

Simulating Low-cost Rotating Panel Designs for the Commercial Buildings Energy Consumption Survey

Adebowale J. Sijuwade, Janice Lent, Michael Winkler

U.S. Energy Information Administration,¹ 1000 Independence Ave., S.W., Washington
DC 20585

Abstract

The U.S. Energy Information Administration's (EIA's) Commercial Buildings Energy Consumption Survey (CBECS) is the primary source of data on energy use in the U.S. commercial sector. The survey collects detailed information about commercial building characteristics, energy consuming equipment, and fuel use in commercial buildings. EIA has collected 11 cycles of CBECS data since 1979. Because CBECS data collection is complicated and increasingly expensive, EIA is researching options to potentially reduce costs for future CBECS cycles. Winkler et al, (2022) examined rotating panel designs recommended for CBECS by the National Academy of Sciences (NAS 2012). In this study, we consider low-cost panel designs involving fewer panels and smaller samples within the panels. Simulation results suggest that a longitudinal CBECS, involving dependent interviewing (Ridolfo et al. 2022), may provide useful time-series data despite increased standard errors.

Key Words: rotating panel surveys, complex surveys, simulation

1. Background

The U.S. Energy Information Administration (EIA) conducts three surveys to measure energy consumption in buildings: the Residential Energy Consumption Survey (RECS), the Commercial Buildings Energy Consumption Survey (CBECS), and the Manufacturing Energy Consumption Survey (MECS). EIA fielded the first RECS in 1978. From October 1979 to January 1980, EIA collected data for the first Nonresidential Buildings Energy Consumption Survey (NBECS), the predecessor of the current CBECS. The NBECS was collected again in 1983 and 1986, with a target population comprising all nonresidential buildings, including industrial buildings.

In 1985, EIA initiated MECS to gather data on industrial energy consumption and, in 1989, renamed NBECS as CBECS to reflect its more limited scope. For CBECS purposes, *commercial* buildings comprise all buildings except residential buildings, buildings on industrial campuses, and parking garages. Government buildings, schools, and houses of worship, for example—though not usually deemed commercial—are all covered by CBECS.

1.1 EIA's Commercial Buildings Energy Consumption Survey (CBECS)

The CBECS program encompasses two surveys:

1. For the CBECS buildings survey, EIA selects a sample of commercial buildings and establishes contact with a knowledgeable respondent for each building. Respondents report

¹ The analysis and conclusions contained in this paper are those of the authors and do not represent the official position of the U.S. Energy Information Administration or the U.S. Department of Energy.

building size, building use, energy-using equipment, and details of the building's energy-usage patterns.

2. In the CBECS energy supplier survey (ESS), EIA collects energy-use information for each responding sampled building from providers of electricity, natural gas, heating oil, and district heat.

The CBECS buildings survey is complicated to conduct, and its sample design is the focus of this paper. Sample selection involves listing units in a selected area and determining which buildings are commercial. After sample selection, field representatives must identify and contact a knowledgeable respondent for each sampled building, a process that can require substantial time. During the CBECS interview, respondents report detailed data on building characteristics, energy sources and uses, and energy-using equipment within the selected building. Because the entire process is often expensive and a challenge to fit within EIA's budget, EIA is researching methods of reducing the data collection costs.

CBECS data are used for benchmarking and calculating the Energy Star scores for commercial buildings. Policymakers also use CBECS data to inform energy policy, and product developers use them to gauge product market potential. Academics and EIA analysts use CBECS data to project energy usage, while building owners and managers use them to compare their energy usage to geographic averages.

The CBECS buildings sample design is a multi-stage national design, and most sampled buildings are drawn from an area frame. Primary Sampling Units (PSUs) are large counties or groups of smaller contiguous counties. Within each PSU, secondary and sometimes tertiary sampling units are drawn. Since no comprehensive list of U.S. buildings exists, EIA builds survey frames using area frames from which samples are geographically chosen, and *list frames*, which are supplemental lists of large buildings. For the area frame, field staff list the commercial buildings within each ultimate sample area, and samples of buildings are then drawn from the ultimate sample areas.

