The Impact of State Level Building Codes on Residential Electricity Consumption*

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Abstract

This paper studies the impacts of state level residential building codes on per capita residential electricity consumption. We construct a timeline of when individual states first implemented residential building codes. Using panel data for 48 US states from 1970-2006, we exploit the temporal and spatial variation of building code implementation and issuance of building permits to identify the effect of the regulation on residential electricity consumption. Controlling for the effect of prices, income, and weather, we show that states that adopted building codes followed by a significant amount of new construction have experienced detectable decreases in per capita residential electricity consumption - ranging from 3-5% in the year 2006. Allowing for heterogeneity in enforcement and code stringency results in larger estimated effects.

Keywords: Residential Electricity Consumption, Building Codes, Regulation
JEL Codes: Q41, Q48

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1. Introduction

U.S. residential electricity consumption, which accounted for 37% of total electricity consumption in 2006, has increased by 570% or on average by 4.2% annually from 1960 to 2007. In 2007, the sector contributed about 21 percent of U.S. CO_2 emissions from fossil fuel combustion, more than two-thirds of which are due to electricity consumption (EIA, 2008).

In order to meet ever increasing demand, utilities have added generating capacity, while at the same time implementing measures to slow the growth of energy demand. One set of such measures is in the form of energy efficiency policies which are thought to reduce the demand for electricity and carbon emissions. These policies can be categorized into four main types: energy efficiency standards (*e.g.* building energy codes and appliance standards), financial incentives for energy efficient investment (*e.g.* rebate programs), information and voluntary programs (*e.g.* advanced metering), and management of government energy use. The major policies that directly affect residential electricity consumption are appliance standards and building energy codes. Appliance standards require manufacturers to meet minimum energy efficient standards to sell their product in the geographic area of adoption (e.g. state). Building energy codes require newly constructed buildings as well as modified existing buildings to meet certain engineering specifications relevant to energy consumption.

In the residential sector, demand for electricity is derived from the use of electrical appliances which provide energy services such as refrigeration, heating and cooling. According to a 2001 household energy consumption survey, appliances (*e.g.* air conditioners, refrigerators, space and water heating systems and lights) are the largest users of electricity in the average U.S. household, consuming approximately two-thirds of all the residential electricity (EIA, 2001). As such, the energy efficiency of these appliances, defined as the units of energy per unit of service provided, is a major factor determining household and aggregate electricity consumption.

Residential building energy codes provide minimum building requirements for heating and cooling systems and for the housing envelope that lead to energy savings. For example, with careful building envelope design, good insulation and window glazing selection, builders can significantly downsize or even eliminate heating and cooling equipment or reduce the frequency and/or intensity of its use. More energy efficient buildings and appliances are designed to offset some of the otherwise predicted demand for energy.

The effectiveness of these codes and standards has been widely studied across disciplines. The vast majority of studies on energy savings due to these codes and standards are ex ante studies conducted by engineers. These studies have the advantage of being able to simulate changes in derived demand from specific policy induced scenarios of technological change at the building or appliance level. In order to simulate future consumption patterns one has to make detailed assumptions about the adoption of each technology and its usage, which are two factors not well understood empirically. A few recent studies attempt to overcome these issues by decomposing aggregate demand for a given state (e.g. Sudarshan and Sweeney, 2008) or across states (e.g. Horowitz, 2008) into price, income, climate and policy effects. Both studies show significant effects of state level policies on electricity consumption.

Our current study makes three specific contributions to this literature. First, instead of focusing on broadly defined energy efficiency policies, we quantify the effect of a specific and widely applied policy tool - residential building codes - on per capita residential electricity consumption. Second, we econometrically identify the effect of building codes on residential electricity consumption by exploiting temporal and spatial variation in the introduction of state level building codes and new construction instead of adopting a bottom-up modeling approach. The econometric approach has the advantage that it uses observed consumption data ex post, which embeds the behavioral response of the consumer. Finally, we control for the endogeneity of price and our policy variable by using an instrumental variables estimation strategy. Our findings should be of broader interest, since national residential and commercial building codes are the core energy efficiency policies in Waxman-Markey climate bill, which the house passed on June 26, 2009.

The next section briefly discusses the history of building codes and standards. Section 3 presents empirical model and describes the data. Section 4 presents estimation results. Section 5 concludes.

2. Background

The energy crisis and growing environmental concerns of the late 1960s and 1970s were key factors stimulating the development of public policies aimed at promoting energy efficiency and conservation in the United States, primarily through technology regulation. California's Warren-Alquist Act, enacted in 1974, established the California Energy Commission and granted it authority to introduce and enforce environmental criteria in the production and consumption of energy. Energy efficiency standards for residential and non-residential buildings were enacted in 1978 through Title 24 of the California Code of Regulations. At the federal level, the 1975 Energy Policy and Conservation Act was amended in 1978 to include, as a condition of receiving federal funding, requirements for state conservation and efficiency programs including building energy codes. Through the 1980s, a number of states adopted codes based on the ASHRAE (American Society of Heating, Refrigerating, and Air Conditioning Engineers) code 90-1075. Other states adopted the Model Energy Code (MEC) developed by the Council of American Building Officials (CABO) (Howard and Prindle 1991). In 1992, the enactment of the Energy Policy Act included a provision for states to review and/or revise their residential building codes regarding energy efficiency to meet the CABO Model Energy Code. The MEC has since been revised and updated, and its successor is the International Energy Conservation Code (IECC). Currently, all states except Hawaii, Kansas, Mississippi, Missouri, Illinois and South Dakota have implemented a statewide version of building codes. Title II of The American Clean Energy and Security Act of 2009, passed by the U. S. House of Representatives in June, includes the establishment of national energy codes for residential and commercial buildings, with the residential codes based upon the IECC 2006 code.

There is a large literature on the underlying policy rationale and the economic logic of technology-based energy efficiency regulations, including building codes. It is primarily addressed to the issue of the so-called "energy efficiency 'gap,'" the difference between observed efficiency investments and those deemed cost-effective by engineering (life-cycle cost) criteria. (Sanstad et al. 2006 is a recent overview.) Estimation of this difference is also the basis for prospective "efficiency potential" analyses (National Action Plan for Energy Efficiency 2007). By contrast, the empirical literature on ex post estimation of electricity and natural gas consumption reductions resulting from energy efficiency policies is relatively limited. Gillingham et al. (2006) estimate U. S. cumulative savings from efficiency policies and programs, but exclusive of building energy codes.

