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Do Building Energy Codes Have a Lasting Effect on Energy Consumption? New Evidence From Residential Billing Data in Florida
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ABSTRACT

This paper provides an ex post evaluation of how changes to a building energy code affect energy consumption. Using residential billing data for electricity and natural gas over 11 years, the analysis is based on comparisons between residences constructed just before and just after a building code change in Florida. While an earlier study using 3 years of data for the same residences showed savings for both electricity an natural gas, new results show an enduring savings for natural gas only. These findings underscore the importance of accounting for age versus vintage effects and all sources of energy consumption when conducting evaluations of building codes. More broadly, the results provide a counterpoint to the growing literature casting doubt on whether ex ante forecasts of energy efficiency policies and investments can provide useful information about actual energy savings. Indeed, more than a decade after Florida's energy code change, the measured energy savings still meets or exceeds the forecasted amount.

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1 Introduction

Are building energy codes effective at saving energy? The answer to this question is important given the growing reliance on building codes as a central part of energy and climate policy in the United States and abroad. The promotion of building energy codes is a priority at the U.S. Department of Energy, which estimates energy expenditure savings in the hundreds of billions of dollars by 2030, with emission reductions equivalent to taking millions of vehicles off the road (US DOE 2011). In the European Union, all member countries must comply with the revised Energy Performance of Buildings Directive that seeks to promote energy efficiency and help meet the EU's greenhouse-gas emissions targets (EU 2012). Despite the growing emphasis on building codes as a regulatory instrument, our understanding of the actual impacts on energy consumption remains thin. There are only a handful of peer-reviewed studies that seek to evaluate the extent to which building energy codes affect construction practices and energy consumption, and among these studies the results are quite mixed.[1]

In one of the more recent papers, Jacobsen and Kotchen (2013), hereafter referred to as J&K, study the effects of a change in Florida's building code using residential billing data for electricity and natural gas. Their study is based on a comparison between residences in Gainesville, Florida that were constructed just before and just after an increase in the stringency of Florida's energy code in 2002. J&K find that the code change caused a 4-percent decrease in electricity consumption and a 6-percent decrease in natural gas consumption, and these savings were close to those predicted *ex ante* for the code change. They also find that energy consumption in post-code change residences is less responsive to weather shocks in ways consistent with greater energy efficiency, and that the social and private payback periods for code compliance range between 3.5 and 6.4 years, respectively.

Even more recently, Levinson (2014) studies the effect of building energy codes on electricity consumption in California. Despite the fact that California is often perceived as a model state promoting energy-efficient buildings, Levinson (2014) finds no evidence that building codes have any effect on residential electricity consumption.[2] An important aspect of Levinson's contribution is the careful attention given to building age as a distinct feature from building vintage with respect to codes. He shows that newer homes consume less electricity simply because they are new, and this observation can be problematic for reli-

[1] Studies that focus explicitly on the effects of regulatory building codes include Jaffe and Stavins (1995), Horowitz and Haeri (1990), Arroonruengsawat *et al.* (2009), Costa and Kahn (2010), Jacobsen and Kotchen (2013), and Levinson (2014).

[2] Levinson's (2014) paper has received a substantial amount of media attention given its counterintuitive finding. Readers may find of interest a 30-minute Freakonomics podcast dedicated to the paper at http://freakonomics.com/tag/arik-levinson/.

ably estimating the effect of building codes. Hence careful methods are needed to separate age from vintage effects, that is, older and newer homes from those built before or after a building code change.

The potential importance of separately identifying age from vintage effects raises questions about J&K's research design and findings in Florida. Did the post-code change residences consume less energy simply because they were new? And, over time, will the energy consumption of post-code change residences more closely resemble the pre-code change residences as the differences in age reflect less of a newness effect? Indeed, Levinson (2014) writes, "I suspect if we revisited those Gainesville homes today, 10 years later, we would find no difference in energy use for households built before and after the 2002 code change" (p. 8).