Five list frames supplement the CBECS area frame:

- **Airport Frame:** A list of airport facilities larger than 200,000 square feet
- **Government Buildings Frame:** The General Services Administration (GSA) list of federally owned or leased buildings over 200,000 square feet
- **University Frame:** The Integrated Postsecondary Education Data System (IPEDS) list of college/university campuses with an aggregate square footage of 1,000,000 or more, from the National Center for Education Statistics (NCES)
- **Hospital Frame:** A list of hospitals larger than 200,000 square feet
- **Common Premises Location Frame:** A list of large buildings developed from the Dun & Bradstreet Common Premises Location (CPL) file, consisting of buildings over 200,000 square feet

All CBECS sampling is probability-proportional-to-size, so large buildings and densely populated areas have higher selection probabilities. Most major metropolitan areas in the United States are in the CBECS sample with certainty (self-representing PSUs).

1.2 Results of the 2022 Simulation Study on CBECS Rotating Panel Designs

In 2012, EIA asked the National Academy of Sciences (NAS) to provide recommendations on the CBECS program. The published recommendations (National Research Council 2012) included that “an overall assessment of the costs and benefits of introducing a rotating sample design should receive priority as part of EIA's planning for the near future.”

In a rotating panel design, a sample is divided into approximately equal-sized sets of sample units called *panels*. One or more panels are selected for each data collection cycle and each panel remains

in the sample for a fixed number of cycles R . After a panel has been in the sample for the R^{th} time it is replaced with a new panel of fresh units. When the number of panels per cycle is constant, the proportion of sample overlap between two consecutive data collection cycles is $p = 1 - \frac{1}{R}$. In some rotation designs, however, the number of panels per cycle varies, and the overlap proportion p changes at regular intervals.

In general, a rotating panel design provides several advantages (Woodruff 1963): (1) By rotating the panels, the burden of reporting spreads across more respondents. (2) Analysts can perform short-term analysis of unit change and long-term analysis of population and subgroup change. (3) It improves the ability to use data from past samples to improve the current cycle’s estimates. (4) Rotation may afford an unbiased solution to the problem of large observations which occur in the sample.

Because a field test of a CBECS rotating panel design would require several years of expensive data collection, Winkler et al. (2022) conducted a simulation study in which they created and sampled from a series of artificial populations and simulated rotation designs suggested by the NAS panel (National Research Council 2012).

In this paper, we continue this research by simulating low-cost rotation designs that involve fewer panels and smaller samples within the panels. In these designs, the use of dependent interviewing, where respondents update their data from the previous year, may help further alleviate the burden of reporting (Ridolfo et al. 2022). In the details to follow, we use the term “imputation” when we’re filling in missing values in an existing dataset, and use the term “simulation” when we’re creating a new dataset.

2. Low-cost Rotating Panel Simulation Designs

2.1 Sampling Frame Simulation

To perform the sampling frame simulation, we extended the approach of Winkler et al. (2022), imputing building use based on available data, to complete the area and list frames so that the PSUs that were not selected in the 2018 CBECS are also included and will be subjected to sampling in the simulation. For the CPL frame, we imputed missing square footage values using multiple imputation by chained equations methods involving Predictive Mean Matching (PMM) and Classification and Regression Trees (CART), where PMM is described in Van Buuren et al. (2011) as a general purpose semi-parametric hot deck imputation method. For the hospital, university, and area frames, we simulated data for the 2018 non-sample PSUs using 2018 CBECS survey data, IPEDS data, or the U.S. Census Bureau’s County Business Patterns (CBP) data, when applicable. At the PSU level, we fit simple linear regression models to estimate square footage (based on the 2018 CBECS estimates) from the number of hospital employees (estimated from CBP data), college enrollment counts (estimated from IPEDS and CBP data), and number of establishments (estimated from CBP data), respectively. For the hospital frame, our results suggest that the regression model was a strong fit, with a R^2 of 0.905.

Our area frame model performed similarly, populating the non-sample PSUs based on the approach from the 2022 study, adjusting square footage based on the sample PSUs and building-level selection probabilities. Our university frame model did not perform as well, as modeling within institution size categories resulted in multiple R^2 of at most 0.323. Then, for each of the hospital, university, and area frames, we used the estimated regression coefficients to estimate square footage for each building in the non-sample PSUs. For the remaining frames (GSA and airport), complete data was available for all PSUs, so we did not simulate data for the 2018 non-sample PSUs. After simulating data for the non-sample PSUs, where necessary, we extended the square footage data to 2050 for buildings within each building-use category and sampling frame by simulating demolition and rebuilding for individual buildings.

