Time to Move On: An Examination of Metering Periods for Small Business Direct Install Participants

Julian Ricardo, NMR Group, Inc.
Joseph Dolengo, National Grid
David Barclay, NMR Group, Inc
Scott Walker, NMR Group, Inc.

ABSTRACT

How long is too long when it comes to selecting a logging period? Standards for the evaluation of commercial and industrial lighting with data loggers call for different periods depending on the operating schedules of monitored sites, with the general requirement that logged data represent at least one typical schedule cycle. Here we compare savings estimates from small business lighting retrofits over a range of metering periods to assess the potential for reduced variability in the estimates and more cost-effective data collection using existing measurement and verification (M&V) technologies.

Lighting loggers, which rely on a photocell to detect on/off state changes, are an established method for M&V of savings from lighting retrofits. Here, we attempt to capture representative lighting usage on a circuit-by-circuit basis at each site.

The paper reports on key findings from up to six months of lighting usage captured with 309 data loggers deployed across 32 small businesses as part of a Northeastern utility program that began in 2016. It focuses on the effects that metering periods have on impact evaluations across observed building end-uses and fixture types. The paper also discusses how these findings might better inform resource allocation in future program evaluations, especially those that aim to make use of near real-time data collection and analyses.

Introduction

In this paper, we investigate the effects of logger metering period from an impact evaluator's perspective, based on lighting energy data from a utility program that facilitates lighting retrofits in small businesses. Data loggers are a simple, relatively low-cost method to measure lighting energy consumption, and in some cases are required for M&V proceeding in compliance with IPMVP and federal guidelines. The study focuses on the extent to which selecting more appropriate metering periods for these devices might improve the robustness of M&V savings estimates derived from them, reduce soft costs in device installation and retrieval, and improve resource allocation in future evaluations. Any potential benefits must also be weighed against the requirement that energy savings from commercial lighting projects be derived from logged data capturing at least one typical schedule cycle—a metric that can vary from project to project.[*]

Our approach assesses the relationship between metering period and evaluation results at three levels, increasing in granularity with each: (1) sample-level; (2) business type; and (3) site-

[*] According to the Commercial Industrial Lighting Evaluation Protocol in the Uniform Methods Project (2013), an office space occupied on weekdays can have cycles of 7, 14, or 21 days. Capturing one schedule cycle at a school requires accounting for when the building is most active (i.e. during the 6,570 hours of the academic year).

level mean daily energy savings. In a separate conference paper titled "Into the Great Wide Open" (2018), we calculate the ratios and root-mean-square-error (RMSE) of savings estimates among various data models. However, here we confine the analysis to on/off data captured using photocell-based data loggers. We define stable savings estimates as a mean week-to-week change of 2% or less.

Without accounting for operating schedule, we observed estimates remaining below this threshold across 3 of 4 sites (75%, n=24) after 14 days logged, whereas the remaining subset (n=8) showed greater volatility over metering periods as long as 84 days. Divided this way, the latter group spanned four business types—assembly spaces, fast food establishments, places of worship, and warehouses—and accounted for about one-sixth (17%) of all logged savings. The disparities in the amount of savings attributable to these two groups, and the relative robustness of the results with respect to metering period, may provide grounds for allocating resources (i.e. loggers) for longer periods to higher-volatility business types like those observed here. This aligns with the evaluation practice of oversampling projects accounting for disproportionately large shares of energy savings, insofar as evaluators may be able to achieve shorter metering periods at sites with relatively high savings. Future investigations could target (1) collecting a larger, broader sample of buildings and business types to allow for statistical significance testing, and (2) additional categorical variables of data collected to classify building end-use and load shape.

Methodology

This paper focuses on the approach used as part of the broader methods comparison for evaluating data logger performance over time. In so doing, it aims to build on comparative analysis of short- vs. long-term metering periods elsewhere in the literature (KEMA 2014). However, here we use savings estimates as opposed to hours of use (HOU) as the main functional unit. Future studies could be expanded to include seasonality, cyclic business activity, and other factors that might be used to adjust lighting usage baselines.

We monitored 32 small businesses as part of this research, using both networked metering devices and standalone data loggers to collect information about lighting usage. A separate conference paper, "Into the Great Wide Open" (2018), details the techniques we used to create a representative sample of buildings; install, retrieve, and perform quality control on advanced metering hardware; and analyze the collected data. Figure 1 shows the distribution of building types included in the study.