Empirical ex post estimation of the energy savings from building codes and standards poses several challenges, whether at the individual building level or at higher levels of aggregation. For example, California has established regulatory requirements and guidelines for ex post measurement of energy savings from utility demand-side management programs, which use information gathered independently of the ex ante engineering savings estimates used to design and implement the programs (Sanstad 2007). By contrast, such measurements for buildings have only recently begun to emerge in a research context, as technology and methods have improved. In turn, even as such data become more commonly available, aggregate, long-term retrospective savings estimates based upon building-level information must rely on construction of a counter-factual - that is, a "version of history" without the policies - for comparison. This requires considerably more than building code data alone. Thus, for example, the California Energy Commission's well-known estimates of historical savings due to state efficiency policies and programs are based upon an energy demand simulation model, which is run over the historical period with and without the policies - including building codes - in order to make the comparison (Marshall and Gorin 2007).

Finally, it is well-known among experts that compliance with existing building codes is problematic; as a recent study noted

"Despite the lack of definitive national-level studies regarding building energy code compliance, and existing state studies which are difficult to compare and contrast, the available data signals a significant and widespread lack of compliance" (Building Codes Assistance Project 2008).

These considerations indicate the value of an alternative, statistical approach to retrospective estimation of savings resulting from building codes. In this paper, by incorporating the adoption of these regulations at the state level in different starting years, we attempt to identify their impact on aggregate demand. Further, adding these regulations into the estimation will potentially improve the efficiency of the demand estimation.

3. Data

3.1 Electricity Data

For each state and year we observe annual total electricity consumption for the residential sector in British Thermal Units (BTUs) from the Energy Information Administration's State Energy Data System (EIA, 2009). The database covers the years 1960 through 2006 for the 48 continental states. In order to translate total consumption into per capita consumption we obtain state level population estimates from the Bureau of Economic Analysis (BEA, 2009) for the same period. Figure 1 displays trends in the per capita series. The national average displays continued growth throughout the entire period. There is a noticeable slowdown in the growth rate in the early 1970s. If we split the states by political preferences, using the most recent presidential election as a guide, we can examine the differential trends in "blue" versus "red" states. Both series display a break in the trend in the early 1970s, yet the leveling off is much stronger in the blue states. If we look at California separately, the picture displays the often cited zero growth in per capita electricity consumption since 1974, which is often called the "Rosenfeld Curve". In addition to quantity consumed, we observe the average price of electricity for the residential sector as well as the average price of the main substitute source of energy in the sector, natural gas from 1970 on. The fact that we only observe the average price, instead of the marginal price, results in the price variable being endogenous in the empirical model.

Table (1) displays the summary statistics. The first four columns of numbers show within state and overall variation in each of the variables. Per capita electricity consumption displays a significant degree of within state as well as overall variation. The last four columns of table (1) display the summary statistics for states which adopted a building code at any point in the sample versus states that never did. The control states have a slightly higher average consumption and lower electricity and natural gas prices. This difference in prices alone makes it necessary to control for these confounders in order to obtain a consistent estimate of the effect of building codes on per capita electricity consumption.

3.2 Building Code Data

We obtained data on the adoption and implementation of building codes at the state level from the building codes assistance program (BCAP, 2009). BCAP is a joint initiative of the Alliance to Save Energy (ASE), the American Council for an Energy-Efficient Economy (ACEEE), and the Natural Resources Defense Council (NRDC). It is partially funded by the US Department of Energy (DOE) and the Energy Foundation. BCAP assists state and local regulatory and legislative bodies with custom-tailored assistance on building energy code adoption and implementation. BCAP has a database, which contains detailed information on the current status of state level commercial and residential building codes as well as their history. We use the history section of the building codes database to construct a date of first implementation of building codes at the state level. In order to confirm the accuracy of these dates, we cross checked with state agency web sites to confirm that the dates are indeed implementation dates and not adoption dates. Figure (2) displays the building code dates for each state.

One could be tempted to use the binary indicator of whether state had a building code or not in a given year as the policy variable. This measure, however, would have several drawbacks. First, it ignores the heterogeneity in intensity of treatment across states. Since only new buildings and additions to existing buildings are subject to building code restrictions, states with higher growth rates new construction are likely to see bigger savings form these policies. Second, building codes vary across states in their stringency and enforcement. Using an undifferentiated binary measure allows one to estimate an average treatment effect of the average policy, but glosses over potentially important sub-national policy variation. Finally, while we know the year of implementation there may be some error as to when the codes actually started being enforced on the ground. This measurement error leads to attenuation bias towards zero of our estimated coefficients.

The "binary" strategy to estimate the effect of building codes on electricity consumption is to simply do a comparison in means before and after in treated versus control states controlling for other confounders. This difference in difference strategy is a valid identification strategy if one has random assignment in treatment. Since building codes apply to new construction and remodeled existing construction only, this strategy glosses over the fact that states with a higher rate of new construction are likely to see a bigger effect of building codes. We have therefore partially hand coded new building permits at the state level from a set of Census Bureau sources (US Census, 2009), to arrive at a measure of new construction before and after the implementation of a building code in a given state. While building permits are not a perfect measure of new construction, they likely are a good proxy and are comparable across states. The empirical measure we use to identify the effect of building codes on per capita residential electricity consumption is the share of the stock of new construction since 1970 which was conducted while a building code was in place. Figure (3) displays our policy measure for six selected states and displays significant variation across these states.

ACEEE (2008) and Horowitz (2007) correctly point out that building codes vary in both their stringency and degree of enforcement across states. In order to explore the potential impact of heterogeneity in building code intensity (e.g. stringency and enforcement), we have collected ACEEE's indicator of building code stringency and enforcement. ACEEE (2008) reports a score for compliance for residential and commercial building codes ranging from one to five and an enforcement score, which ranges from zero to three. We exclude the commercial score in order to arrive at an overall score which we scale to range from zero to one for states with residential building codes. Our measure of intensity for a given state and year is defined as the product of this intensity indicator multiplied by a dummy whether the state had a building code during a given year or not.