2.2 Sampling and Estimation

Our “low cost” rotating panel designs are intended to reduce data collection and processing costs and respondent burden, while allowing additional provisions in the case that a CBECS cannot be completed in a given year. We address respondent burden by selecting annual or biennial samples with a sample size targeting 750 to 1,500 completed interviews per year (a reduction from methods examined in the 2022 study, which targeted up to 6000 per year), allowing gap years due to funding constraints. We further aim to reduce costs by limiting the number of sample PSUs per stratum to one, rotating PSUs in and out of the sample periodically.

To avoid small sample sizes within frame/PSU cells and select enough rotating panels through the year 2050, we first drew four samples of 3,000 buildings each distributing the sample proportionally among frame/PSU cells as they were distributed in the 2018 CBECS. We then divided each sample randomly into four panels of 750 units each. Even with the larger sample size (3,000 rather than 750), we had to collapse some strata to draw samples for some frames, because some frame/PSU sample sizes for the list frames were less than one.

We divided each sample randomly into four panels (denoted by pj , where j is the panel number) of 750 units each. We explored five rotation patterns, denoted by Rotation k ($k = 4, 5, 6, 7, 8$), where a panel remains in sample for $k - 1$ years. In its first sample year, the new panel joins the previous panel; in its last sample year, it is joined by a new incoming panel. Figure 1 shows the patterns for Rotations 4 and 5.

Rotation 4	Rotation 5
Year 1: $p1$	Year 1: $p1$
Year 2: $p1 + p2$	Year 2: $p1$
Year 3: $p2$	Year 3: $p1 + p2$
Year 4: $p2 + p3$	Year 4: $p2$
Year 5: $p3$	Year 5: $p2$
Year 6: $p3 + p4$	Year 6: $p2 + p3$
Year 7: $p4$	Year 7: $p3$

Figure 1: Rotation patterns 4 and 5, with 50% to 100% sample overlap

Sampling

Because the low-cost designs are one-PSU-per-stratum designs, as described above, we selected a (potentially) different sample PSU in each non-self-representing (NSR) stratum for each of the four samples. We collapsed some of the NSR strata into superstrata, because their sample sizes were less than one. To collapse these strata, we sorted the strata geographically and combined the first two consecutive strata with sample sizes less than one, adding as many strata as needed to achieve a sample size of one or more. By combining the strata in this way, we ensure that the order of the superstrata aligns with the original strata while ensuring that the sample size associated with each stratum is as close to 1 as possible.

We formed the sample PSU datasets by combining the frame data across the six CBECS sampling frames. For the collapsed strata (“superstrata”), we also combined the sample PSUs across the PSUs in the superstratum to make the sample PSUs more representative of the superstrata. Then, for each PSU, we extracted the frame data for the PSU (or set of collapsed PSUs) and stratified the buildings in the dataset by size, using building square footage as size measures. We then selected a simple random sample of units within each size class when possible, omitting the stratification in the case of small PSU sample sizes (four or less).

The CBECS uses a probability-proportional-to-size (PPS) design to select buildings within a PSU. The 2022 CBECS panel simulation documented by Winker et al. (2022) showed that, with smaller samples, PPS sampling can induce an upward bias in the square footage estimates. In PPS sampling

without replacement, a larger sample size increases the probability of selecting smaller units for the sample. Each time we draw an additional unit, we're drawing it from a population that has already most likely had large units removed, so we're more likely to select smaller units. With very small samples, we are more likely to draw only larger units in some sampling strata, creating an upward bias. The weighting (inversely proportional to the selection probability) can't correct for the upward bias if there are no smaller units in the sample for the sampling stratum. The observed sampling variance is also affected due to the small sample sizes. In the CBECS, the size distributions of the buildings within a PSU tend to be non-Gaussian and are sometimes multi-modal, which is problematic for simple random sampling, contributing further to the selection of too many large or small units. For these reasons, we omitted the PPS feature of sample selection for this simulation.

Estimation

To estimate square footage, we combine list frame and area frame data after imputation and simulation. For each rotation pattern k , we read in the sample data and pattern data, assigning the panel information to the sample units and combining appropriate panel data for each year within the projection period from our simulations (2019-2050).

