2) as:

$$\Delta C / \Delta A = \sum_j \varepsilon_j (P_j X_j / A) \quad (3)$$

We expect $\varepsilon_j \leq 1$, as a 1% increase in A raises the usage of X_j by less than 1%. This is because if electricity availabil-

ity is not a binding constraint in the state's aggregate production process, the percentage increase in X_j is zero. When the constraint is binding, the percentage increase in X_j is at most equal to 1. As the empirical value of ε_j is seldom known, we assume ε_j 's maximum value of 1.0 to obtain the following short-run EOC formula:

$$EOC = \sum_j P_j X_j / A \quad (4)$$

B. Data description

The EIA (<https://www.eia.gov/electricity/data.php>) publishes the state-level data for (a) the prices and total usages by energy type listed in Table 1 and (b) annual electricity consumption and generation for constructing the variable A .

The US Bureau of Labor Statistics (BLS) (www.bls.gov) publishes state-level data for average workhours per week and annual earnings of all nonfarm workers for calculating P_5 and X_5 . Specifically, $P_5 = E / W$, where E is the annual earnings per employee and W is the annual workhours per employee computed as average workhours per week \times 52 calendar weeks per year. Further, $X_5 = N W$, where N = total number of nonfarm workers.

III. Results

Table 1 presents the descriptive statistics for $\{P_j\}$, $\{X_j\}$ and A .

The following observations emerge from Table 1. First, electricity prices average \$0.11/kWh and exhibit discernible variations based on their standard deviation, coefficient of variation, and minimum and maximum values. Second, the prices for natural gas, fuel oil, and propane have respective averages of \$3.75/Mcf, \$2.58/gallon and \$2.19/gallon with discernible variations. Third, energy and labor usage at the state level are large with notable dispersions. Finally, the average amount of electricity available exceeds the average amount of electricity usage, affirming the US electricity

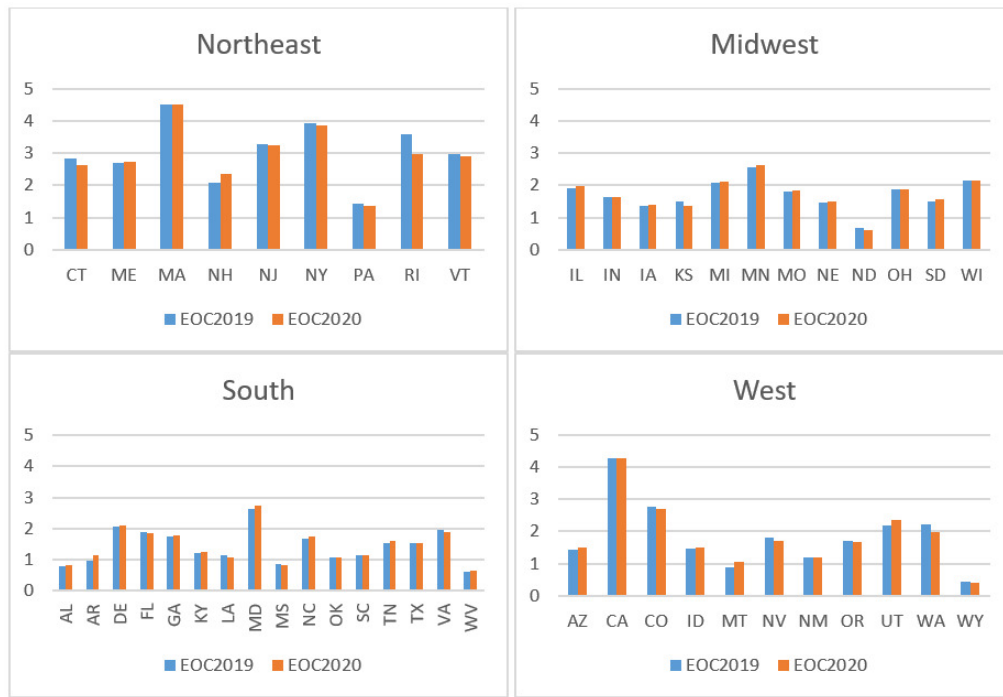


Figure 1. Average Electricity Outage Cost (EOC) Estimates (\$ per kWh unserved) for the lower 48 states and years 2019 and 2020 grouped by Census Region (Northeast, Midwest, South, and West) based on the Market Data Published by the EIA and BLS

industry's goal of providing highly reliable service through interstate electricity trading.