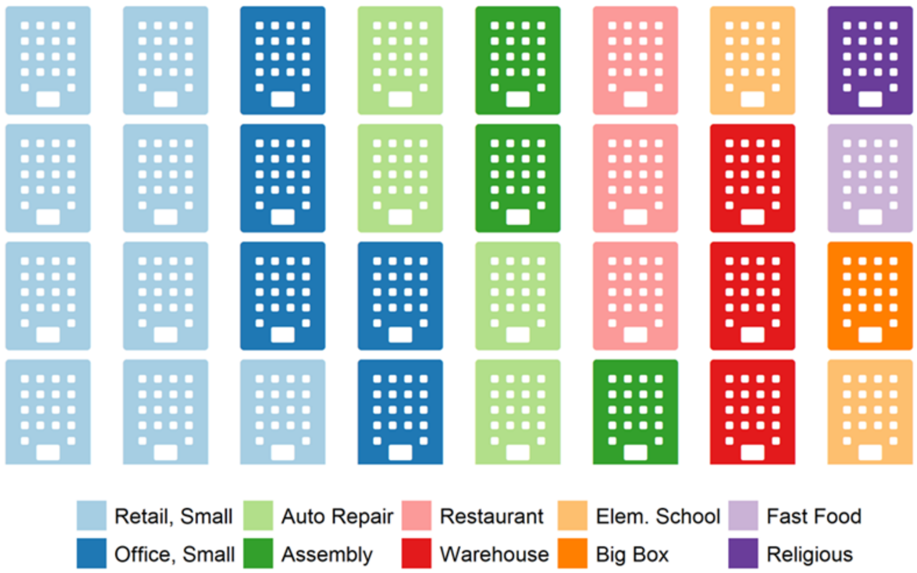

Figure 1. Typography of sites studied as part of this research, adapting the categories from those listed in the NYS Technical Resource Manual (NYTRM v5 2017).

The photocell-based logging equipment deployed to monitor light changes consisted of Onset HOBO UX90-002x Data Loggers. Mounted near or on the inside of fixtures, the loggers monitored state changes in lighting equipment as opposed to continuously sampling its state. Altogether, 309 data loggers were installed in lighting troffers on a representative sample of fixtures while performing direct installs of the new equipment, with a mean of ten loggers at each site and a median metering period of 84 days.

We extracted the retrieved loggers' on/off data and merged them with site-level information, including pre- and post-retrofit light fixture wattages, quantities, and descriptions. We then supplemented the logger data with variables representing building end-uses, operating hours, lighting HOU as estimated by implementers, and circuit-level identifiers.

Once combined with metadata, the logged usage data was pre-processed to account for unmonitored 24/7 fixtures and validated against deemed HOU estimates. Next, for each logger in the dataset, we trimmed the first and last two days of the metering period and combined all associated wattages.[†] The final layer of pre-processing consisted of converting the loggers' default on/off data format to time-series (ten-minute intervals).

At this stage, we generated four variables on an hourly basis for subsequent data validation and analysis: number of on/off events, fractional HOU, and pre-/post-retrofit power and energy savings (in kW and kWh, respectively).

All savings estimates reflected HVAC interactive effects multipliers from Appendix D of the New York State Technical Resource Manual (NYTRM v5 2017). We then aggregated these hourly figures into daily estimates, most notably the daily kWh savings reported in the study. In testing for the sensitivity of savings estimates to the amount of time logged, we calculated separate estimates using logged data from metering periods of varying length.

[†] Trimming the ends of the logger time-series data mitigates the effects of artifacts from partially recorded days and installation/retrieval on subsequent analysis.

Results

The following section begins with an overview of sample-level savings as a function of logged timespan, before drilling down to assess results by business type and explore two specific business types: warehouses and assembly spaces (n=3 each). At all levels of granularity, we evaluate the stability of logged savings estimates as they are traced out in time—keeping in mind the potential for leveraging this information as rapid-feedback M&V in future programs. We also examine the results in the context of existing TRM guidelines suggesting 7, 14, or 21-day metering periods for similar studies.

Sample-Level

Analyzing metering periods of up to 84 days, sample-level mean daily savings estimates changed <1.5% from week to week after 14 days. Figure 2 shows the full range of savings estimates as metering periods increase: the largest week-to-week increase (785-825 kWh) from 7-14 days, followed by a correction of the trend between 14 and 35 days, and a more-gradual leveling off after 35 days. The differenced time-series[‡] in Figure 3 corroborates this overall trend, showing decreases of roughly 1% from 21-28 and 35-42 days, preceded by an increase of 5% from 7-14 days.