Let π_b denote the PSU probability of selection for building b and p_b the within-PSU probability of selection for building b . We compute the building PSU weight $B_b = 1/\pi_b$, which we note, is 1 in the case of a self-representing PSU. Since 4 panels of size 750 are randomly selected from each sample of 3000, we determine the panel multiplier weight in year y , for building b under the sampling scheme corresponding to rotation pattern k . $m_{b,y,k}$ is 4 in the case of one panel (since only one subsample is used) and 2 in the case of two panels: during each half-rotation due to the use of two different subsamples selected from the same sample, and during a sample revision when we introduce the first panel from the new sample, where we use a composite estimator (weighted average) of two single-panel independent-sample estimates, each with a weight of 4.

We determine the total square footage estimate $\hat{F}_{y,i,k}$ by weighting the estimated square footages $f_{b,y,i}$. We estimate total square footage by adding the weighted square footages of each building b across the samples S_k in rotation pattern k in building -use category i

$$\hat{F}_{y,i,k} = \sum_{b \in S_{k,i}} \frac{f_{b,y,i}}{p_b} \cdot B_b \cdot m_{b,y,k}. \quad (2.1.2.4)$$

In other words, the weighted square footage is determined from the product of the estimated square footage for year y , the within-PSU inverse probability weight for that building, the building PSU weight and the panel multiplier (either two or four depending on whether there is more than one panel for that year and rotation pattern). To get a clearer picture of the underlying trends, we smoothed our estimates using Nadaraya-Watson kernel smoothing, described in Nadaraya (1964) and Watson (1964). To compute the true values from the frame, we combine all the list and area frame data across the sampled PSUs for the 2018 CBECS and the simulated nonsampled PSUs, separating by building-use category i for each year y . We then computed the mean absolute percentage error (MAPE) for each building category, finding them to be substantial, in general.

3. Results

Figures 3.0 through 3.5 show time series results for total commercial building square footage in the United States, across various building categories under Rotations 4 through 8. The square footage estimates taking all five low-cost rotation patterns into account generally follow the trends of the true values from our simulation. Concentrating on a single building category, such as Service, we tend to find that we underestimate the "truth." We find from examining specific rotation patterns

and building use category series, that higher frequency rotation patterns, such as rotations 4 and 7 tend to feature frequent turning points and follow the true values more precisely than the lower frequency rotation patterns. Some series were seen to be quite vulnerable to outlier effects, such as Healthcare, Inpatient, Other, and Warehouse and Storage, leading to some overestimation. Our findings indicate a turning point overlap between the true values and estimated values, of at most 36%, rising to 56% overlap within 2 years, and 60% within 5 years. In Table 1, we examine the turning point overlap within 5 years, of each rotation pattern, by building category.

Table 1: Turning point overlap within 5 years, by building category.

	Rotation4	Rotation5	Rotation6	Rotation7	Rotation8
EDUCATION	0.300	0.433	0.533	0.300	0.333
ENCLOSED AND STRIP MALLS	0.367	0.433	0.500	0.367	0.433
FOOD SALES	0.300	0.233	0.467	0.333	0.267
FOOD SERVICE	0.400	0.333	0.467	0.367	0.300
HEALTH CARE, INPATIENT	0.333	0.367	0.400	0.400	0.300
HEALTH CARE, OUTPATIENT	0.333	0.467	0.533	0.300	0.433
LODGING	0.333	0.433	0.500	0.300	0.433
OFFICE	0.367	0.400	0.333	0.367	0.400
OTHER	0.367	0.433	0.533	0.467	0.400
PUBLIC ASSEMBLY	0.367	0.667	0.500	0.400	0.633
PUBLIC ORDER AND SAFETY	0.267	0.600	0.600	0.300	0.533
RELIGIOUS WORSHIP	0.400	0.467	0.533	0.433	0.367
RETAIL (OTHER THAN MALL)	0.433	0.533	0.500	0.400	0.400
SERVICE	0.400	0.400	0.400	0.367	0.433
VACANT	0.400	0.400	0.500	0.367	0.400
WAREHOUSE AND STORAGE	0.367	0.200	0.233	0.333	0.200

