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# The impact of building energy codes on household electricity expenditures

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ABSTRACT

Home energy use is a major source of a typical US household's carbon emissions. This study uses the American Community Survey (ACS) micro data to estimate the impact of building energy codes on household electricity expenditures, using multiple regression and difference-in-difference models. In California and US samples, I present new evidence that energy codes were modestly effective. Homes built in the decade after energy codes were first adopted spend between 1.5% and 4% less on electricity compared to homes built prior to their adoption.

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## 1. Introduction

Activities associated with home energy use (space heating, air conditioning, water heating, lighting, refrigeration) together are the source of approximately 14.9% of the average US household's carbon emissions (Nordhaus, 2013, p. 161). Building energy codes have been adopted by most states and continue to be tightened. This study leverages micro data from the nation's largest household survey, the American Community Survey (ACS), to present new evidence on their effectiveness.

I adopt two empirical approaches in this study. If energy codes were effective, then homes built under them should, all else equal, use less electricity than homes built before energy codes were enacted. For this first test, I adopt a control variable strategy to account for household self-selection into homes. I find homes built in California in the decade after codes were adopted use 1.5% less electricity than homes built in the decade before codes, but this estimate is marginally significant. In addition, if energy codes were effective, household electricity use should fall after code adoption relative to states that did not adopt them. The second test uses a difference-in-difference approach. Using a national sample, I find household electricity use falls by about 4% after energy codes were adopted, in states that adopted them.

This study uses the ACS to replicate and build on prior literature. Using a sample of California homes built between 1960–2000 and using the (long form) 2000 decennial Census, Costa and Kahn (2011) find that electricity prices prevailing when the home was constructed were important determinants of the home's energy use decades later, suggesting "birth price" electricity prices impacted building practices. Several studies focus on building codes at the US national level. In a panel analysis with state-level aggregate data, Aroonruengsawat et al. (2012) find building codes are associated with between 0.3 ad 5% lower energy consumption. This study also provided data on date of adoption of building codes, utilized in the next section. Koirala et al. (2014) is closely related to the present study by its use of the ACS micro data, as well as a state-level building code measure, but estimates rather different models. The approach here is to adopt empirical models drawing on the most compelling recent literature.

Using household energy consumption surveys with smaller sample sizes than the ACS, but with more detailed questions regarding household energy consumption and its determinants, Levinson (2016) is one such compelling study. He estimates construction era effects for California in a way that is similar to the approach in Costa and Kahn (2011). He also develops a difference-in-difference model using a national sample.

Econometric studies of energy codes from outside the U.S. include El-Shagi et al. (2017), which is the only previous attempt we are aware of to systematically review the econometric literature on building codes. Although most studies found energy codes

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[1] I thank an anonymous reviewer and participants at the 2019 WEAI conference in San Francisco for helpful comments. All errors are my own.

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**Table 1**
Variable descriptions.

| Variable | Description | Source |
|---|---|---|
| logCOSTELEC | Natural log of household electricity expenditures | ACS |
| YB1930 | Indicator for homes built between 1930 and 1939 | ACS |
| YB1940 | Indicator for homes built between 1940 and 1949 | ACS |
| ... | ... | ACS |
| YB2010 | Indicator for homes built between 2000 and 2009 | ACS |
| ELEHEAT | Electric heat indicator for home | ACS |
| logHHINCOME | Natural log of annual household income | ACS |
| SEI | Socioeconomic Index (composite variable) | ACS |
| WHITE | White race indicator for head of household | ACS |
| ROOMS | Number of rooms in home | ACS |
| HHSIZE | Number of persons in household | ACS |
| AGE | Age of head of household | ACS |
| OWNERSHP | Homeowner indicator | ACS |
| COLLEGE | Indicates head of household has college degree | ACS |
| YEARSIN | Number of years head of household has lived at address | ACS |
| CALIFORNIA | Indicates home built in California | ACS |
| BIRTHPRICE | Electricity price prevailing when a home was constructed | CK |
| CODESTATE | Indicates home built in state that adopted codes in 1970s | AAS |
| STAVGPRICE | Average 2017 electricity price in state home is located | EIA |

Note on sources: ACS: Ruggles et al. (2018); AAS: Aroonruengsawat et al. (2012); CK: Costa and Kahn (2011); EIA: www.eia.gov (Table E3). Residential Sector Energy Price Estimates, 2017 (Dollars per Million Btu).

were effective in reducing energy consumption or expenditure, the magnitude of findings in the studies they reviewed ranged from no effect to 6%, which is small compared to ex-ante estimates produced before these codes were enacted. For example, Levinson (2016) cites the California Energy Commission who in 1979 reported estimates indicating building codes would cause California's household energy consumption to fall by 80% within a decade of their adoption.[2]

## 2. Data and methods

All of the models presented below use ACS data from 2012 to 2017, obtained from IPUMS-USA (Ruggles et al., 2018). I merged on data from three additional sources.[3] A description of all variables and their sources is provided in Table 1.