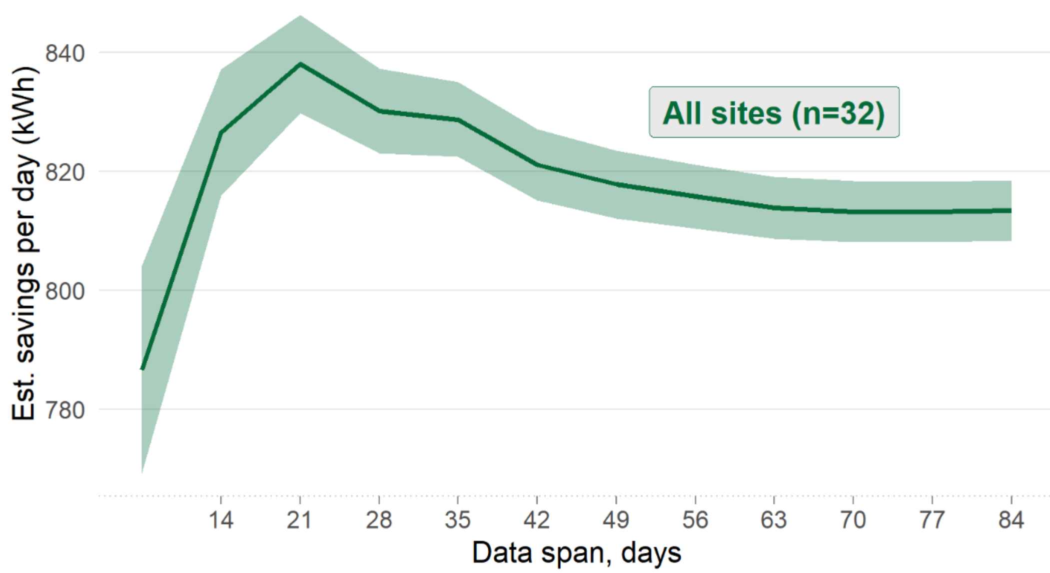

Figure 2. Time-series of daily savings estimates based on the full sample of 32 sites. The graph shows the mean (line) and the standard error of the mean (ribbon) calculated over successively longer metering periods.

[‡] Taking the difference in value between consecutive time-series data points.

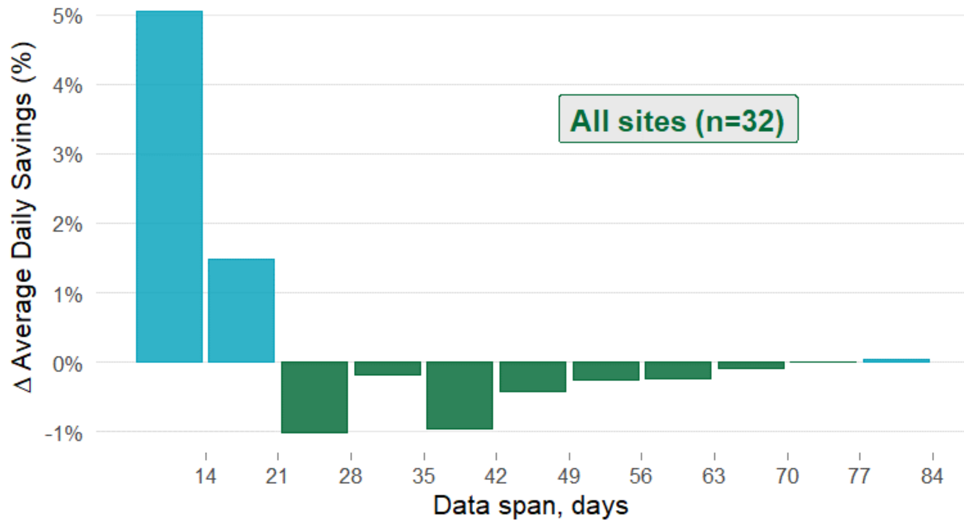

Figure 3. Differenced time-series of mean daily savings estimates based on the full sample of 32 sites.

We can unpack the differenced savings estimates further by comparing “high” and “low” volatility subsets of the full dataset, comprising a 3:1 split of sites in the study. Figure 4 compares the mean and standard error of the mean in aggregate daily savings estimates among these two groups, over a span of different metering periods. The smaller, high-volatility subset (n=8) includes three assembly spaces, three warehouses, a fast food business, and a religious establishment. The high-volatility group has pronounced increases in estimated savings between 7-14 and 28-35 days, and accounts for a disproportionately small share (17%) of total sample savings. Figure 5 shows the same savings estimates as percentage changes from week to week. It also shows that both groups reflect the trend observed in Figure 2: savings estimates that increase initially and then decrease more gradually after two weeks.