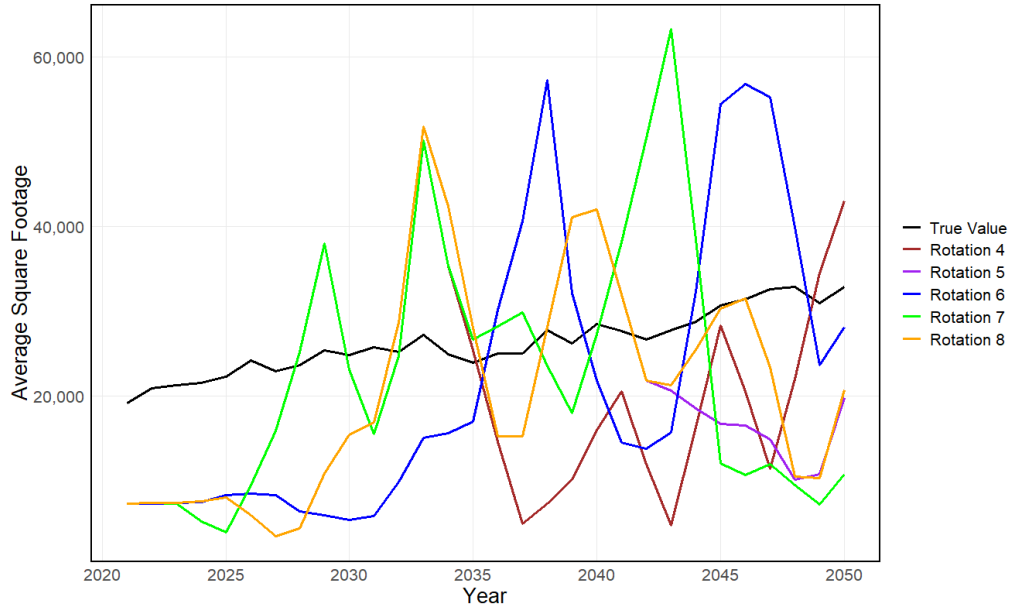


Figure 3.0: Average square footage estimates (million sqft) across all CBECS building categories, using our proposed full-rotation designs.

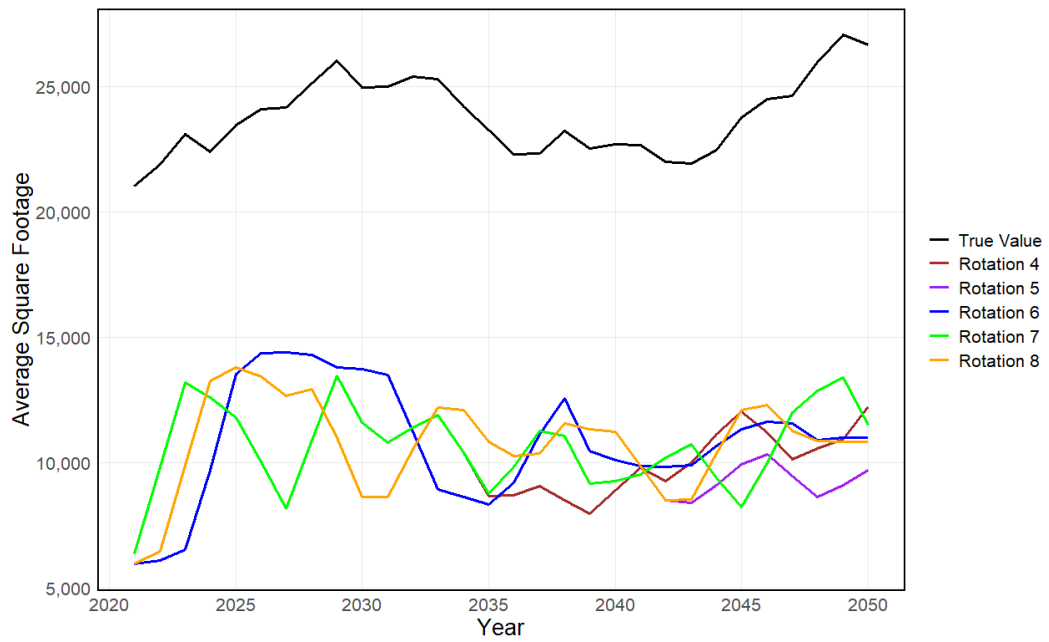


Figure 3.1: Average square footage estimates (million sqft) for the Service building category, mirroring results from Winkler et al. (2022) Figure 2.0, using our proposed low-cost full-rotation designs, showing some of the consistent underestimation in our estimates.