I estimate models using California and nationwide samples. The main approach with the California sample is to estimate decade of construction effects in an energy expenditure model, while controlling for home and household characteristics. The general construction-decade equation is:

$$ln(E_i) = X_i\beta + \sum_j \theta_j ConstructDecade_{ji} + \varepsilon_i,$$

where the dependent variable $ln(E_i)$ is the log of annual electricity expenditures in household $i$. The matrix $X_i$ contains control variables (such as number of rooms, household income, and household size) as well as, in one specification, the average prevailing electricity price in the decade in which the home was built (this variable is named $BIRTHPRICE_{ji}$ below.) The model also includes fixed effects at the Public Use Microdata Area (PUMA) level, which will account for differences in contemporary electricity prices as well as other geographic-specific factors like climate.

The $\theta_j$'s are the key coefficients in the model. These are the coefficients on the construction decade dummies. If California's building codes really were effective, we would expect the $\theta_j$'s to be lower for $j$ greater than or equal to 1980, the decade after California first enacted building codes, compared to both the 1960s and the 1970s.

Levinson (2016) also estimates a version of the equation above that uses a nationwide sample with a California dummy, construction era dummies, and interactions between the California and the construction era dummies. This enables comparing construction era effects in California to the rest of the country, before and after code adoption. Formally, this second model is:

$$ln(E_i) = X_i\beta + \sum_j \theta_j ConstructDecade_{ji} + a(CA_i) + \sum_j \sigma_j(CA_i \times ConstructDecade_{ji}) + \varepsilon_i$$

where $CA_i$ represents an indicator that the household is in California. The goal of estimating this model in Levinson (2016) was to see if California's energy codes were uniquely effective. However California was by no means the only state to adopt building codes in the 1970s nor was it the first, as is clear from the data presented in Aroonruengsawat et al. (2012). Therefore I also estimate a model where I substitute a variable $CODESTATE_i$ for the variable $CA_i$ in the equation above. $CODESTATE_i$ is a variable equal to one if the home was built in one of the 33 states that adopted a building code in the 1970s.[4]

## 3. Results

Table 2 presents results of estimating equation 1 using the California sample. The main coefficients of interest here are the construction-decade dummies. Columns (1) and (2) replicate Costa and Kahn (2011) using the ACS data. Column (3) contains my preferred specification. It is identical to column (1) but contains two additional covariates which if omitted could lead to omitted variable bias, as discussed in Levinson (2016). My preferred specification also omits the SEI variable, due to the debate surrounding the use of composite variables,[5] and the variable

[2] In recent work (Novan et al., 2017, p. 45) question whether 80% was actually the impact policy makers at the time expected. Their empirical results and policy analysis suggest California's energy codes do pass the cost-benefit test.

[3] The first is the date of adoption of building codes for each state. Aroonruengsawat et al. (2012) provided data on the date of adoption of building codes for the 48 contiguous states. I added data for AK, HI and DC. The second is the historical electricity prices for California geographies from Costa and Kahn (2011), and the third is state average electricity prices for 2017 from the Energy Information Administration. All the data and code for the present study has been archived online at https://www.openicpsr.org/openicpsr-112285.

[4] The nuance of building codes matters, and not all states that adopted building codes focused on energy-related provisions. Obtaining more detailed measures of state building code regulations is an important avenue for future research.

[5] See: https://usa.ipums.org/usa/chapter4/sei_note.shtml.

**Table 2**
Regression results, California sample.

| | *Dependent variable:* | | |
|---|---|---|---|
| | logCOSTELEC | | |
| | (1) | (2) | (3) |
| YB1970 | −0.005 | −0.052*** | −0.004 |
| | (0.007) | (0.013) | (0.007) |
| YB1980 | −0.020** | 0.003 | −0.015* |
| | (0.009) | (0.011) | (0.009) |
| YB1990 | −0.003 | 0.046*** | 0.007 |
| | (0.013) | (0.018) | (0.013) |
| ELEHEAT | 0.131*** | 0.131*** | 0.131*** |
| | (0.011) | (0.011) | (0.011) |
| logHHINCOME | 0.108*** | 0.108*** | 0.116*** |
| | (0.005) | (0.005) | (0.004) |
| SEI | 0.00002 | 0.00003 | |
| | (0.0001) | (0.0001) | |
| WHITE | 0.126*** | 0.126*** | 0.121*** |
| | (0.009) | (0.009) | (0.009) |
| ROOMS | 0.060*** | 0.060*** | 0.061*** |
| | (0.001) | (0.001) | (0.001) |
| HHSIZE | 0.082*** | 0.082*** | 0.079*** |
| | (0.004) | (0.004) | (0.004) |
| AGE | 0.003*** | 0.003*** | 0.001* |
| | (0.0004) | (0.0004) | (0.0004) |
| logBIRTHPRICE | | −0.239*** | |
| | | (0.058) | |
| YEARSIN | | | 0.003*** |
| | | | (0.0003) |
| COLLEGE | | | −0.055*** |
| | | | (0.006) |
| Observations | 142,620 | 142,620 | 142,620 |
| $R^2$ | 0.158 | 0.158 | 0.160 |
| Residual Std. error | 6.786 | 6.786 | 6.778 |