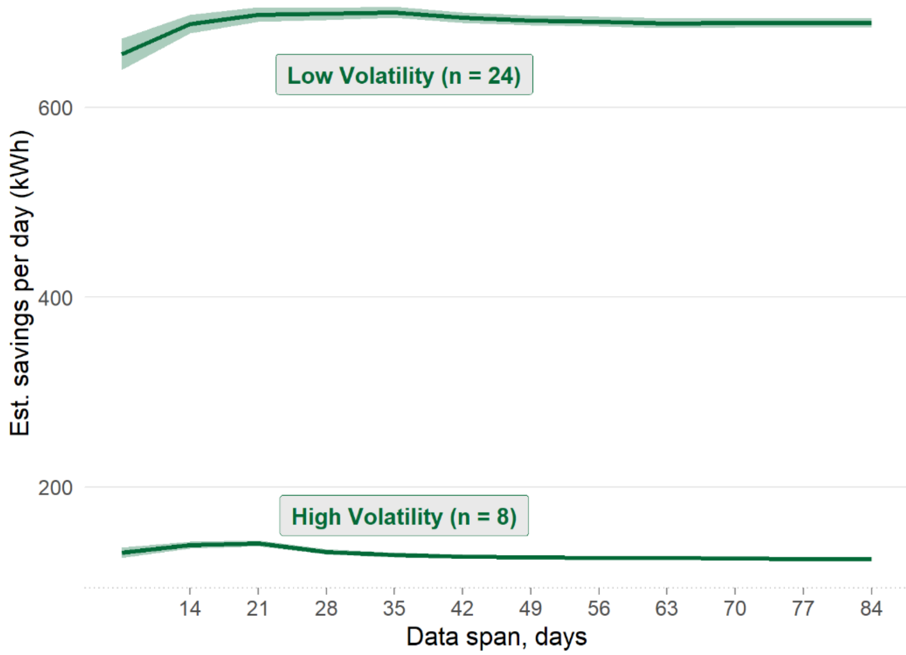

Figure 4. Time-series of sample-level mean daily savings estimates, grouped based on volatility of savings estimates over time. The graph shows the mean (line) and the standard error of the mean (ribbon) calculated over successively longer metering periods.

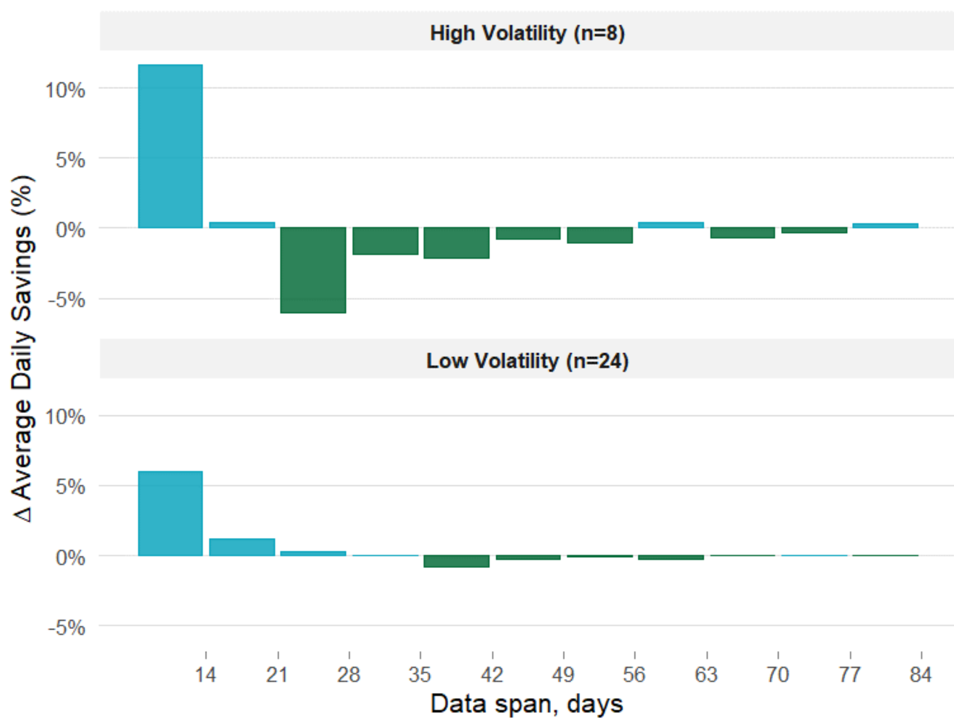

Figure 5. Differenced time-series of sample-level mean daily savings estimates, grouped based on volatility of savings estimates over time.

