Do Energy Codes Really Save Energy?

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ABSTRACT

A large United States utility implements a program with local jurisdictions to promote building energy code adoption. The utility has energy savings goals and recognized that energy codes offered the potential to provide significant savings to help achieve those goals. The program provides various types of support to local jurisdictions.

The utility developed initial savings estimates using simulation analyses results, but wanted to conduct an evaluation to determine verified savings. Cadmus proposed billing data analyses to produce an empirical savings estimate, and the utility agreed. We obtained monthly billing data for all new single family homes, multifamily units, and commercial buildings in jurisdictions that adopted recent energy codes, merged billing and floor area data, cleaned and filtered the data, and analyzed the billing data analysis using regression analysis with local weather data. The analysis produced weather-normalized energy use intensities (EUIs) for baseline (pre-code) buildings and buildings constructed under the codes. We compared the pre- and post-code EUIs and estimated unit energy savings.

Over the course of conducting the analysis, we identified good analysis practices and lessons learned. Cadmus generated reliable residential code savings estimates. We encountered significant problems estimating savings for commercial buildings, but produced reasonable savings estimates and identified key challenges analyzing commercial buildings. This study represents a significant step forward using measured energy data to estimate code savings. This study demonstrated the feasibility and reliability, as well as limitations, of using this method.

Introduction

Building energy codes are regulations that establish construction and performance requirements to limit the energy consumption of buildings. Energy codes apply to new buildings and often to major renovations in existing buildings. Local governments—states, counties, and cities—have the authority to adopt and enforce energy codes. States or local jurisdictions usually adopt some version or variant of model energy codes developed by organizations such as the International Code Council[1] and ASHRAE.[2] Although it does not have the authority to adopt or enforce energy codes for the private sector, the U.S. Department of Energy (DOE) has been actively involved in supporting energy codes for more than two decades through the Building Energy Codes Program.[3] DOE's involvement has included reviewing the technical and economic basis of the model codes, recommending amendments to these codes, and encouraging adoption of all technologically feasible and economically justified energy efficiency measures. Federal statute requires states to certify to DOE on a regular basis that they have determined whether it is appropriate to adopt a residential building code equivalent to the latest model code and have adopted a commercial building code at least as stringent as the latest model code.

For the analysis to estimate savings from energy codes, DOE has relied on building energy simulation models. Using prototypical buildings and software, Pacific Northwest National Laboratory (PNNL) simulates the energy savings from a new code compared to a prior code. To date, most other estimates of code savings have been based on a similar type of approach.

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[1] See https://www.iccsafe.org/ for information on the International Code Council.
[2] See https://www.ashrae.org/ for information on ASHRAE.
[3] See https://www.energycodes.gov/ for information on DOE's building energy code program.

Figure 1 shows the significant improvement in the energy performance of residential buildings based on simulation estimates of energy use under different model codes over time.