Note: *p<0.1; **p<0.05; ***p<0.01. The data are from ACS sample years 2012–2017, and the sample includes only California single-family owned homes constructed between 1960–2000, where the head of household is aged 30–65, and the household has nonnegative income. All models include PUMA-level fixed effects, and standard errors are clustered at the utility district level. The omitted construction decade dummy is the 1960s.

BIRTHPRICE, because the adoption of energy codes may have been influenced by these prices, making estimating the separate impact of regulation from prices fundamentally unanswerable in this context.[6]

In column (3) of Table 2 we see the coefficient on YB1980 is −0.015, indicating a household living in a home built in 1980 use about 1.5% less electricity than would the household if it lived in an otherwise identical house constructed in the 1960s. The effect is arguably small in magnitude and is only marginally significant statistically.

Table 3 presents results of estimating equation 2, the interaction models, estimated on the nationwide sample. Column (1) contains the CA version and column (2) is the CODESTATE version.[7] The interaction coefficients are both plotted in Fig. 1. My findings with regard to California parallel those from Levinson (2016), where the interaction coefficients post-1970s are not less than those on decades prior to code adoption. In other words, electricity expenditures, controlling for state average prices and numerous other factors, have increased in California homes built post 1970s relative to the rest of the nation, which is not the result we would expect to see if California energy codes were uniquely effective.

The results from the CODESTATE version of the difference-in-difference model stand in sharp contrast to those from the California version, and indicate building codes have successfully reduced electricity expenditures. The coefficient on the interaction between CODESTATE and YB1980 is smaller than the 1960s and 1970s interactions, and the difference between these coefficients is statistically signifiant. Electricity expenditures are about 4% smaller in homes built in the 1980s and 1990s in states that adopted building codes, compared to homes built in the 1960s or 1970s in these states.

**Table 3**
Regression results, National sample.

| | *Dependent variable:* | |
|---|---|---|
| | logCOSTELEC | |
| | (1) | (2) |
| CALIFORNIA | −0.26*** | |
| | (0.02) | |
| CODESTATE | | −0.004 |
| | | (0.01) |
| AGE | −0.003*** | −0.003*** |
| | (0.0001) | (0.0001) |
| ROOMS | 0.05*** | 0.05*** |
| | (0.0002) | (0.0002) |
| logHHINCOME | 0.10*** | 0.10*** |
| | (0.001) | (0.001) |
| WHITE | −0.03*** | −0.03*** |
| | (0.001) | (0.001) |
| OWNERSHP | 0.06*** | 0.06*** |
| | (0.002) | (0.002) |
| COLLEGE | −0.09*** | −0.09*** |
| | (0.001) | (0.001) |
| YEARSIN | 0.001*** | 0.001*** |
| | (0.0001) | (0.0001) |
| logSTAVGPRICE | 0.45*** | 0.31*** |
| | (0.01) | (0.004) |
| Observations | 2,273,709 | 2,273,709 |
| $R^2$ | 0.10 | 0.10 |
| Residual Std. error | 5.67 | 5.67 |

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are in parentheses. The data are from ACS sample years 2012–2017, and the sample includes US households in single-family (homeowners and renters), where the head of household is aged 30–65, and the household has nonnegative income. Both models include decade of construction dummies (omitted from paper) and interactions between the dummies and a California dummy in (1) and a CODESTATE dummy in (2), which are not reported in the table but are plotted in Fig. 1.

## 4. Conclusion

Using the ACS micro data, I find evidence that the state-level energy codes adopted in the 1970s were responsible for modest reductions in energy expenditures. The results from the CODESTATE difference-in-difference model add to the literature and indicate energy expenditures would be modestly lower in states that did not adopt energy codes in the 1970s had they done so. Future research that uses the ACS to study energy codes could estimate models with natural gas as a dependent variable, use subsamples of multifamily homes, replicate studies of small geographic areas (like Jacobsen and Kotchen's 2013 study of Gainesville, Florida), and can also further probe the impact of alternative modeling strategies.

[6] In addition, the BIRTHPRICE variable is highly aggregate. Costa and Kahn (2011) calculated it using data from only five utility districts and averaged the prices across districts in some cases (which they fully acknowledged). This of course reduces the variance of the birth price variable. For a discussion of my successful reproduction and a replicating using the 2000 Census data as in the original study, see: http://mattholian.blogspot.com/2019/07/replicating-costa-and-kahn-2011-part-ii.html.