Figure 1 presents the EOC estimates by census region and year. These estimates have median values of \$1.38 to \$2.97 per kWh unserved for 2019 and \$1.39 to \$2.90 per kWh unserved for 2020, well below the estimate of \$9 per kWh unserved as adopted by Texas for optimal reliability planning (Potomac Economics, 2019). Hence, adopting the EOC estimates shown in Figure 1 is likely to reduce the Texas electric grid's least-cost capacity reserve target of ~13.5% of system peak demand forecast. However, reducing an electric grid's reserve target is highly controversial, a topic that is well beyond our paper's narrow focus on EOC estimation.

IV. Conclusion

Our paper's research focus reflects that EOC estimates are essential input data for least-cost resource planning and efficient electricity pricing, and the extant EOC estimates are highly diverse, complicating their use by these applications. Our key findings are as follows: First, our EOC estimates are well below the estimate adopted by Texas for optimal reliability planning. Second, our proposed approach is easy to use with minimal data requirement, thus readily applicable to international regions with market data akin to those published by the EIA and BLS. Hence, it can serve as a quick reality check of EOC estimates obtained through

other approaches that are far more time-consuming to implement.

The policy implications of adopting our lower EOC estimates are (a) a reduction in an electric grid's optimal planning reserve that improves the grid's cost efficiency; and (b) a decline in the grid's marginal cost-based retail price that encourages welfare-enhancing end-use consumption. However, (a) and (b) represent a sharp departure from the *status quo*. Hence, they should be a policy debate topic among the stakeholders of a region's electricity industry (e.g., Woo et al., 2023).

Funding

This study was partially funded by the Ford Foundation (#134371 and #139746) and the Research Matching Grant Scheme of the Research Grant Council of the HKSAR Government, and supported by Shenzhen Humanities & Social Sciences Key Research Bases.

Acknowledgment

We thank the editors and two reviewers for their helpful comments. Without implications, all errors are ours.

Submitted: July 21, 2023 AEST, Accepted: August 29, 2023 AEST



This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CCBY-SA-4.0). View this license's legal deed at <https://creativecommons.org/licenses/by-sa/4.0> and legal code at <https://creativecommons.org/licenses/by-sa/4.0/legalcode> for more information.