3.3 Other Data

The remaining major confounders of residential electricity consumption found in the empirical literature are income and weather. We have obtained per capita personal income for each state back to 1970 and converted it into constant year 2000 US$ using the national CPI. This measure of income is a standard measure used in state panel data studies, since gross state product is not available as a consistent series back to 1970 due to the switch from the SIC to NICS product accounting system.

Finally we have obtained annual measures of weather relevant to heating and cooling demand in the form of heating and cooling degree days at the state level. Degree days are quantitative indices designed to reflect the demand for energy needed to heat a home or business and are non-linear in temperature (NOAA, 2009). They report population weighted degree days using decadal census information to re-weight degree days. A smoother measure of degree days would entail calculating the weights on an annual basis, but unfortunately such a measure is currently not available. Another potential problem is that the base temperature, which is currently set at 65deg F for CDD and HDD should be different for different areas, yet this is likely a minor issue

4. Empirical Model

In order to estimate the effect of building codes on per residential electricity consumption, we estimate the following equation:

$$\log(q_{it}) = \beta_1 p_{it}^e + \beta_2 p_{it}^{ng} + \beta_3 y_{it} + \beta_4 CDD_{it} + \beta_5 HDD_{it} + \beta_6 Share_{it} + Z_{it}\boldsymbol{\gamma} + \varepsilon_{it} \tag{1}$$

where is q_{it} is state i's per capita residential electricity consumption (million BTUs per person) in year t. p_{it}^e is the real average price of electricity to residential customers ($ per million BTUs), p_{it}^{ng} is the real average price of natural gas to residential customers ($ per million BTUs). y_{it} is real per capita income (thousands dollars), CDD_{it} and HDD_{it} are cooling and heating degree days respectively. $Share_{it}$ is the share of total new construction since 1970 which was permitted while a building code was active in state i. Z_{it} is a vector of random or deterministic variables which vary across states or time or both. We will estimate equation (1) using panel data from 48 U.S. states excluding Hawaii and Alaska. The sample period is from 1970 - 2006, since prices are only available from 1970 on.

One issue that has been widely pointed out in electricity demand estimation is price endogeneity due to the increasing block price structure in place in most states (e.g. Hanemann 1984). The average price will be affected by the quantity consumed, which leads to an upward-bias (in absolute value) in the estimate of the demand response. To deal with this simultaneity problem, a common procedure is to use estimated marginal price data instead (Berndt, 1996), which unfortunately are not available for the 48 states and 37 years of data in our sample. It is often noted that households do not know the marginal price of electricity and respond to the total monthly energy bill. Marvin (2004) provides supporting evidence of such a price exogeneity assumption. While Baltagi et al. (2002) and Maddala et al. (1997) in similar studies assume price exogeneity citing these studies, we instrument for price using predetermined lagged values of average price.

There are three different avenues to estimate the parameters for equation (1). First, the most basic approach is to assume homogeneity of the parameters across states and estimate a single demand equation by pooling data. Ordinary Least Squares is consistent if the disturbance is orthogonal to all right hand side variables. Second, one can allow for a limited degree of heterogeneity in time invariant unobservables by adopting a fixed effects estimator. This approach still assumes that all coefficients, with the exception of the intercept, are identical across states. Finally, one can assume that all coefficients vary across states. Under this assumption, one could estimate the equations state by state, which results in very imprecisely estimated coefficients due to the short time series for any given state. One approach proposed in the literature to mitigate this effect is a so called "shrinkage estimator", that allows for some, but not complete, heterogeneity of the parameters by shrinking the coefficient from each state towards the overall mean. Maddala et al.(1997) tested and rejected the null hypothesis of homogenous coefficients in electricity demand estimation using an older version of the dataset employed in this paper. They show that when estimated state by state, the estimated coefficients have unreasonable signs. They argue that the shrinkage estimators are the most reasonable method.

However, Baltagi and Griffin (1997) explored a much larger number of estimators, including an instrumental variables estimator, and compared the plausibility and forecasting performance of these estimators using dynamic demand for gasoline in 18 OECD countries. They found that the homogeneous pooled estimators yielded much more plausible estimates and gave a better out-of-sample forecast. More recently, using the same data employed in this paper, albeit for a shorter time period, Baltagi et al. (2002) showed that the pooled estimators significantly outperformed the heterogeneous coefficient models for both U.S. demand for electricity and natural gas. Following

Baltagi et al. (2002), we will assume homogeneity of the slope coefficients. The goal of the paper is to identify the effect of building codes adopted by states on residential per capita electricity consumption. We will control for time invariant heterogeneity across states by including fixed effects in our preferred estimation.

The most restrictive set of assumptions are that $\varepsilon_{it} \sim iid(0, \sigma^2)$, all independent variables are independent of this disturbance term and that there are no time invariant differences in unobservable across states or common unobservable shocks across states in any given year. As mentioned above, if these assumptions hold, ordinary least squares is consistent. Using OLS, the regulation treatment effect would be identified if the regulation variables were exogenous and thus not correlated with the error terms (ε_{it}). However, each state can choose whether or not to adopt regulations and that choice could be correlated with time invariant differences in unobservable characteristics of each state, which we do not include in the model. We partially control for this problem by assuming two-way error component disturbances: $\varepsilon_{it} = \alpha_i + \phi_t + u_{it}$ where $u_{it} \sim iid(0, \sigma^2)$

This specification allows us to capture the unobservable time invariant state specific effects (α_i) (e.g. unobservable geographic characteristics) that might be correlated with the regulation variables. One example where omitting fixed effects would result in bias of the regulation variables is that the median voter in adopter states may be more concerned about energy and environmental issues than the median voter in non-adopter states. These green voters are likely to consume less electricity in the absence of regulation. Without controlling for state fixed effects, this green voter effect wound confound the estimated effect of the policy. By including unobservable time effects (ϕ_t), we can control for the time-specific shocks that commonly affect per capita consumption in all states, such as oil shocks, recessions and federal policies applicable in all states.