Business type

A similar analysis of the dataset, this time segmented by business type, reveals a range of different trends between estimated savings and length of time logged. Figure 6 shows each business type in the sample. Sample sizes are generally small when aggregating the dataset this way, creating a good deal of uncertainty in any findings we could derive from the results. This caveat aside, the most common response observed among business types is savings converging over time, as at the following types: auto repair, big box, elementary school, small office, and small retail. The remaining business types—assembly, fast food, religious, and warehouse—show greater volatility and less convergence, if any. The differenced time-series in Figure 6 corroborates the fact that a minority of business types contain the largest measured week-to-week changes in estimated daily savings.

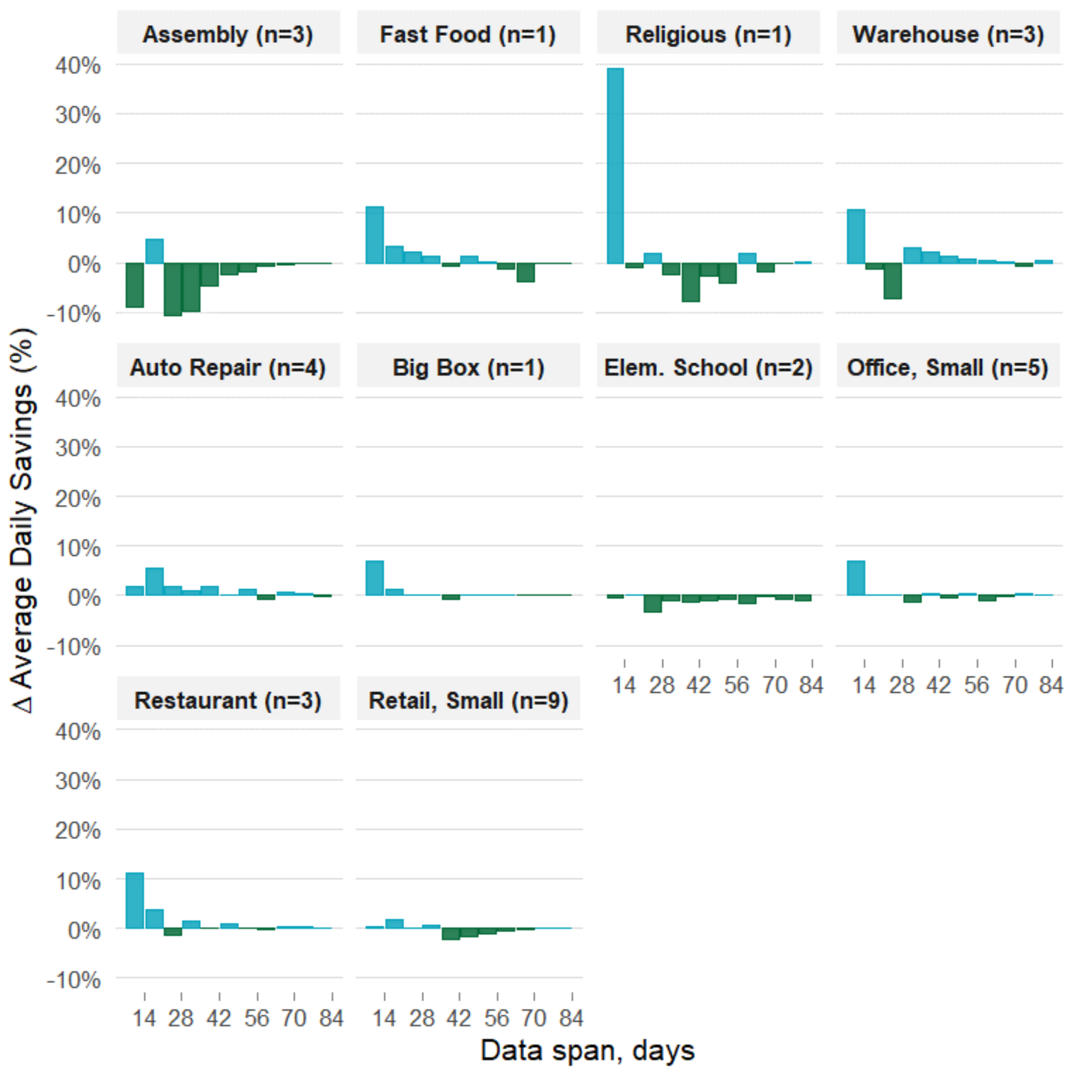

Figure 7. Differenced time-series of mean daily savings estimates, grouped by building end-use.