References

- Cao, K. H., Qi, H. S., Tsai, C. H., Woo, C. K., & Zarnikau, J. (2021). Energy trading efficiency in the US Midcontinent electricity markets. *Applied Energy*, 302, 117505. <https://doi.org/10.1016/j.apenergy.2021.117505>
- Caves, D. W., Herriges, J. A., & Windle, R. J. (1990). Customer demand for service reliability in the electric power industry: A synthesis of the outage cost literature. *Bulletin of Economic Research*, 42(2), 79–121. <https://doi.org/10.1111/j.1467-8586.1990.tb00294.x>
- Chao, H.-P. (1983). Peak load pricing and capacity planning with demand and supply uncertainty. *Bell Journal of Economics*, 14(1), 179–190. <https://doi.org/10.2307/3003545>
- Cheng, D., & Vankatsesh, B. (2014). *Literature survey and comparison of consumer interruption costs in North America and Europe*. <https://doi.org/10.1109/ccece.2014.6901156>
- Cheng, Y. S., Wong, W. K., & Woo, C. K. (2013). How much have electricity shortages hampered China's GDP growth? *Energy Policy*, 55, 369–373. <https://doi.org/10.1016/j.enpol.2012.12.015>
- Fisher-Vanden, K., Mansur, E. T., & Wang, Q. (2015). Electricity shortages and firm productivity: Evidence from China's industrial firms. *Journal of Development Economics*, 114, 172–188. <https://doi.org/10.1016/j.jdeveco.2015.01.002>
- Hartman, R. S., Doane, M. J., & Woo, C.-K. (1991). Consumer rationality and the status quo. *Quarterly Journal of Economics*, 106(1), 141–162. <https://doi.org/10.2307/2937910>
- Hobbs, B. F. (1995). Optimization methods for electric utility resource planning. *European Journal of Operational Research*, 83(1), 1–20. [https://doi.org/10.1016/0377-2217\(94\)00190-n](https://doi.org/10.1016/0377-2217(94)00190-n)
- Hoyos, D. (2010). The state of the art of environmental valuation with discrete choice experiments. *Ecological Economics*, 69(8), 1595–1603. <https://doi.org/10.1016/j.ecolecon.2010.04.011>
- Mao, S., Wang, C., Yu, S., Gen, H., Yu, J., & Hou, H. (2018). Review on economic loss assessment of power outages. *Procedia Computer Science*, 130, 1158–1163. <https://doi.org/10.1016/j.procs.2018.04.151>
- Matsukawa, I., & Fujii, Y. (1994). Customer preferences for reliable power supply: using data on actual choices of back-up equipment. *Review of Economics and Statistics*, 76(3), 434–446. <https://doi.org/10.2307/2109969>
- Mitchell, R. C., & Carson, R. T. (1989). *Using surveys to value public goods – the contingent valuation method*. Resources for the Future.
- Moeltner, K., & Layton, D. (2002). A censored random coefficients model for pooled survey data with application to the estimation of power outage costs. *Review of Economics and Statistics*, 84(3), 552–561. <https://doi.org/10.1162/003465302320259547>
- Ozbaflı, A., & Jenkins, G. P. (2016). Estimating the willingness to pay for reliable electricity supply: a choice experiment study. *Energy Economics*, 56, 443–452. <https://doi.org/10.1016/j.eneco.2016.03.025>
- Potomac Economics. (2019). *2018 State of the Market Report for the ERCOT Electricity Markets*. <https://www.potomaceconomics.com/wp-content/uploads/2019/06/2018-State-of-the-Market-Report.pdf>
- Reichl, J., Schmidthaler, M., & Schneider, F. (2013). The value of supply security: The costs of power outages to Austrian households, firms and the public sector. *Energy Economics*, 36, 256–261. <https://doi.org/10.1016/j.eneco.2012.08.044>
- Schröder, T., & Kuckshinrichs, W. (2015). Value of lost load: an efficient economic indicator for power supply security? a literature review. *Frontiers in Energy Research*, 3. <https://doi.org/10.3389/fenrg.2015.00055>
- Sreedharan, P., Miller, D., Price, S., & Woo, C. K. (2012). Avoided cost estimation and cost-effectiveness of permanent load shifting in California. *Applied Energy*, 96, 115–121. <https://doi.org/10.1016/j.apenergy.2011.08.029>
- Takayama, A. (1985). *Mathematical Economics*. Cambridge University Press.
- Tishler, A. (1993). Optimal production with uncertain interruptions in the supply of electricity: Estimation of electricity outage costs. *European Economic Review*, 37(6), 1259–1274. [https://doi.org/10.1016/0014-2921\(93\)90134-v](https://doi.org/10.1016/0014-2921(93)90134-v)
- Wilkerson, J., Larsen, P., & Barbose, G. (2014). Survey of Western U.S. electric utility resource plans. *Energy Policy*, 66, 90–103. <https://doi.org/10.1016/j.enpol.2013.11.029>
- Woo, C. K., Milstein, I., Tishler, A., & Zarnikau, J. (2019). A wholesale electricity market design sans missing money and price manipulation. *Energy Policy*, 134, 110988. <https://doi.org/10.1016/j.enpol.2019.110988>
- Woo, C. K., & Pupp, R. L. (1992). Costs of service disruptions to electricity consumers. *Energy*, 17(2), 109–126. [https://doi.org/10.1016/0360-5442\(92\)90061-4](https://doi.org/10.1016/0360-5442(92)90061-4)
- Woo, C. K., Tishler, A., & Cao, K. H. (2023). Options for change: restructuring California's residential inclining rates for a better electricity future. *The Electricity Journal*, 36(1), 107234. <https://doi.org/10.1016/j.tej.2023.107234>
- Woo, C. K., Tishler, A., Zarnikau, J., & Chen, Y. (2021a). A back of the envelope estimate of the average non-residential outage cost in the US. *The Electricity Journal*, 34(4), 106930. <https://doi.org/10.1016/j.tej.2021.106930>
- Woo, C. K., Tishler, A., Zarnikau, J., & Chen, Y. (2021b). Average residential outage cost estimates for the lower 48 states in the US. *Energy Economics*, 98, 105270. <https://doi.org/10.1016/j.eneco.2021.105270>