This conjecture is the starting point for the present paper. I test whether J&K's findings still hold 11 years after the building code change. This is important for at least two reasons. First, J&K's approach provides a clear identification strategy for estimating building code effects, and their results are some of the very few that find an effect. Knowing whether the results endure is therefore highly policy relevant. Second, regarding energy efficiency investments more generally, a growing literature finds that *ex ante* engineering studies significantly overestimate realized savings in *ex post* evaluations.[3] Yet J&K's study provides a counterpoint in the important context of building codes. Because they find that the engineering forecasts are in line with the estimated savings, the question is whether or not the results hold up.

This paper also contributes with new insight about the effect of building codes on energy consumption over time and how future studies should approach *ex post* evaluations. The results do not yield a simple "yes" or "no" to an enduring building code effect. There are differences between the results for electricity and natural gas. While the initial estimates of the building code effect on electricity consumption diminish over time in ways consistent with Levinson's (2014) conjecture, the original results for natural gas underestimate the longer-term energy savings. Nevertheless, the overall net effect on energy consumption in a combined measure of million British thermal units indicates a rather consistent level of code-induced energy savings over the 11-year period. Together, the results highlight the importance of not focusing exclusively on electricity consumption—as most studies have done—and for waiting a few years after an energy code change to begin evaluation.

[3] Examples include Dubin *et al.* (1986), Metcalf and Hassett (1999), and Fowlie *et al.* (2015). The general issues are also reviewed in Allcott and Greenstone (2012), Gillingham and Palmer (2014), and Gerarden *et al.* (2015).

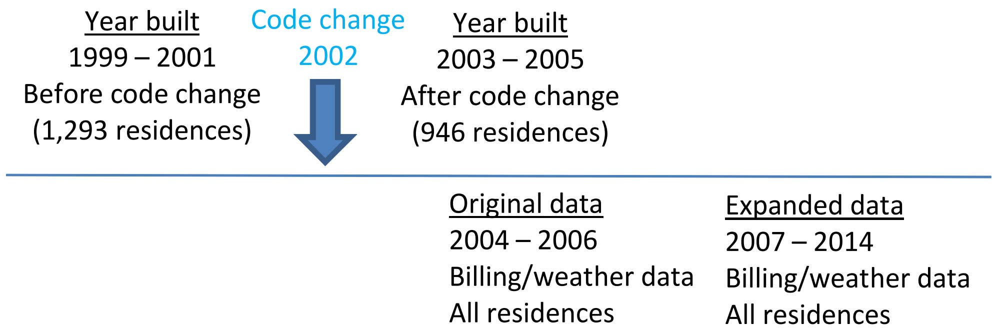

Figure 1: Before and after code change residences and the original and expanded data

2 Empirical Setting and Data Collection

Florida's residential building code that took effect in March 2002 included provisions to strengthen the energy efficiency of newly constructed houses. The new requirements focused on energy used for space heating, space cooling, and water heating.[4] To evaluate the effect of the code on residential energy consumption, J&K use monthly billing data on electricity and natural gas consumption for residences in Gainesville, Florida. They focus on residences constructed 3 years before and 3 years after the building code change. A unique feature of their data set is that billing data were combined with information about the physical characteristics of each residence, in addition to monthly weather data.

Figure 1 illustrates the basic research design, the original data set, and the expanded data set used in the present paper. Before code change residences (BCCRs) were built in years 1999-2001, and after code change residences (ACCRs) were built in years 2003-2005. Unless otherwise indicated, residences built in 2002 are excluded from the analysis because they cannot be clearly identified as having been subject to the before or after code change requirements. J&K used billing data for the years 2004-2006 to test for differences in energy consumption between the before and after code change residences. In this paper, I use an expanded data set that includes billing and weather data for the additional years 2007-2014, yielding 11 years total of energy consumption data after the building code change. Importantly, the additional billing data is for the identical set of before and after code change residences.

Most of the expanded data are from the same sources. Billing data were obtained from Gainesville-green.com, and weather data on monthly average cooling degree days (ACDD) and average heating degree days (AHDD) were obtained for the weather station located at

[4]See J&K for a detailed description of specific changes to the 2002 code and methods of compliance.

the Gainesville Regional Airport.[5] The new data were merged with the original to form a monthly panel from January 2004 through December 2014 for 2,239 residences, of which there are 1,293 BCCRs and 946 ACCRs.[6] The time-invariant variables on the physical characteristics of each residence are square footage; number of bathrooms, bedrooms, and floors; and indicators for central air-conditioning and a shingled roof.[7]

The top panel of Figure 2 shows the average monthly electricity and natural gas consumption for all residences from January 2004 through December 2014. The hotter months of the year—May through October—are shaded in the figure. There is a clear pattern where electricity consumption is higher during the summer months when demand for air-conditioning is greater, and natural gas consumption is higher during winter months when demand for heating is greater. The bottom panel of Figure 2 shows the patterns of monthly ACDD and AHDD based on the standard 65° Fahrenheit threshold. Comparisons between the panels of Figure 2 reveal how electricity demand closely follows cooling degree days, while natural gas follows heating degree days.