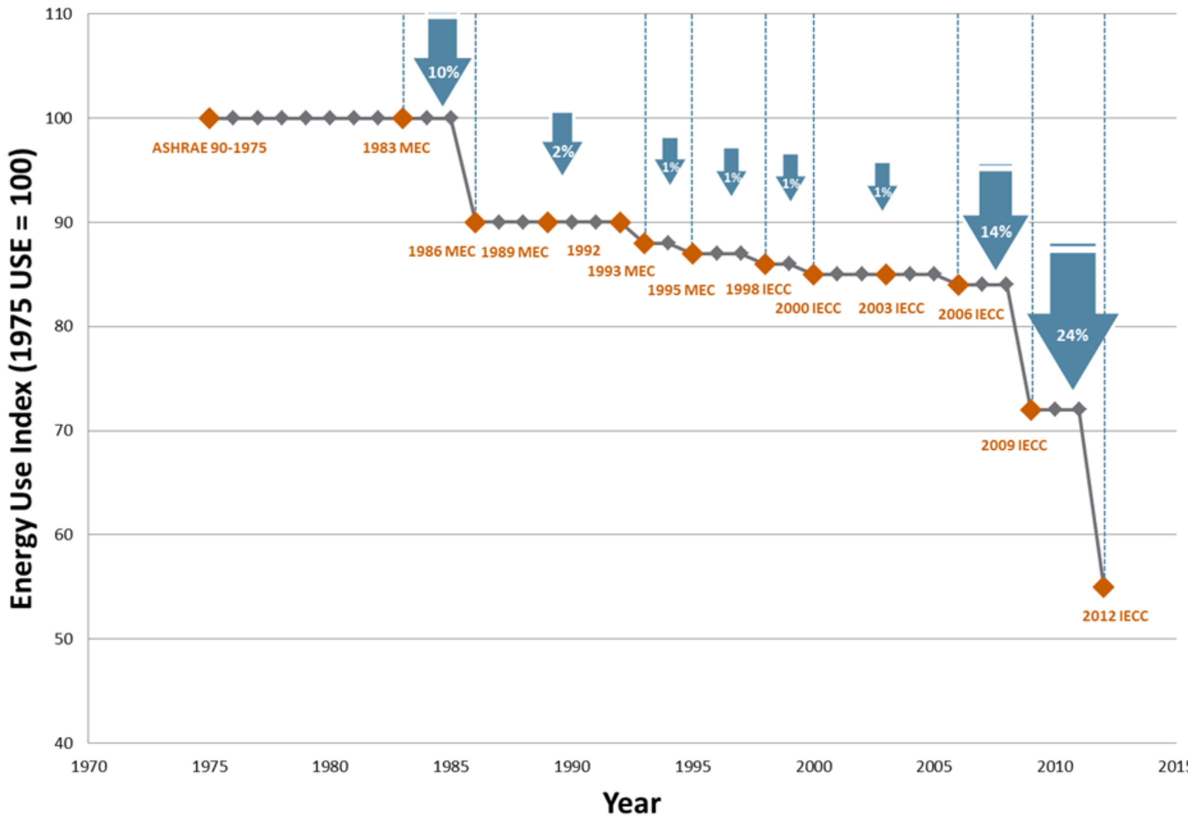

Figure 1. Trends in estimated residential energy use under different model codes. *Source*: PNNL 2014

Recognizing the potential for energy savings from more stringent codes, several utilities across the country have engaged in activities to promote code adoption. Most notably, since 2000, the California investor-owned utilities have supported a statewide program to develop and support adoption of codes and appliance standards; this program is now the single largest energy saver in the utilities' portfolio (Cadmus 2014).

A few other utilities have similar programs. A large utility in the southwest determined that energy codes offered the potential to provide significant savings to help achieve its energy-savings goals. Its management decided to implement a program to support adoption of building energy codes. Because code adoption in the utility's service area occurs at the local level, the utility program provides support to local jurisdictions in the form of technical assistance, materials, advice, and advocacy with stakeholders and decision-makers. The utility developed initial savings estimates using simulation analyses results, but wanted to conduct an evaluation to determine verified savings. Cadmus proposed performing billing data analyses to produce an empirical savings estimate, and the utility agreed.

This paper compares modeled and measured energy use approaches to estimate codes savings, discusses past billing data studies, then presents our approach and findings.

Modeled and Measured Code Energy Impacts

Energy use based on a model is referred to as an asset rating because it reflects a building's performance modeled using standardized operating conditions. On the other hand, energy use based on billing or metered energy data is referred to as an operational rating because metered consumption accounts for actual building occupancy and operations. Analysts use asset ratings to estimate savings by comparing modeled energy use of a building as built with the same building modeled with specified energy efficiency measures. Analysts use metered usage data to estimate savings by comparing the metered energy usage of one building or group of buildings to another building or group of similar buildings.

Studies have used both methods—modeling and energy usage measuring—to estimate building energy code savings. Each has advantages and disadvantages.

One issue in analyzing code energy savings is the degree to which buildings as constructed comply with code requirements (Lee and Groshans 2013). If buildings do not comply fully, their expected energy savings will not achieve predicted levels. Analysts can use simulation models to estimate how much noncompliance affects energy consumption, independent of operations. Typically, site visits are conducted to a sample of buildings to document how they are built under the code and a model is used to compare the energy use of each building as built to the same building if it had been built to just meet the code. For each building and for the sample of buildings, the difference in the asset rating energy use is an estimate of the effect of noncompliance on energy use compared to buildings just meeting the code.