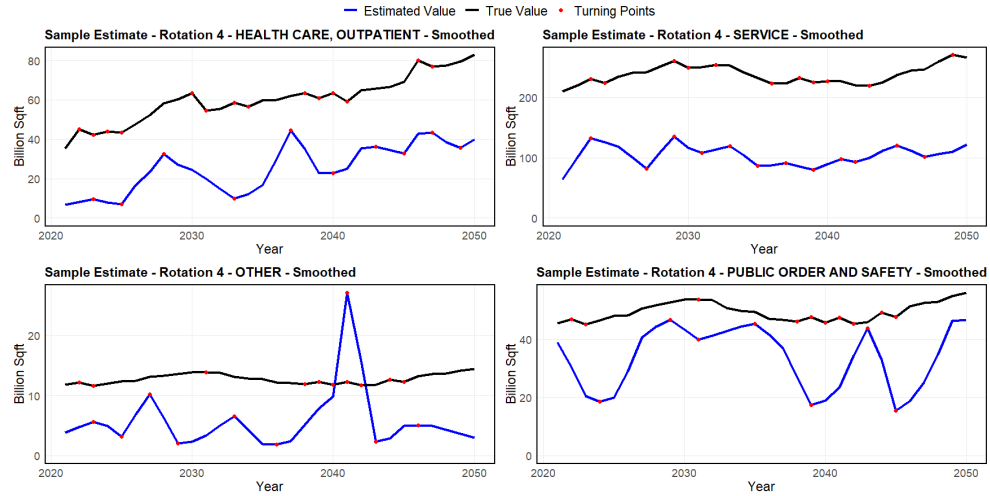


Figure 3.2: Smoothed rotation 4 (high frequency rotation pattern) estimates (billion sqft), for Health Care, Outpatient (top left), Service (top right), Other (bottom left) and Public Order and Safety (bottom right) featuring frequent turning points. The estimated series, generally follow the true value trends, and we see the influence of outliers on Other.

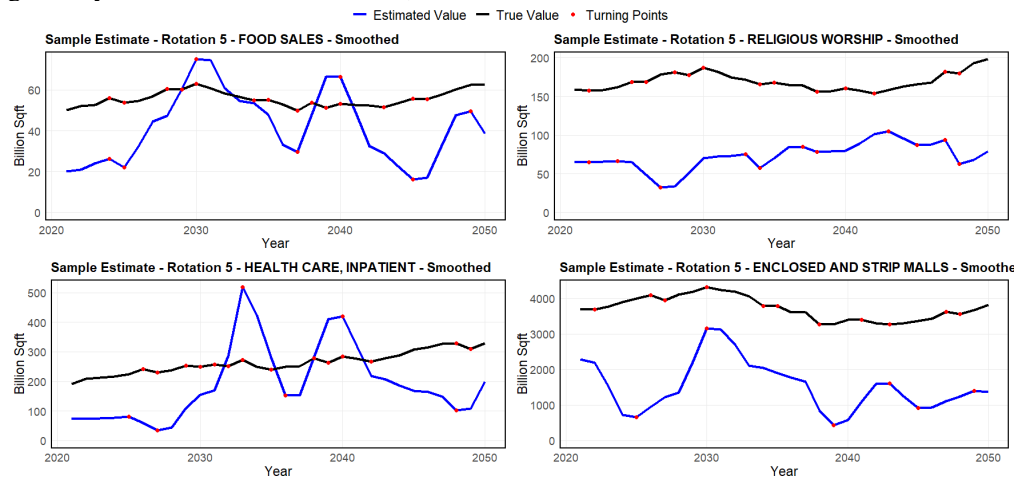


Figure 3.3: Smoothed rotation 5 (middle-frequency rotation pattern) estimates (billion sqft), for Food Sales (top left), Religious Worship (top right), Health Care, Inpatient (bottom left) and Enclosed and Strip Malls (bottom right). We see frequent turning points across the building categories, with outlier influence raising the estimates for Food Sales and Health Care, Inpatient.