Warehouse

All three warehouse spaces in the study (labeled A1 through A3 in Figures 8 and 9) showed week-to-week changes in the mean daily savings estimates near or greater than 10%. Estimates in all three cases oscillate by roughly 5% within the first 28 days and, at two of three sites, change by at least 10% over this span. This cyclical behavior suggests that weather, occupancy, and/or warehouse output data might be fitting for normalizing the logged savings by an external variable in future analysis.

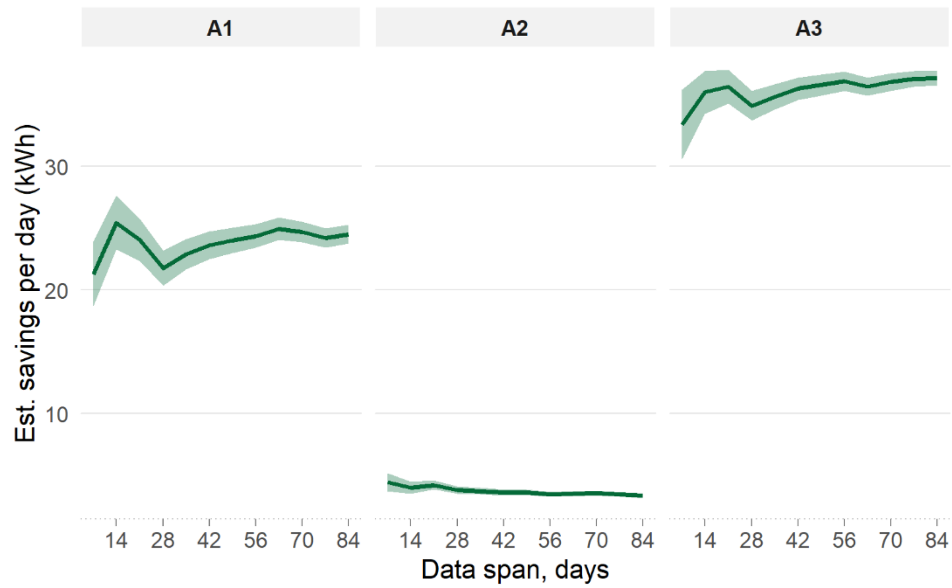

Figure 8. Time-series of mean daily savings estimates at three warehouse sites. The graph shows the mean (line) and the standard error of the mean (ribbon) calculated over successively longer metering periods.

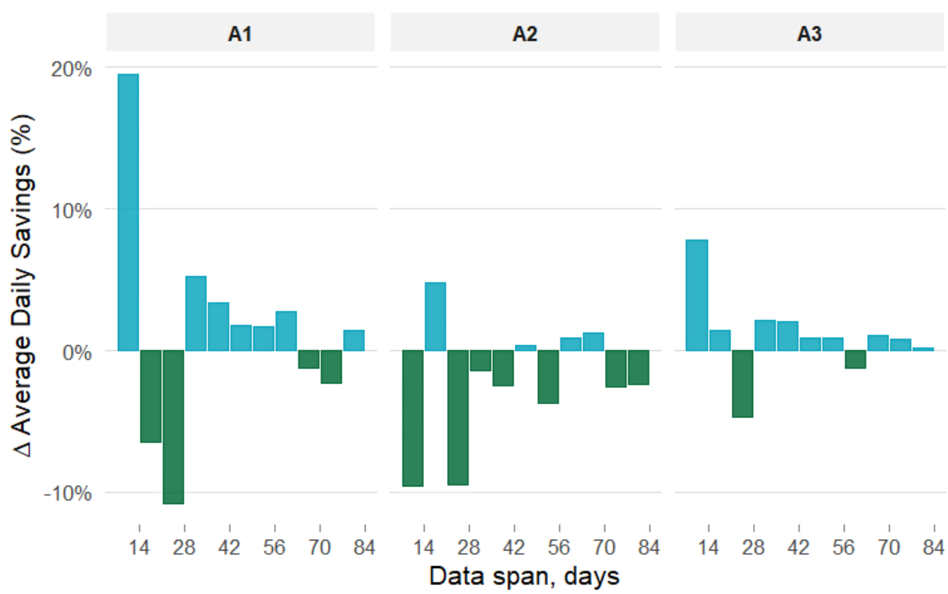

Figure 9. Differenced time-series of mean daily savings estimates at three warehouse sites.