If regulations were randomly assigned to states at the same point in time, we could identify the average treatment effect of regulations via a simple dummy variable approach. In that case, the average treatment effect would be measured by the difference in electricity consumption of the treatment group (states that adopt) and control group conditional on other state characteristics such climate, prices etc. Here, some states choose to adopt regulations while others do not, and states also adopt regulations at different points in time. Further, intensity of treatment varies by the degree of new construction in a given state as well as the stringency of the actual building code and its enforcement. A building code in a state with no new construction, a weak building code or any building code without enforcement will be ineffective. To address the first concern, we use the interaction of a dummy of building code treatment with the share of the total building stock constructed since 1970 (the first year of our sample) as our variable of treatment. This variable in theory can range from zero to one.

Since this variable is potentially endogenous, we use an instrumental variables technique to obtain consistent estimates of the effects of building codes on per capita residential electricity consumption. Since harsh winters in the early 1970s were the trigger for the first building codes, we instrument with twice lagged cooling degree days as well as lagged heating degree days. We also use the predetermined lagged share variables as instruments.

In order to explore the potential impact of heterogeneity in building code intensity across states, we estimate the following model:

$$\log(q_{it}) = \beta_1 p^e_{it} + \beta_2 p^{ng}_{it} + \beta_3 y_{it} + \beta_4 CDD_{it} + \beta_5 HDD_{it} + \beta_6 Share_{it} + \beta_7 Intensity_{it} + Z_{it}\boldsymbol{\gamma} + \varepsilon_{it} \quad (2)$$

where $Intensity_{it}$ is the building code intensity measure based on ACEEE (2008), which ranges from zero to one for each state-year with an active building code and is zero for all state/years without building codes. β_7 therefore measures the effect of a more intense building code. We would expect states with more stringent and well enforced building codes to have lower per capita residential electricity consumption.

Using a panel data set which includes states from both treated an control groups as well as both time periods (before and after treatment) and econometric techniques which control for factors leading to time differences in adoption and intensity of treatment, we hope to address the counterfactual question of how per capita electricity consumption would have changed if an adopting state did not adopt regulations.

5. Estimation Results

Models (1) through (8) in table (2) show the results from estimating variants of equation (1). The first model is the pooled specification without building codes or fixed effects. The estimated coefficients should be interpreted as reflecting the short run response of electricity consumption in prices, climate and income. Since the estimated specification is a log-linear functional form the coefficients should be interpreted as the approximate percent change in residential per capita electricity consumption due to a one unit change in the covariate. In order to get an elasticity one multiplies the coefficient by a value of interest of the covariate (e.g. its sample mean). For the pooled model in column (1), the own price elasticity at the sample mean is -0.22, the cross price elasticity with natural gas is 0.35, the income elasticity is -0.11 and the elasticities for cooling an heating degree days are 0.17 and 0.05 respectively. All coefficients lie within the range of those found in the literature (e.g. Maddala et al. (1997)), with the exception of the negative income elasticity.

Column (2) controls for year and state fixed effects. The own price elasticity is now a smaller (-0.14), the cross price elasticity is -0.23 and the income elasticity is now a positive and significant 0.35. The CDD and HDD elasticities changed significantly, since we switch to an identification strategy relying on within state variation. The coefficient on CDD is no longer significant and the elasticity is 0.05, while the HDD elasticity is now a significant 0.16.

Column (3) addresses the issue pointed out in the previous section, that due to the fact that we observe average and not marginal prices, the price of electricity is endogenous. We therefore instrument with the predetermined lagged price of electricity and price of natural gas. The own price elasticity recovers slightly to -0.18, as we would expect a least squares coefficient being biased towards zero. The cross price elasticity becomes even smaller (0.09), which is consistent with the findings in the literature. The income elasticity is closer to other short run estimates found in the literature (0.10) as are the statistically significant coefficients on HDD and CDD.

Column (4) is the first model which includes our measure of policy - the share of newly permitted construction since 1970 under an active building code. The variable itself varies between 0, for states which either did not have a building code in a given year or did not have any construction after the implementation of the regulation, and one. The coefficient estimates on the remaining confounders are almost identical to those in model (3). The point estimate on the share variable is -0.053, which is suggests that if all construction in a given state has been built under an active building code, per capita electricity consumption is approximately 5% lower than in a state without such a building code.

Before we discuss what the magnitude of this coefficient implies, we want to check its robustness. One reason for potentially obtaining a significant and negative coefficient estimate on our policy variable is that states which have adopted building codes and have experienced significant new construction, may have had preexisting trends in per capita electricity consumption, which have nothing to do with policy, but may give rise to this significant coefficient estimate. We include linear time trends separately for states that have and have not adopted building code regulation to control for this potential phenomenon in column (5). The coefficients are almost identical to those in column (4). Model (6) includes second degree polynomial trends for building code and non building code states separately and again, the coefficients are almost identical.

Column (7) attempts to deal with the issue of endogeneity of our policy variable. Both the regulation and building construction are highly correlated with climate. Costs of construction are higher in years with sever climate outcomes (longer winters delay the construction season). Further, the first building codes were motivated by the severe winters in the early 1970s. We therefore use the first and second lag of HDD and CDD as instruments as well as the predetermined share variables. The coefficient on the policy variable moves very slightly away from zero, which is what one would expect. The other coefficient estimates, again, are almost identical to those in the previous columns.

Finally, five states had adopted appliance standards prior to the federal appliance standards passed in 1987. If these states are also building code adopters and appliance standards are actually effective at reducing electricity use, we may confound the impact of building codes with that of state specific appliance standards. For building codes we do have a proxy for intensity of treatment, which is the amount of new construction. We do not know how many air conditioners and refrigerators satisfying the state specific appliance standards were sold in any given year. We therefore control for appliance standards via a dummy for whether the standard was on or off in any given year. We also include a trend variable, which is 0 if a given state does not have an appliance standard in a given year, 1 for the first year of the appliance standard, 2 for the second year etc. Column (8) displays the estimation results from this model. Again, the coefficient estimates on the building code policy variable remains roughly unchanged. The other coefficients are also almost identical to the previous specifications. While we do not display the estimates on the appliance standard variables here, the coefficient on the dummy variable is not statistically different from zero, and the coefficient on the trend variable is very close to zero, albeit statistically different from zero.