[7] I include a measure of average electricity prices at state level for 2017 in both of these models. It is not possible to fully control for within-state differences in electricity prices, but unlike with the model from Table 2 I cannot use fixed effects to control for contemporary prices here. In unreported results I find omitting the logSTAVGPRCE variable from the model does not to change the general results presented in Fig. 1.

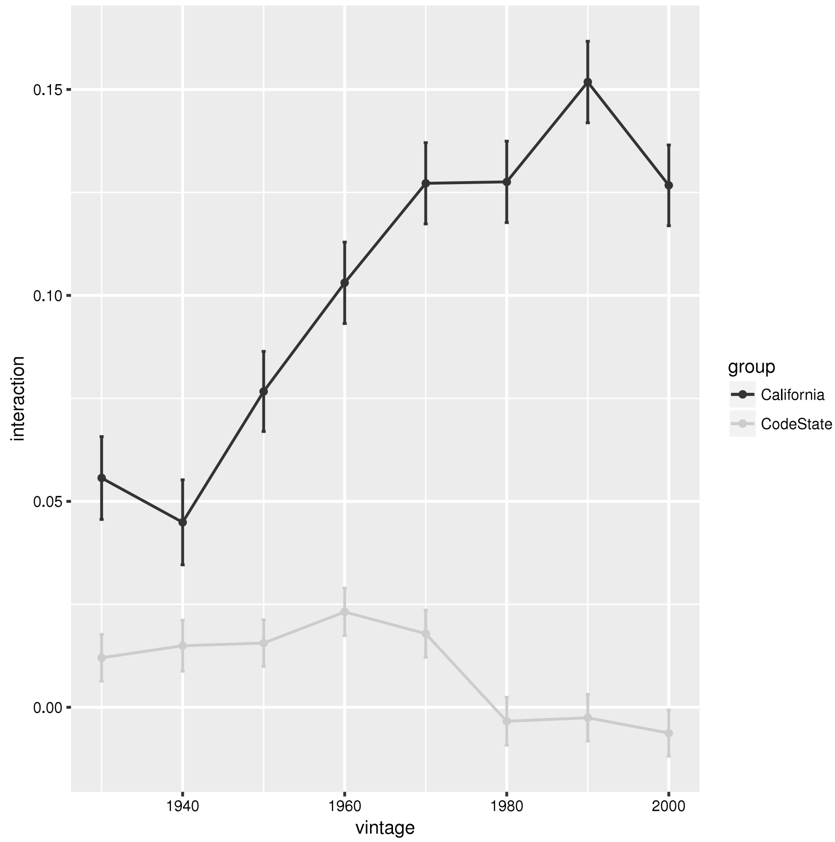


**Fig. 1.** This figure plots the regression coefficients on the interaction terms (the $\sigma_j$'s) estimated in the models shown in Table 3. Black (gray) dots are point estimates from the California (CODESTATE) models, and bars show one standard error of the estimates. The omitted category in those regressions is homes built after 2010, and the 1930 category includes all homes built before 1940.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References


Aroonruengsawat, Anin, Auffhammer, Maximilian, Sanstad, Alan H, et al., 2012. The impact of state level building codes on residential electricity consumption. Energy J. 33 (1), 31.

Costa, Dora L., Kahn, Matthew E., 2011. Electricity consumption and durable housing: understanding cohort effects. Amer. Econ. Rev. 101 (3), 88–92.

El-Shagi, Makram, Michelsen, Claus, Rosenschon, Sebastian, 2017. Empirics on the long-run effects of building energy codes in the housing market. Land Econom. 93 (4), 585–607.

Jacobsen, Grant D., Kotchen, Matthew J., 2013. Are building codes effective at saving energy? evidence from residential billing data in florida. Rev. Econ. Stat. 95 (1), 34–49.

Koirala, Bishwa S., Bohara, Alok K., Berrens, Robert P., 2014. Estimating the net implicit price of energy efficient building codes on US households. Energy Policy 73, 667–675.

Levinson, Arik, 2016. How much energy do building energy codes save? evidence from California houses. Amer. Econ. Rev. 106 (10), 2867–2894.

Nordhaus, William D., 2013. The Climate Casino: Risk, Uncertainty, and Economics for a Warming World. Yale University Press.

Novan, Kevin, Smith, Aaron, Zhou, Tianxia, 2017. Residential building codes do save energy: Evidence from hourly smart-meter data. UC Davis.

Ruggles, Steven, Flood, S, Goeken, Ronald, Grover, J, Meyer, Erin, Pacas, Jose, Sobek, Matthew, 2018. IPUMS USA: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2018.