Assembly

The dominant trend at all three assembly spaces in the study (in Figures 10 and 11) was to see decreasing savings estimates as metering periods got longer. Accounting for seasonal effects and/or occupancy data might have been useful in normalizing the logged savings by an external variable—a possibility to consider for future analysis. For example, the assembly space might have gone unoccupied during an academic break period or been closed off for renovation. Without additional information about building use over the logged timespan, metering data cannot fully explain the decreasing savings estimates.

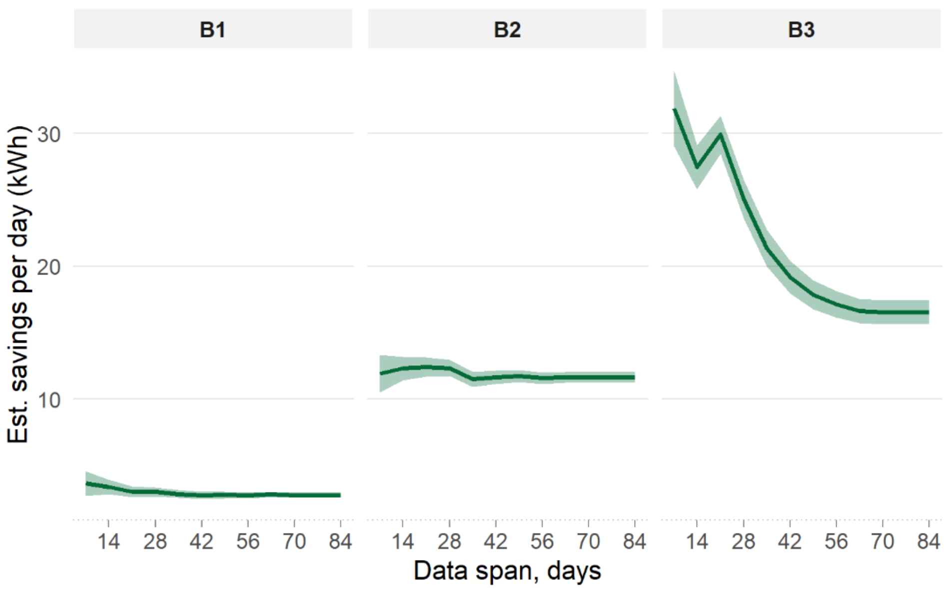

Figure 10. Time-series of mean daily savings estimates at three assembly spaces. The graph shows the mean (line) and the standard error of the mean (ribbon) calculated over successively longer metering periods.

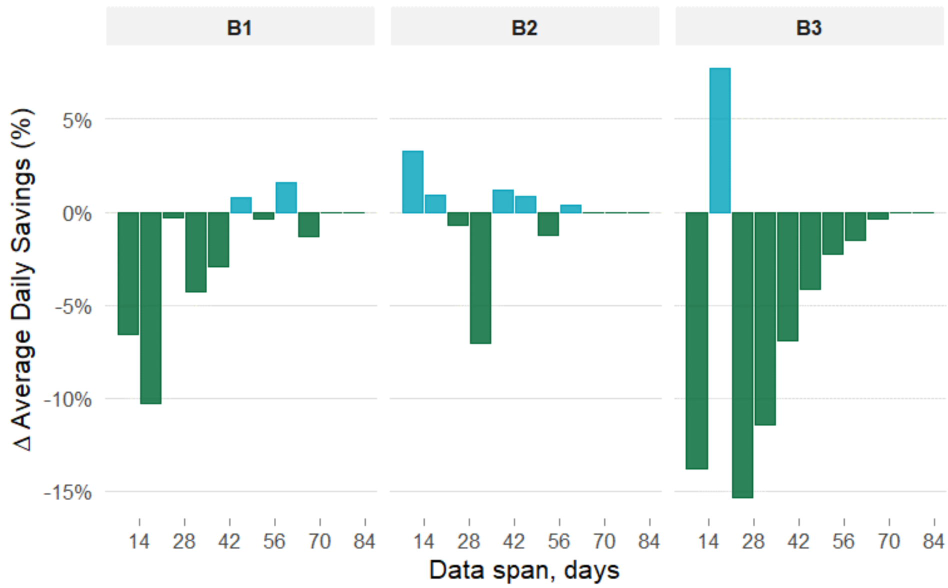

Figure 11. Differenced time-series of mean daily savings estimates at three assembly spaces.