3 Before and After Code Change Comparisons

3.1 Overall Differences

The key estimates from J&K are regression-based, average differences in electricity and natural gas consumption between before and after code change residences. The preferred specification is

$$Y_{ijt} = \delta CodeChange_i + \boldsymbol{\beta}\boldsymbol{X}_i + v_{jt} + \varepsilon_{ijt} \tag{1}$$

where the dependent variable represents consumption of either electricity (kilowatt-hours, kWhs) or natural gas (therms) in residence i, zip-code j, and month t; $CodeChange_i$ is an indicator for whether a residence was built after the code change; $\boldsymbol{X}_i$ is a vector of the observable residence characteristics; v_{jt} represents zip-code by month-year fixed effects; and ε_{ijt} is an error term. The residence characteristics included in the model are the natural

[5] One difference in the source of data was necessary because natural gas data were not fully up to date at Gainesville-green.com. I obtained natural gas billing data from October 2013 through December 2014 directly from the Gainesville Regional Utilities (GRU), which makes all billing data publicly available for the two most recent years and ultimately provides the source for updating Gainesville-green.com.

[6] Two areas of missing billing data are for the majority of residences between April 2007 and February 2008, and natural gas data for all residences in July 2014. Attempts to obtain the missing data from GRU have been unsuccessful. In what follows, I include all of the available data in the analysis, but all results are robust to dropping the months were there are missing data.

[7] Summary statistics for residence characteristics remain unchanged from J&K's original analysis (see J&K's Tables 1 and 2). The only difference with a potentially meaningful magnitude and statistical significance is that ACCRs are 4.5 percent smaller.