Column (9) augments the model from column (8) by including the building code intensity measure. As expected, the coefficient estimates on the building code policy variable of interest ($share_{it}$) moves slightly towards zero and is only statistically different from zero at the 10% level. The other coefficients are also almost identical to the previous specifications. The measure of building code intensity is statistically and economically significant. A state with the most stringent implementation of their building codes, such as California or Oregon, can expect to have a 5% lower per capita electricity consumption relative to states with a zero rating. The overall effect of a building code for a given state and year can therefore be calculated by $\beta_6 \cdot Share_{it} + \beta_7 \cdot Intensity_{it}$.

We now turn to putting the coefficient estimates on the share variable into perspective. Figure (4) displays the estimated impact of state building codes from both models (8) and (9). The grey bars show the effect building codes on per capita electricity consumption based on model (8). For each state we calculate $\beta_6 \cdot Share_{it}$ and its 95% confidence interval, as indicated by the whiskers. The white bars show the effect building codes on per capita electricity consumption based on model (9). For each state we calculate $\beta_6 \cdot Share_{it} + \beta_7 \cdot Intensity_{it}$ and its 95% confidence interval, as indicated by the whiskers. Figure (5) displays a map of the share variable for the year 2006. States with the majority of the new construction activity after the implementation of the building code appear as dark green. It is not surprising that early adopter states experiencing recent rapid population growth such as Nevada, Georgia and Utah appear as states with a high share variable here. This variable drives the estimated effects in figure (4) of the grey bars. Once we combine these effects with the building code stringency variable, we obtain large estimated effects for Oregon, Washington, Wisconsin, Florida and California, due to their large share of new construction as indicated by figure (5), their long history of stringent and well enforced building codes. It is important to note, however, that if one is interested in aggregate savings, one has to consider the total number of new buildings in a given state. Figure (6) displays the total number of new building permits by state, which shows that California and Florida due to their size and growing populations account for 28% of the building permits issued in states with an active building code.

It is interesting to compare our estimates of savings from building codes to estimates obtained from bottom up engineering models. While we are not aware of a comprehensive accounting exercise using the most recent set of building codes at the national level, we have obtained such estimates from the California Energy Commission (CEC, 2007). By calculating attributed savings from each type of policy across California's utilities, the CEC arrives at 5,259 GWh in savings due to building codes out of a total consumption of 86,069 Gwh resulting in attributed savings of roughly 6%. Our estimate for the same year for model (9) is 7.7%. Due to the sizable confidence interval, it includes the estimate provided by the CEC. The estimate based on model (8) is savings of 4.03%, yet the confidence interval still includes the figure cited by the CEC. The smaller estimate of model (8) is the average effect of building codes across states. If *e.g.* California, has a more stringent or better enforced building code, we would expect that savings for that specific state are higher. The identification strategy in this model, however, cannot reliably identify state level treatment effects, since it uses across state and time variation in policy introduction and building intensity to identify the average policy effect. Model (9) attempts to overcome this shortcoming and identifies a much larger effect for states with more intensive building codes. Further, our estimate does not control for spillover benefits from first adopter states. For example, the California standards for refrigerators are argued to have had a US wide effect long before federal standards were promulgated in 1987. Our estimates therefore only capture the effects of the policy on the treated.

One interesting question is how much energy in 2006 has been saved overall from the residential building codes currently in place? In order to calculate this figure, we set the building code indicator to zero for all states and calculate overall energy consumption. If we calculate total predicted savings for each state and predict total savings from model (8), we arrive at an estimate of 2.09% in reductions of aggregate residential electricity demand due to these programs for the year 2006 counting all states in the denominator. The model allowing for heterogeneity in building codes estimates overall savings from building codes using model (9) at 4.98%. Our interpretation is that the true number lies in between these two figures, since the estimate on the building code stringency variable is likely to be confounded with the effect of other programs. A regulator imposing a more stringent building code is also likely to impose other more aggressive conservation measures, which may be captured by our intensity measure.

6. Conclusion

We regard this paper as a first step in using an econometric model to identify an average treatment effect of the average building code on residential electricity consumption. We use information from time varying state specific regulation adoption to identify the effect of the regulations on consumption. We find a significant effect of building codes on residential per capita electricity consumption ranging from 0.3-5% depending on the state. Aggregating savings to the national level, our estimates suggest savings in residential electricity consumption of 2.09-4.98% for the year 2006. Various studies have shown that compliance with building energy codes may be low. According to a ACEEE (2003) report, in most cases, builders are not completely compliant with energy codes. This may be due to a lack of informed builders, the complexity of the building code and insufficient training of code officials. Our results show that if authorities were able to ramp up compliance and enforcement, current estimates of program effectiveness likely represent a lower bound of what is possible. Further research is necessary to quantify the range of state specific treatment effects of building codes on residential electricity consumption. Another interesting topic of research is to assess the costs of these building codes and compare them to the derived benefits.