On the other hand, using measured data to assess how noncompliance affects performance is nearly unachievable for various reasons. Using this method requires knowing the characteristics of each building in addition to having the energy consumption data available for each building. Accounting for the variability in occupancy and operations would necessitate a large sample of buildings, as would estimating performance accurately and assessing the effect of noncompliance. Both the scope of data and sample sizes required would necessitate very large resource commitments. Consequently, we are not aware of any studies that have used operational ratings to assess code compliance.

However, using measured data can provide a very accurate estimate of the actual effects of an energy code on utility system loads, regardless of the compliance level and other factors, as long as three conditions are met. First, buildings available for analysis need to represent the populations of interest, including buildings built under the current code and baseline reference buildings. Second, the number of buildings for analysis needs to be large enough to minimize the effects of outliers or data errors. Third, no exogenous influences should affect the current code and reference buildings differently.

A few studies have been performed using measured consumption data to estimate code savings. Aroonruengsawat, Auffhammer, and Sanstad (2009) used an econometric model to estimate per capita residential energy use by state as a function of several parameters, including the share of new construction since 1970 permitted while an energy code was in place. Their study estimated code savings ranging from 0.3% to 5.0%, depending on the state. Jacobsen and Kotchen (2013) estimated savings of the Florida residential energy code implemented in 2002 by comparing the electricity and natural gas usage of homes built before and after the code went into effect, for a total of 2,239 homes. The authors used regression analyses that included several home characteristics to show that the code decreased electricity use by about 4% and natural gas use by about 6%. Withers and Vieira (2015) used both billing and submetered data to compare 31 Florida homes built under the 2007 state code to 42 built to the code in effect in 1985, and estimated overall savings of 13%.

Methodology

Our analysis is focused primarily on billing data analyses we performed on residential buildings, both single family and various multifamily housing types.[4] We recently analyzed commercial buildings, and this paper highlights differences between our residential and recent commercial building analyses. The overall methodology involved the following steps:

- Use utility data to identify new buildings built just prior to and after the code went into effect
- Obtain utility monthly billing data and buildings' floor areas
- Clean data and screen buildings

[4] Multifamily homes included apartments, condominiums, and town houses.

- Model annual energy use for each building and normalize based on normal weather conditions
- Compare the consumption of buildings built before and after code went into effect—referred to as baseline buildings and code buildings, respectively

This research is sponsored by an electric utility that provided data on new customer accounts from January 2006 through February 2017, along with building floor area and electric billing data for all those customers from the first month they initiated electrical service. Although some customers had natural gas service, no natural gas consumption data were available.[5]

We separated the buildings into two groups: (1) baseline buildings were built before the new code went into effect and (2) code buildings were most likely built under the new code. We were able to identify the baseline group unambiguously. Identifying code buildings was more problematic. Buildings must be built to the code in effect when permitted, so we needed to identify buildings initiating electric service that were permitted after the new code went into effect. Permit data for each new building would have made it possible to determine with certainty which buildings were built under the new code; however, permit data were not available, and collecting that data is usually very labor intensive, if even feasible.

Based on experience, we applied a decision rule to identify code buildings. For each jurisdiction, we determined the effective date of the code. For both single family and multifamily residential buildings, we assumed all buildings initiating service after eight months had elapsed since the code effective date were permitted under the new code. For commercial buildings, we used 12 months after the effective date as the threshold. These intervals accounted for the expected construction lag. Although it is likely that some of the code buildings selected based on these tests were actually baseline buildings, any error in identification would make the savings estimates more conservative because some buildings identified as code buildings would perform as baseline buildings.[6]

We completed several additional steps to filter both the baseline and code buildings. We eliminated all homes that participated in the utility's new homes efficiency programs because we were estimating code savings. We also used utility and online data to identify homes with swimming pools, and eliminated them to avoid biasing the estimates due to the presence of a pool. Commercial buildings did not require similar screening.

Before analyzing the billing data, we removed all buildings with less than 10 months of data. By capturing a swing season, as well as winter and summer months, this screen ensured we had enough billing data to analyze the weather response of each building. Figure 2 illustrates the effect of the residential construction lag and required billing data for a code effective date of July 1, 2013. Starting with data covering almost two years, only homes with service start dates during a four-month period (March to July 2014) would be suitable for analysis.

Jul-13	Sep-13	Nov-13	Jan-14	Mar-14	May-14	Jul-14	Sep-14	Nov-14	Jan-15	Mar-15
Construction Lag (Eight months)										
				Usable Homes						
						Billing Data Requirement (at least 10 months)*				

* In most cases, we had 12 months of billing data for analysis.