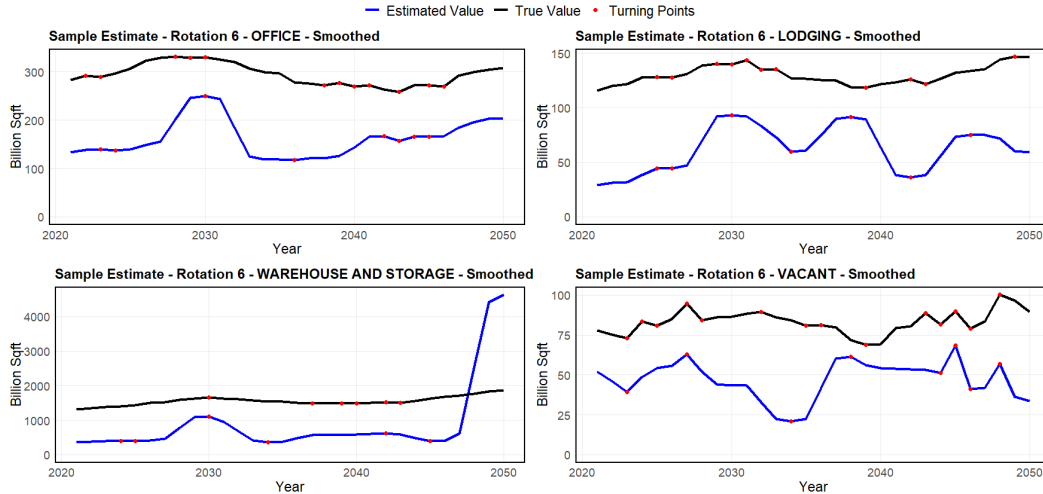


Figure 3.4: Smoothed rotation 6 (low frequency rotation pattern) estimates (billion sqft) for Office (top left), Lodging (top right), Warehouse and Storage (bottom left) and Vacant (bottom right), generally featuring less frequent series breaks than the high frequency rotation estimates. We also see outlier effects for Warehouse and Storage.

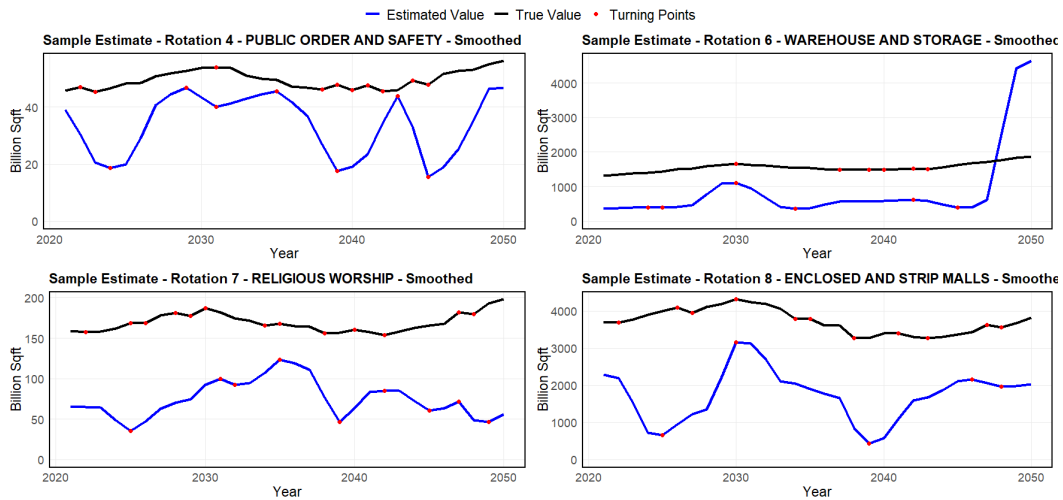


Figure 3.5: Smoothed estimates in (billion sqft) for Public Order and Safety (top left, high frequency rotation), Warehouse and Storage (top right, low frequency rotation), Religious Worship (bottom left, high frequency rotation) and Enclosed and Strip Malls (bottom right, middle frequency rotation), featuring turning points similar to the true series, outlier effects, and underestimates.