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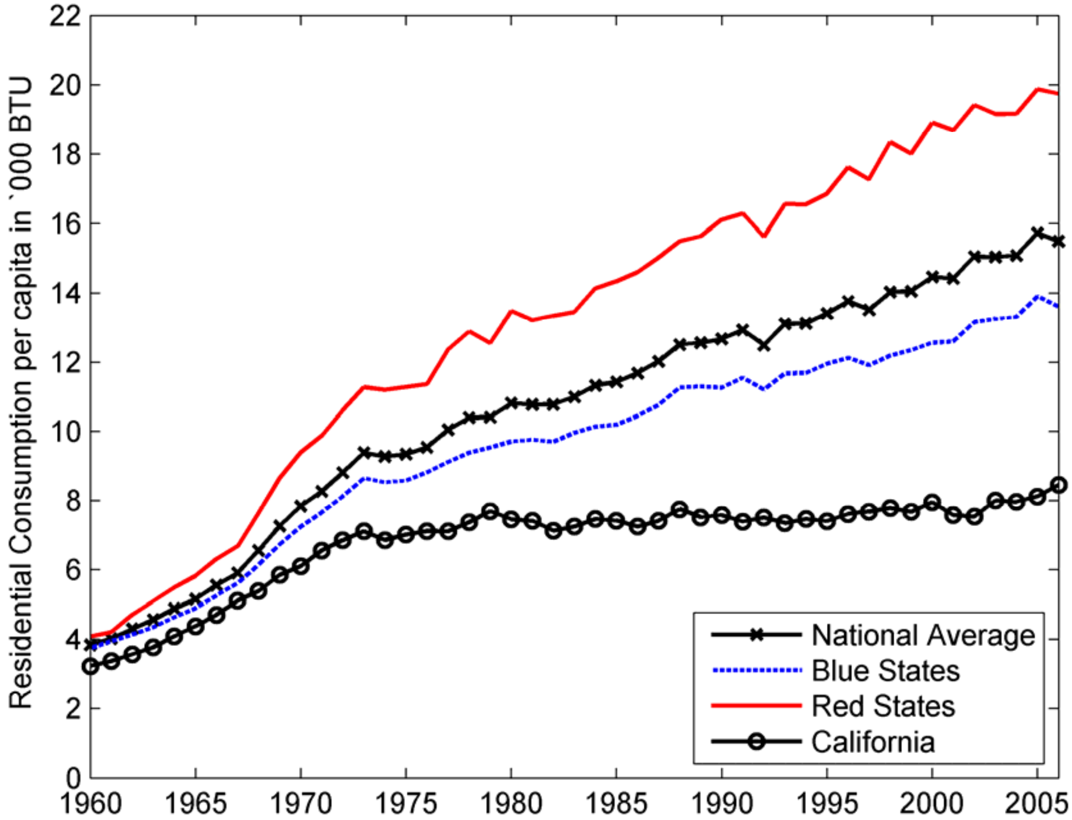
Figure 1: Per Capita Residential Electricity Consumption Trends



Note: Figure depicts the population weighted average per capita electricity consumption in BTU for the states with a majority voting for the democratic candidate for president in the 2008 presidential election (blue states), and the republican candidate (blue states) as well as the national average and California. Source: EIA State Energy Data System (2009)