Figure 2. Effect of construction lag and billing data requirement on homes suitable for analysis

After the initial data screening and cleaning, we performed regression analyses for each building in the baseline and code groups using monthly billing and weather data. We used the Princeton Scorekeeping Method (PRISM)[7] to estimate building energy use as a function of weather (heating and cooling degree days). After completing these analyses, we conducted additional quality checks to screen out unreliable observations,

[5] The load estimates identified as heating related from our analysis did not provide any indications of a change in fuel mix.
[6] Cadmus did not include buildings starting service after a code went into effect in the baseline.
[7] See http://www.marean.mycpanel.princeton.edu/~marean/ for information on PRISM.

including dropping sites with unrealistically small energy usage (probably due to vacancies), wrong regression signs, and missing floor areas. This step required rigorous reviews of the monthly billing data and all PRISM results. These steps typically reduced the usable residential populations by about 20%; among residential buildings, the reduction was largest for multifamily buildings where we dropped units that were unoccupied during any month. We then used the results to estimate the normalized annual consumption by using typical meteorological year (TMY3)[8] weather data.[9]

We used a similar approach to analyze code savings in commercial buildings. We anticipated this analysis would be more challenging, because fewer commercial buildings are constructed, construction takes longer, and commercial buildings are less homogeneous. To allow for the longer construction time, we used a construction lag of 12 months to screen observations. We selected office buildings for initial analysis because the data suggested they were the most common type of new commercial building.

Analysis Details and Results

First Residential Building Analyses

Cadmus completed our first analysis of the residential code savings in July 2014, focusing on the 2009 International Energy Conservation Code (IECC). Four jurisdictions had adopted this code; two of them later adopted the 2012 IECC, along with six other jurisdictions that adopted the 2012 IECC directly. We used a more stringent test to screen out likely 2012 IECC homes in the 2009 IECC jurisdictions by eliminating any buildings where a utility account was opened six or more months after the effective date of the 2012 IECC.

We defined baseline homes as those with service starting between January 2008 and the effective date of the 2009 IECC (from July 2011 to January 2012, depending on the jurisdiction), and 2009 IECC homes as those meeting our construction gap criterion based on the code effective date in each adopting jurisdiction. After applying our initial data screening, only two jurisdictions had enough 2009 IECC single family homes and one jurisdiction had enough multifamily homes for analysis.[10]

For each home, we estimated three monthly PRISM models: (1) heating and cooling, (2) cooling only, and (3) heating only. We then selected the model for each home with the best fit (based on the regression R-squared value).

For each remaining baseline and 2009 IECC home, we performed detailed screening of the model results. Cadmus removed homes with a normalized annual consumption less than 1,000 kWh or with very low monthly consumption indicative of vacancy. We also reviewed the available floor area data for each home, and removed observations with missing or clearly erroneous data. Table 1 shows how much attrition occurred for each screen based on the initial population of baseline and 2009 IECC homes. For single family 2009 IECC homes, the biggest reduction occurred due to the need for at least 10 months of billing data. The presence of swimming pools caused the largest reduction in baseline single family homes. Multifamily homes were affected most by vacancies. Table 2 shows the quantitative effects of attrition.

[8] See http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/ for TMY3 data.

[9] We used the same year to estimate the PRISM models, then used TMY3 data to calculate standardized consumption and savings. Actual savings could differ if TMY3 data do not capture climate trends accurately.

[10] Based on expected variances and desired statistical significance, we needed at least 70 to 100 homes in each sample.

Table 1. Attrition data for first residential analysis, showing percentage of initial population removed

Screen	Single family		Multifamily	
	Baseline	2009 IECC	Baseline	2009 IECC
Home built < 8 months after 2009 IECC in effect	--	3.9%	--	0%
Less than 10 months of billing data	21.4%	64.6%	0%	7.9%
Cooling usage <300 kWh or total usage <1,000 kWh	1.6%	0.2%	0%	0.1%
PRISM screen: wrong signs on PRISM parameters	1.2%	1.1%	0%	1.0%
Outlier removal (monthly outlier/vacancy checking)	12%	5.6%	7.7%	56.1%
Missing or unreliable square footage	0.6%	0.1%	0%	0.1%
Home has a pool	24.8%	7.4%	0%	0%