Conclusion / Discussion

The effects of metering period on the savings estimated from small business lighting retrofits in a Northeastern state utility program offer insights into how evaluators and/or implementers can more effectively (and cost-effectively) deploy data loggers in similar studies. Here, we recorded saving estimates over time and monitored their stability, defining stable as a mean week-to-week change of 2% or less. Without accounting for operating schedule, 14 days of logging was sufficient for mean savings across 24 sites (69%) and a majority of total sample savings (83%) to stabilize—in line with recommendations from the NYTRM to select 7, 14, or 21-day metering periods. For this reason, we recommend a 14-day baseline metering period for using photocell loggers in commercial lighting M&V. This result, albeit based on a small sample size, aligns with the evaluation goal of disproportionately sampling sites that account for a larger portion of program savings.

However, greater volatility persisted over metering periods beyond 21 days, and as long as 70, at the remaining 8 sites (25%) in the study. The smaller group spanned four business types—assembly spaces, fast food establishments, places of worship, and warehouses—and accounted for a disproportionate minority (18%) of all logged savings. As such, we can conclude from the data these high-volatility business types may merit longer metering periods in future studies, and perhaps more-meticulous discussions with customers about occupancy and output patterns (where the facility produces goods or services) as well.

Topics for future investigations include (1) probing for auto-correlations in the logged time-series of lighting usage, (2) incorporating sensitivity to seasonality and business- or industry-specific cyclical effects into logger analysis, and (3) expanding the analysis to account for different business types and lighting controls. Assessing whether any statistically significant relationships exist between logger performance and business type (or load shapes, occupancy patterns, etc.) would require larger sample sizes and/or additional metadata. An ongoing analysis of existing, and additional sites in the latter half of 2018, will in part aim to determine whether the findings reported here carry over in a larger sample size, if not to address other topics among those listed.

References

CalTRACK Technical Documentation. 2017. *CalTRACK Site-level Daily Weather Normalized, Metered Energy Savings Estimation*. http://docs.caltrack.org.

———. 2017. *CalTRACK Site-level Monthly Weather Normalized, Metered Energy Savings Estimation*. http://docs.caltrack.org.

Dolengo, et. al. 2018. "Into the Great Wide Open: A Comparison of M&V 2.0 and Traditional Evaluation Methods for a Small Business Direct Install Program," *ACEEE Summer Study on Energy Efficiency in Buildings.* Washington, DC: ACEEE. *In press*.

KEMA. 2014. *Impact Evaluation of New York Small Business Services Energy Efficiency Program, 2010 and 2011 Program Years*. Albany: New York Public Service Commission.

Kleinhenz, et. al. 2013. "Comparison of Metering and Verification Methodologies of Compressed Air Systems for Utility-Based Energy-Efficiency Programs: A Case-Study," *ACEEE Summer Study on Energy-Efficiency in Industry* 4:1-13. Washington, DC: ACEEE. http://aceee.org/files/proceedings/2013/data/papers/4_214.pdf.

National Renewable Energy Laboratory. 2013. *The Uniform Methods Project: Methods for Determining Energy Efficiency Savings for Specific Measures*: *Commercial and Industrial Lighting Evaluation Protocol*. https://www.energy.gov/eere/about-us/ump-protocols.

New York State Joint Utilities. 2017. *New York Standard Approach for Estimating Energy Savings from Energy Efficiency Programs – Residential, Multi-Family, and Commercial/Industrial Measures*. Version 5. http://www3.dps.ny.gov/W/PSCWeb.nsf/96f0fec0b45a3c6485257688006a701a/72c23decff52920a85257f1100671bdd/$FILE/ATTV3NKB.pdf/TRM%20Version%205%20-%20January%202018.pdf.

Richman, EE. 2012. *Standard Measurement and Verification Plan for Lighting Retrofit Projects for Buildings and Building Sites*. Washington: Pacific Northwest National Laboratory. PNNL-21983. https://www1.eere.energy.gov/buildings/publications/pdfs/alliances/lighting_measurement_evaluation_protocol.pdf.