Figure 2: Implementation of Building Codes by State

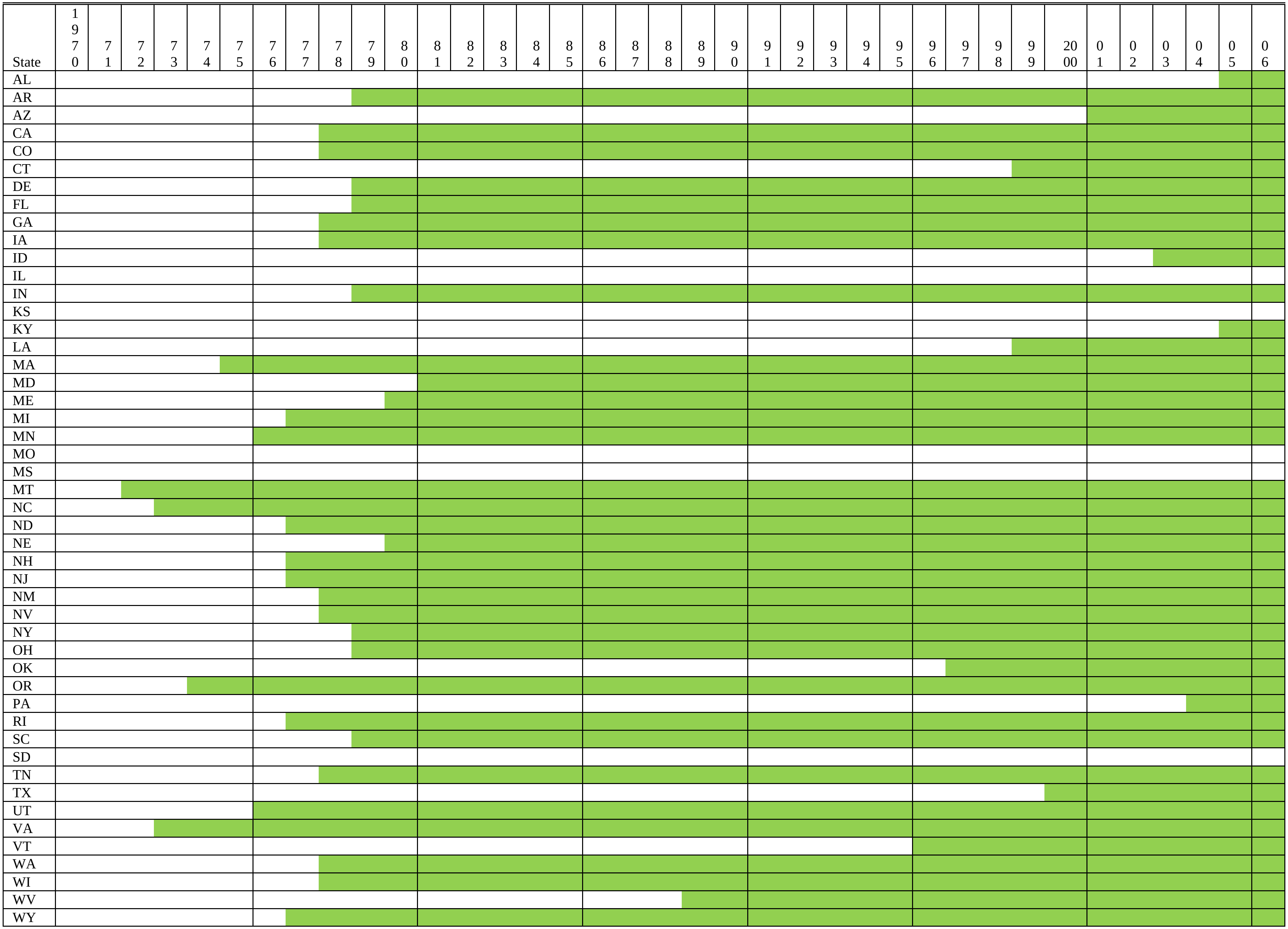
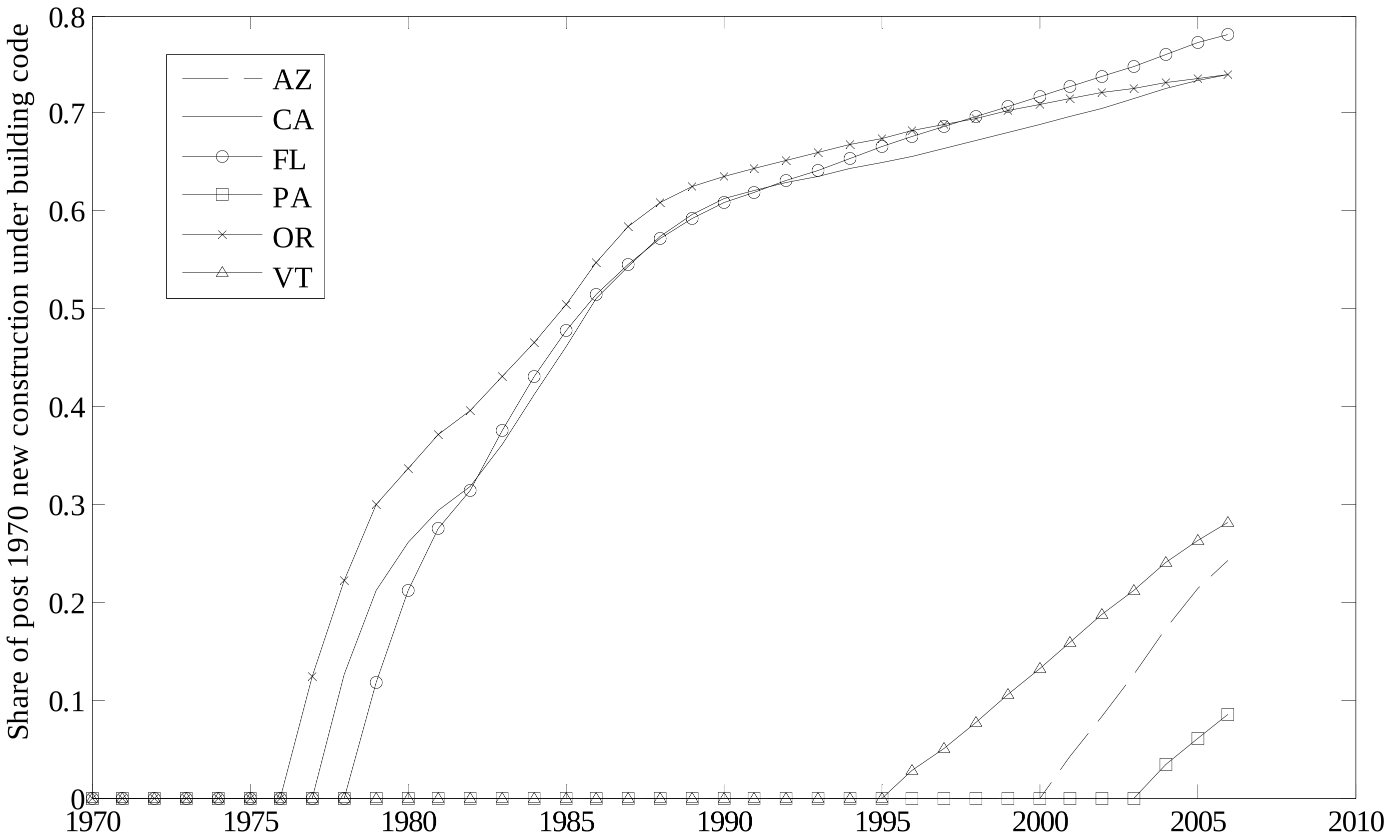
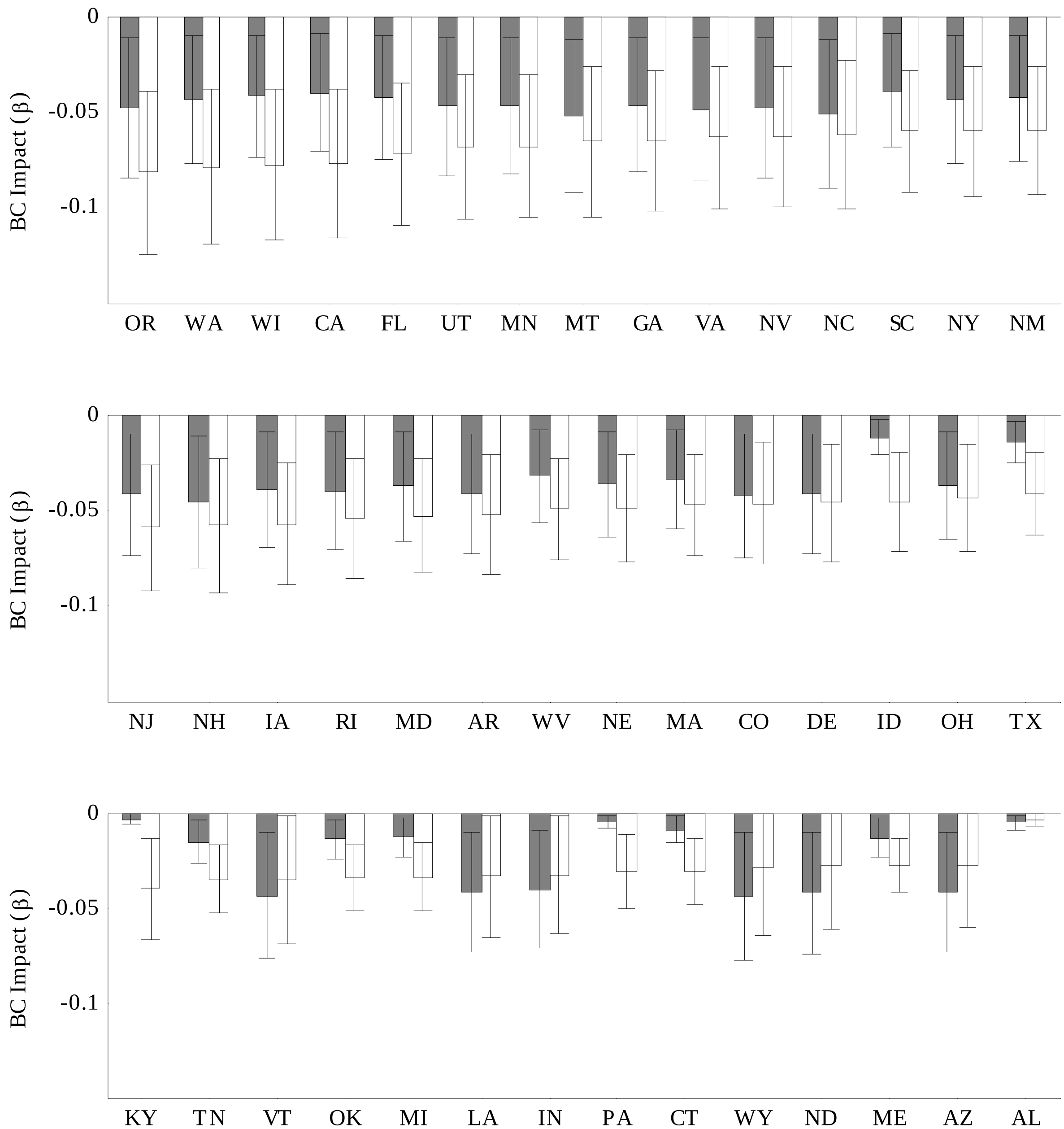