Table 2. Comparison of original populations and final samples for first residential analysis

Home type	Group	Initial population	Final analysis sample sizes	Percentage of original population in final sample
Single family	Baseline	1,589	611	38%
Multifamily		208	192	92%
Single family	2009 IECC	947	162	17%
Multifamily		759	264	35%

Using the regression results for the baseline and 2009 IECC homes, we calculated the electricity use and EUI for the groups of homes. For single family homes, the reported results were based on the results of the two jurisdictions separately, weighted by the proportion of homes constructed in each jurisdiction after the 2009 IECC went into effect. Table 3 shows the average energy consumption and estimated savings for single family and multifamily homes. The 2009 IECC savings were about 13% for single family and 20% for multifamily homes compared to baseline homes.

Table 3. 2009 IECC first residential consumption and savings estimates

Home type	Baseline			2009 IECC			Savings	
	kWh/yr	Average square feet	kWh/ sq.ft.	kWh/yr	Average square feet	kWh/ sq.ft.	kWh/ sq.ft.	Percentage
Single family	18,843	2,771	6.80	17,931	3,036	5.91	0.89	13.1%
Multifamily	11,404	1,386	8.23	7,500	1,136	6.60	1.62	19.8%

Updated Residential Building Analyses

In August 2015, we updated the estimates for the 2009 IECC to include additional homes built under this code and attempted to analyze savings from the residential 2012 IECC. Eight jurisdictions had adopted the 2012 IECC, but after we screened the single family data, only 78 homes remained for analysis, with no more than 23 in any one jurisdiction. However, 238 multifamily 2012 IECC homes remained after the screens. Based on these sample sizes, we decided that enough observations were available to estimate 2012 IECC savings for multifamily homes, but not for single family homes.

Due to the passage of time, more 2009 IECC homes were available to analyze in the two original jurisdictions, so we first updated the 2009 IECC estimates. Table 4 shows that the number of single family homes analyzed increased by a factor of nearly 3.5 (162 to 550) and multifamily homes increased by a factor of nearly 5

(264 to 1,289). Savings, both in terms of EUI and percentage, increased slightly for single family homes and decreased slightly for multifamily homes. The savings percentage was almost identical for single family and multifamily homes, averaging about 16.5%. Given the increased sample sizes, we considered these estimates to be more accurate than the initial ones.

Table 4. 2009 IECC updated consumption and savings estimates

Parameter	Single family homes	Multifamily homes
Number of jurisdictions in analysis	2	3
Number of 2009 IECC homes analyzed	550	1,289
Average floor area (sq.ft.)	2,815	1,089
Savings (kWh/sq.ft.)	1.12	1.53
Average unit savings (kWh/yr)	3,144	1,670
Average percentage savings	16.2%	16.7%

Table 5 shows the results for 2012 IECC multifamily homes. The populations in two jurisdictions were adequate to conduct the analysis. The results showed that EUI savings from the 2012 IECC compared to the 2009 IECC increased by 0.69 kWh per square foot (2.22-1.53), or 45%.

Table 5. 2012 IECC updated consumption and savings estimates for multifamily homes

Number of baseline homes	2,945
Number of 2012 IECC homes	238
Average floor area (sq.ft.)	1,050
Savings (kWh/sq.ft.)	2.22
Average unit savings (kWh/yr)	2,334
Average percentage savings	23.5%

By 2016, enough single family homes had been constructed under the 2012 IECC to allow for calculating an accurate savings estimate for this code, as shown in the last column in Table 6. To compare this estimate with one based on the multifamily results, we applied the 45% savings increase calculated for multifamily homes going from the 2009 IECC to the 2012 IECC to the updated estimate of single family 2009 IECC savings (shown in Table 4). The middle column in Table 6 shows that the estimate using the multifamily results (23%) was almost identical to the results from the 2012 IECC single family billing analysis (22%) derived from the sample of 500 single family buildings.