4. Summary and Conclusions

Our results show that, with a rotating panel design, small CBECS samples can detect major changes and overall trends in commercial building use square footage. We also see consistent underestimation of the square footage values. Implementing the low-cost rotating panel designs we examined would, however, require significantly redesigning the CBECS sample to enlarge the PSU/frame sample sizes, allowing a size-class stratification like that used by Winkler et al. (2022). We noticed non-Gaussian population distributions within the PSU/frame cells, and there is a chance of selecting too many large or too many small units, explaining some of the underestimation. If we were to implement the low-cost

designs, we may see better results by using larger subsets of the population to increase the sample size in each subset and using PPS with the size stratification.

In addition to these overall conclusions, we note the following:

- The high percentage of sample overlap (50% to 100%) in the low-cost rotation patterns induces correlation in the sampling errors in the estimates for consecutive years. Estimates with strongly auto-correlated sampling errors often consistently positive or negative, causing the estimates to be consistently high or low.
- In our simulation, many sampling strata had small sample sizes, and the population distributions were non-Gaussian. Implementation of the low-cost rotation patterns would require larger per-stratum sample sizes, allowing size class stratification (as in the 2022 study), rather than SRS.
- The smaller samples from the low-cost designs make the estimates vulnerable to outlier effects. In practice, these may be addressed using outlier detection and mitigation methods.
- We saw turning point overlap rates of at least 20%, tending to occur less frequently for middle and low frequency rotations (e.g. Rotations 6 and 8), especially for building categories where outliers were more frequent.

Despite these limitations, most of the estimated series pick up the strong trends and large turning points, of the population series.

We also found that higher frequency rotation patterns with frequencies of 3-4 years, rather than 5 years tended to cause more series breaks and frequent panel rotation. We saw some of the closest turning point tracking from Rotations 4 and 7. While some year-to-year estimates were erratic compared to the results from the 2022 study, we were able to address this through time series smoothing.

We concluded, however, that implementing the low-cost rotating panel designs would require substantial changes to the CBECS sampling plan, primarily collapsing of strata for sampling purposes. The rotating panel designs examined by Winkler et al. (2022) would not require these changes but would be more costly to implement.

Acknowledgements

The authors gratefully acknowledge the contributions of EIA colleagues, including David Kinyon, Samson Adeshiyan, Pushpal Mukhopadhyay, and Ian Mead.

References

- National Research Council. (2012). *Effective Tracking of Building Energy Use: Improving the Commercial Buildings and Residential Energy Consumption Surveys*. Panel on Redesigning the Commercial Buildings and Residential Energy Consumption Surveys of the Energy Information Administration. W.F. Eddy and K. Marton, Editors. Committee on National Statistics, Division of Behavioral and Social Sciences and Education, and Board on Energy and Environmental Systems, Division on Engineering and Physical Sciences. Washington, DC: The National Academies Press.
- Nadaraya, E.A., 1964. "On estimating regression." *Theory of Probability & Its Applications*, 9 (1), pp.141-142.
- Watson, G. S. (1964). "Smooth regression analysis". *Sankhyā: The Indian Journal of Statistics, Series A*. **26** (4): 359–372

- Ridolfo, H. and Morales, G. (2022). "Use of Dependent Interviewing in Federal Establishment Surveys." EIA research report, available from the authors upon request.
- U.S. Energy Information Administration, Documentation for the Commercial Buildings Energy Consumption Survey, available at <https://www.eia.gov/consumption/commercial/survey-background-technical-information.php>
- Van Buuren, S (2018). *Flexible imputation of missing data*. Second Edition. CRC press, 2018.
- Van Buuren, S. and Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of statistical software*, Vol. 45 (3), pp.1-67.
- Westat (2021). "2018 Commercial Buildings Energy Consumption Survey Final Report." Internal survey documentation available from authors upon request.
- Winkler, M., Lent, J., and Steiner, C. (2022). "Rotating Panels for the Commercial Buildings Energy Consumption Survey: A Simulation Study." *Proceedings of the 2022 Joint Statistical Meetings*.
- Woodruff, Ralph S. (1963). "The Use of Rotating Samples in the Census Bureau's Monthly Surveys." *Journal of the American Statistical Association*, Vol. 58 (302), pp. 454-467. Taylor & Francis, Ltd. on behalf of the American Statistical Association. <https://www.tandfonline.com/doi/abs/10.1080/01621459.1963.10500858>