Figure 3: Share of New Construction Permitted Under Building Code



Note: The figure depicts the share of housing permits issued after the passing of a state specific building code in the total stock of building codes issued since 1970.

Figure 4. State specific impact of building codes for the year 2006



Notes: The grey bars indicate the predicted impacts of building codes from model (8) from table (2). They are obtained by multiplying the 2006 building code construction share variable times the estimated coefficient. The whiskers indicate the 95% confidence interval. The white bars indicate the predicted impacts of building codes from model (9) from table (2). They are obtained by multiplying the 2006 building code construction share variable times the estimated coefficient and adding the product of the building code intensity value for 2006 with its estimated coefficient. The whiskers indicate the 95% confidence interval.

Figure 5. Year 2006 Share of post-1970 permitted new construction conducted under an active building code by state

Figure 6: Total number of building permits issued for each state since enactment of building codes.

Table 1: Summary Statistics

Sample		Complete (n=1776)				Treated (n=1591)		Control (n=185)	
Variable	Variation	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Mean	Std. Dev.
Electricity Consumption	overall	12.88	4.18	4.76	23.99	12.86	4.25	13.03	3.47
	within		2.55	5.24	20.38		2.52		2.83
Electricity Price	overall	0.15	0.10	0.01	0.58	0.15	0.10	0.14	0.08
	within		0.10	-0.07	0.52		0.10		0.08
Natural Gas Price	overall	0.05	0.04	0.00	0.24	0.05	0.04	0.04	0.04
	within		0.04	-0.02	0.22		0.04		0.04
Per Capita Income	overall	23.21	5.13	11.48	44.20	23.33	5.17	22.13	4.71
	within		4.04	13.48	36.02		4.09		3.57
Cooling Degree Days	overall	1.09	0.78	0.08	3.88	1.06	0.80	1.31	0.50
	within		0.14	0.59	1.64		0.14		0.16
Heating Degree Days	overall	5.24	2.04	0.40	10.75	5.24	2.08	5.25	1.73
	within		0.37	3.72	6.75		0.36		0.41
New Housing Stock (p. cap.)	overall	6.05	4.34	0.14	27.34	5.70	4.11	9.05	5.03
	within		2.70	-12.18	14.58		2.41		4.48
New Housing Stock * Building Code (p.c.)	overall	4.72	5.92	0.00	31.37	5.27	6.02	N/A	N/A
	within		4.46	-10.36	21.01		4.72		N/A
Building Code Intensity	overall	0.31	0.34	0.00	1.00	0.35	0.34	N/A	N/A
	within		0.22	-0.58	1.02		0.23		N/A

Note: T-test fail to reject the null of equality of means between treatment and control states in the pre-treatment year 1970 for all variables.

Table 2: Ordinary Least Squares and Instrumental Variables Fixed Effects Regression Results

Dependent Variable: $\ln(q_{it})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Electricity Price	-1.480***	-0.942***	-1.220***	-1.207***	-1.209***	-1.208***	-1.188***	-1.185***	-1.174***
	(0.155)	(0.325)	(0.105)	(0.105)	(0.105)	(0.105)	(0.104)	(0.105)	(0.104)
Natural Gas Price	7.091***	4.819***	2.001***	1.985***	1.987***	1.985***	1.999***	1.996***	2.003***
	(0.335)	(0.782)	(0.250)	(0.250)	(0.250)	(0.250)	(0.246)	(0.249)	(0.245)
Per Capita Income	-0.004*	0.015**	0.004**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**
	(0.002)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cooling Degree Days	0.154***	0.050	0.084***	0.084***	0.084***	0.084***	0.088***	0.088***	0.090***
	(0.018)	(0.040)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)
Heating Degree Days	0.010	0.031**	0.051***	0.049***	0.049***	0.049***	0.046***	0.045***	0.045***
	(0.007)	(0.013)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Building Code Construction Share				-0.053***	-0.052***	-0.052***	-0.056***	-0.056***	-0.037*
				(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.022)
Building Code Intensity									-0.050***
									(0.019)
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV Electricity Price	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BC/Non-BC Trends Linear	No	No	No	No	Yes	Yes	Yes	Yes	Yes
BC/Non-BC Trends Non-Linear	No	No	No	No	No	Yes	Yes	Yes	Yes
IV BC Share	No	No	No	No	No	No	Yes	Yes	Yes
Appliance Standard Trend & Dummy	No	No	No	No	No	No	No	Yes	Yes
Observations	1776	1776	1728	1728	1728	1728	1680	1680	1680
R^2 (within)	0.376	0.799	0.826	0.828	0.828	0.828	0.819	0.819	0.820
Number of States	48	48	48	48	48	48	48	48	48

Note: Robust standard errors are in parentheses (*** p<0.01, ** p<0.05, * p<0.1)