Table 6. 2012 IECC consumption and savings estimates

Parameter	Estimates based on multifamily 2009 IECC to 2012 IECC savings results	Estimates based on 2016 single family sample billing analysis
Number of jurisdictions in analysis	2	8
Number of homes analyzed	238 (multifamily)	500
Average floor area (sq.ft.)	2,737	2,669
Savings (kWh/sq.ft.)	1.62 (1.45*1.12)	1.67
Average unit savings (kWh/yr)	4,434	4,471
Average percentage savings	23.0%	22.0%

To compare our savings estimates to simulation estimates, we reviewed estimates in PNNL (2014). Differences between the assumptions (such as internal loads) built into the prototype modeled and actual buildings made it difficult to make a direct comparison. The most meaningful comparison was for the EUI savings between the 2009 IECC and 2012 IECC. PNNL estimated savings of 0.65 kWh per square foot, while Cadmus estimated 0.55 kWh per square foot. One factor that could have contributed to the difference between the two estimates was that the PNNL estimate was for electric heat, while the Cadmus estimate was determined by the unknown fuel mix in the homes we analyzed. Nevertheless, the two estimates were relatively consistent and suggested that the simulation results were fairly accurate for a population of new homes.

Commercial Building Analyses

In March 2017, we received complete billing data for all commercial buildings initiating electric service from 2006 through February 2017. Because the preliminary building counts indicated offices were the most common type of new building, Cadmus screened the accounts to limit them to sites identified as offices (based on NAICS codes) that had at least 10 months of billing data available, no billing gaps or zero usage months, and EUIs that were not improbably large.[11] For buildings with service start dates after a code went into effect, we took the additional step of ensuring that at least 12 months elapsed between the time the code went into effect and electricity service was initiated.

The utility had identified the NAICS code for each site and used it to categorize the building: these categorizations were very accurate overall, but we found some random and systematic errors. One type of systematic error was a site being classified as an office when the electricity customer was a property manager. From Internet searches, we found some sites listed as property managers because the electricity account was held by a property manager, but they were not actually offices.

For the code sites, we discovered a categorization problem when we tried to confirm the site age. Some sites that initiated electricity service 12 months or more after a code went into effect were actually built before the electricity service date, and were therefore not subject to the energy code. This occurred frequently with customers in suites—many of these initiated service at a time that would qualify them to be covered by the energy code, but they were in buildings constructed much earlier. In addition, we had no way of knowing whether suites were billed for their complete electrical service or just a portion (for example, lighting and plug loads). For these reasons, and to prevent introducing potential errors because of these issues, we removed all sites identified as suites from both the baseline and code populations except when we were able to aggregate several suites into a complete building. Table 7 illustrates the attrition that occurred in the population of sites that were originally identified as probable 2009 or 2012 code buildings.[12] The largest share of sites removed were those new service accounts for buildings that were built before the code went into effect.

Table 7. Attrition of potential 2009 and 2012 code buildings

Screening factor	Building count	Percentage of total
None	238	0%
Pre-code accounts in building	100	42%
Internet verified pre-code building	63	26%
Suites	44	18%
Remaining buildings	32	13%

[11] In some cases, consumption data were incorrect, floor areas were erroneous, or the combination of consumption and floor area indicated that the account was for a facility such as a cell tower.

[12] We refer to the commercial codes as the 2009 and 2012 codes for consistency with the residential codes, but the commercial buildings could comply based on the equivalent ASHRAE 90.1-2007 and 90.1-2010 standards, respectively.

We conducted initial analyses of the code and baseline buildings that remained and found unexpected differences between the two populations. Figure 3 shows that the baseline buildings had a size distribution skewed more toward smaller buildings than the 2009 code buildings, which had more of a bi-modal distribution. These results suggested a recent shift in the types of office buildings constructed, with larger buildings being more common in recent years. Partly because of these distributions, we decided to divide each building group into two strata based on floor area[13] and analyze and compare the EUIs of these separate strata.

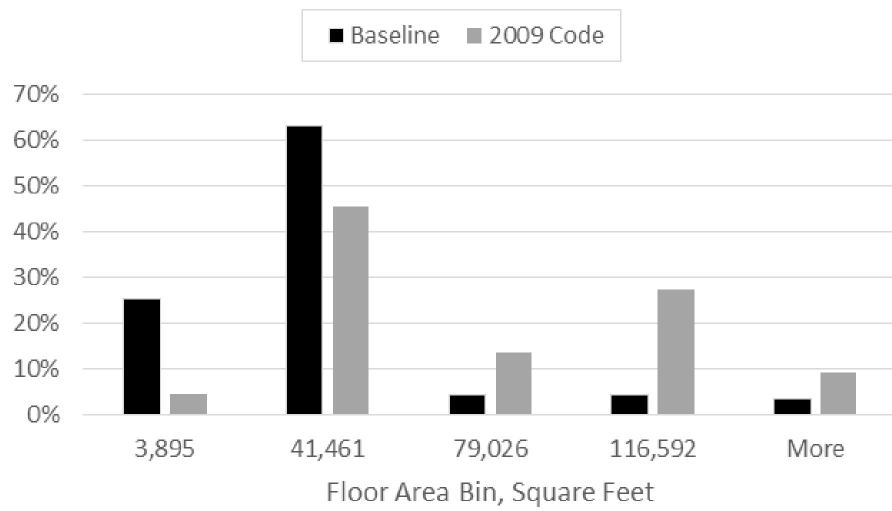

Figure 3. Size distribution of baseline and 2009 code buildings

Table 8 summarizes findings from the billing data analysis for baseline, 2009-code, and 2012-code offices. The results demonstrate that code offices in the small and large categorize use less energy than baseline offices and that the 2012 code saves more energy than the 2009 code. However, the accuracy of the results is diminished by the small populations available to analyze: the relative precisions of the savings estimates all exceed 100%.

Table 8. Code commercial building consumption and savings relative to baseline buildings

Stratum	Building group	Count	Average annual kWh/sq.ft.	Savings (kWh/sq.ft.)	Savings percentage
Small	Baseline	126	15.5	--	--
	2009 code	11	14.0	1.5	10%
	2012 code	5	9.0	6.5	42%
Large	Baseline	18	17.7	--	--
	2009 code	11	12.7	5.0	28%
	2012 code	5	8.6	9.1	51%

The EUI does not vary significantly between small and large offices in either code group. There appears to be a pronounced difference for baseline offices, though, with large baseline offices having an EUI that is 14% larger than for small baseline offices. Given the small population of baseline small offices, however, the difference is not statistically significant.

It is important to note that the baseline population was not required to meet a specific energy code. Consequently, there is likely to be considerable variability in building practices and variance in the baseline EUI.

[13] The mean floor area of the small office category was ~10,000 square feet and the mean area of the large category was ~130,000 square feet.

The more consistent results for the code offices suggests that the energy code leads, as would be expected, to more uniformity in the energy performance.

To assess the reasonableness of these results, we compared our findings to savings estimated for the ASHRAE 90.1-2010 standard relative to the 90.1-2007 standard; these codes are approximately equivalent to the 2012 and 2009 codes, respectively. PNNL (2013) estimated that a national average EUI of 14.2 kWh per square foot for a medium-size office built to the 90.1-2007 standard would be reduced to 10.9 kWh per square foot under the 90.1-2010 standard, for a decrease of 3.3 kWh per square foot, or 23%. For comparison, our large building category (which is comparable in size to PNNL's medium category) showed savings of 4.1 kWh per square foot, or 32% of the 2009 code value of 12.7 kWh per square foot. Given the differences in these estimates—simulation estimates compared to billing data and national averages compared to geographically specific results—the values are very comparable. This provides support for our billing data results, even though they are based on small populations, and provides preliminary empirical confirmation of the PNNL simulation results.

As described above, Cadmus made a significant effort to identify as clean a population and sample of offices as possible. This reduced the proportion of buildings that were miscategorized, but it significantly diminished the number of buildings available for analysis as offices. The small population sizes limited the confidence we could place in the commercial building energy code savings estimates, but further analysis was beyond the scope of this code study. We did make some observations about possible avenues for further commercial building code billing data research:

- *Analyze savings from one code to another:* Our initial analysis used a baseline of buildings constructed prior to uniform adoption of an energy code, and the data showed the baseline building EUIs were distributed nearly uniformly over a wide range. Code building EUIs, on the other hand, tended to be more normally distributed, with 60% within 20% of their mean EUI and no EUIs as large as 18% of the baseline buildings. Consequently, it is likely that more statistically reliable estimates of average impacts could be derived for changes between codes rather than from a pre-code baseline to a code.
- *Study other building types:* Offices appeared to be the most promising type for analysis because of the apparent quantity of new offices. However, our research demonstrated that the original counts overstated the actual new offices that could be analyzed. Other building types that are likely to be less likely to be miscategorized, such as restaurants, might be good candidates to analyze. Retail buildings are another possibility, although some of the same issues confronting research on offices, such as buildings with many different retail stores, could limit the available population.
- *Conduct analysis in larger geographic areas:* Cadmus conducted this study in a state where codes were adopted by municipalities and our study was limited to a relatively small group of cities. Conducting a similar study across a state with a single energy code could provide more commercial buildings to analyze. Similarly, the study could be conducted for several collaborating utilities to increase the available building population.
- *Aggregate building types:* Some building types have very similar EUIs and code changes often have similar effects on their energy use. In these cases, it might be sufficiently accurate to combine building types and estimate savings for the combined category.

Uncertainties and Limitations

Although measured energy use data has rarely been utilized to estimate building energy code savings, using measured energy data to estimate code savings can provide the most accurate, real world estimates. However, this approach poses special challenges and uncertainties. The most significant challenge is ensuring that baseline buildings properly represent the counterfactual (that is, what energy use would have been without the code). We addressed this issue by defining the baseline as those buildings built as recently as possible prior to the new code. This assumes that, without the new code, building practices would have continued as they were before.

Another challenge is ensuring that buildings are properly categorized according to the code to which they are built. We assigned each building to a specific code by assuming a construction lag between the code effective date and utility service date; any buildings miscategorized into the code group will tend to produce a conservative estimate of savings. In an ideal situation, we would use building permit data for each building to assign it to the correct code, but these data are difficult to obtain. Our approach is to assume a reasonably conservative construction lag to minimize miscategorization.

Other issues involve factors that might cause systematic differences between the code and baseline buildings. For example, if data are available for only one fuel type, but the fuel mix differs significantly between baseline and code buildings, then the change in fuel mix could bias the savings estimates for the one fuel type with available data. Using the most recently built buildings for the baseline minimizes the uncertainty caused by this factor because it is unlikely that the fuel mix changed dramatically in a few years. Also, any systematic occupancy behavior differences—such as pet ownership—could bias savings estimates.[14] Using both recent baseline buildings and populations and samples as large as possible help alleviate these potential biases.

A related issue is any exogenous change that might affect new code and baseline buildings differently. Appliance efficiency standards are one example. Standards affecting equipment installed in new buildings produce savings that would show up in the billing data and should not be attributed to the building code. In the analyses reported here, there were no standards that would have confounded the estimates, but this issue needs to be addressed for each code.

Conclusions

Based on our research, building energy codes do save energy. Our analyses of building billing data revealed that the electricity use of both residential and commercial (office) buildings was significantly less for buildings built after an energy code went into effect in jurisdictions where no code had existed before. They also showed that a subsequent, more stringent energy code reduced building energy consumption even more. Our results provide strong evidence that codes reduce energy use and that the effect is significant.

Our research demonstrates that billing data analysis can be used to estimate the actual impacts of energy codes on real buildings in the market. Building energy simulations will continue to be useful for predicting code impacts and estimating the effects of factors such as noncompliance on energy consumption, but billing analysis can provide empirical data on the effects of the code, accounting for real-world behavior and building construction.

The relatively good agreement between our estimates and those from simulations suggests that the simulation models used to estimate code effects come close to estimating actual code energy impacts. This finding provides support for continued use of these models to predict code impacts.

Through conducting this research, we identified several good practices, limitations, and cautions that should be observed in future code savings studies using billing data analysis. These include:

- Residential building populations and usable sample sizes should be sufficient in most cases to produce accurate results.
- Studies of commercial building codes may require large geographic areas to ensure that large enough building populations and usable sample sizes are available to analyze.
- If a mix of fuel types is common, analyses should include natural gas and electricity billing data.
- Floor area data should be included to allow for EUI analyses.
- Sufficient construction lags should be established or permit data should be used to categorize buildings under the proper energy code.
- For commercial building code studies, special care should be taken to ensure that the building type is defined correctly.

[14] There is some evidence that pet owners keep their homes warmer than non-pet owners.

- For both residential and commercial building code studies, the analysis should account for the effects of efficiency programs, unique energy uses (e.g., swimming pools), appliance standards, and other exogenous factors that impact energy use.
- Baseline or reference building populations should be buildings constructed as recently as possible before the code being analyzed.

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