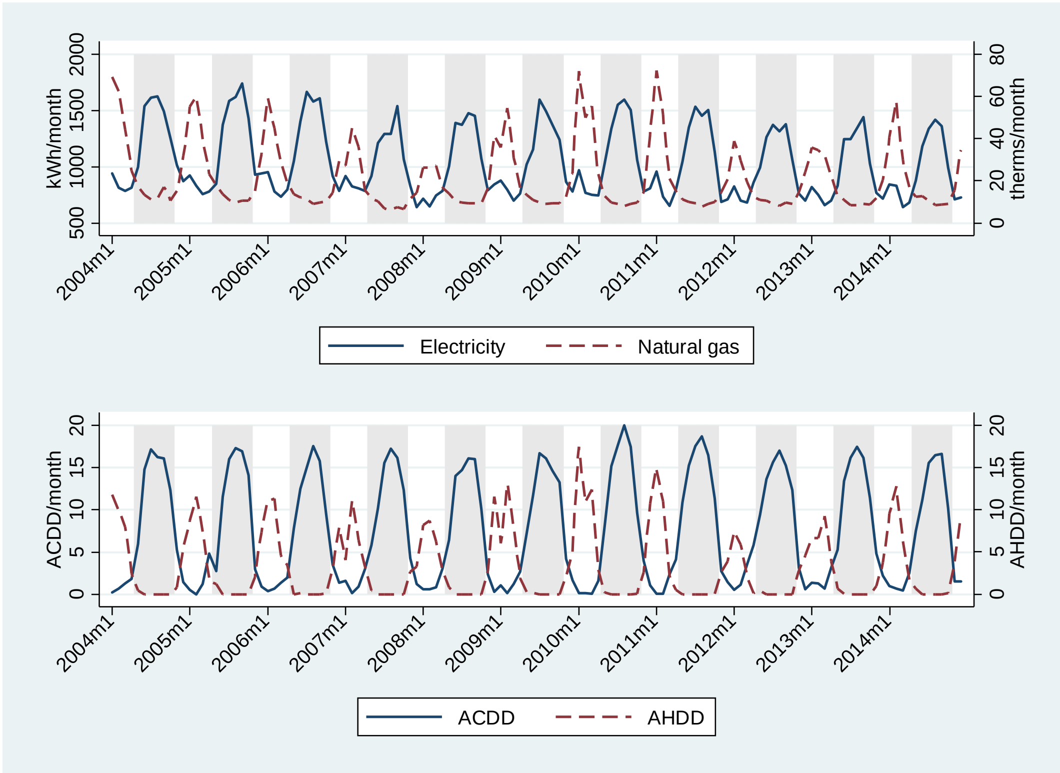

Figure 2: Average monthly electricity and natural gas consumption and cooling and heating degree days from 2004-2014, with months May-October shaded each year

log of square footage, an indicator for central air-conditioning, an indicator for a shingled roof, and categorical variables for the number of bathrooms, bedrooms, and stories.[8] When reporting results for this model, and all others throughout the paper, I use standard errors that are clustered at the residence level.

Table 1 reproduces J&K's results with the original 2004-2006 data for electricity and natural gas in the first column. I report the coefficients of interest, the δ's, along with the mean monthly consumption and percentage difference between before and after code change residences. J&K found that ACCRs consumed 4.27 percent less electricity and 6.67 percent less natural gas. The second column of Table 1 reports analogous results using the expanded data set through 2014. With the longer span of data, the difference in electricity consumption between before and after code change residences is no longer statistically significant and has a point estimate very close to zero. Levinson's (2014) conjecture is therefore consistent with the data for electricity; however, the pattern is very different for natural gas. The difference

[8] J&K also estimate models that include simply month-year fixed effects. Unless otherwise indicated, I focus throughout this paper on models with zip-code by month-year fixed effects because they are less restrictive and therefore preferred.

Table 1: Average differences in energy consumption between before and after code change residences

	Electricity	
	Original 2004-2006	All data 2004-2014
Code Change	-48.922***	-0.502
	(20.295)	(15.651)
Mean kWh/month	1,146.4	1,049.1
Percent difference	-4.27%	-0.05%
Observations	64,471	256,635
	Natural gas	
	Original 2004-2006	All data 2004-2014
Code Change	-1.572**	-2.875***
	(0.704)	(0.537)
Mean therms/month	23.6	21.3
Percent difference	-6.67%	-13.5%
Observations	64,471	254,467
	Combined: mmBtu	
	Original 2004-2006	All data 2004-2014
Code Change	-0.324***	-0.290***
	(0.109)	(0.080)
Mean mmBtu/month	6.3	5.7
Percent difference	-5.14%	-5.09%
Observations	64,471	254,467

Notes: Each coefficient is from a different regression model that includes residence characteristics and zip-code × month-year fixed effects. Standard errors in parentheses are clustered at the residence level. One, two, and three asterisks indicate significance at the 90-, 95-, and 99-percent levels, respectively.

in natural gas consumption between before and after code change residences for the initial 2004-2006 period provides an underestimate of the difference over the whole period through 2014. Using the full series of data, I find that ACCRs use 13.5 percent less natural gas on average—double the initial estimate, and with a high level of statistical significance.

The bottom panel of Table 1 reports the results of new models that combine electricity and natural gas into a single measure of overall energy consumption, quantified as millions of British Thermal Units (mmBtu).[9] Combining electricity and natural gas into a single measure of energy consumption has the advantage of estimating an overall effect that accounts for potential substitution between energy sources. The focus on overall energy use is also more appropriate for a performance-based code, such as Florida's, where builders can trade off among different energy options. Because compliance is based on an overall rating, rather

[9] The exact conversion is based on $mmBtu = 0.0034121416 \times kWhs + 0.1 \times therms$.

than conforming to specific requirements, there is no reason to expect that consumption of both electricity and natural gas would necessarily decrease. These results indicate that for the initial period of 2004-2006, ACCRs consume 5.14 percent less energy overall, and the difference is highly statistically significant. Then, when using all the data through 2014, the average difference remains nearly identical, at 5.09 percent with the same level of statistical significance.

3.2 Differences by Effective Year Built

The previous estimates are for overall differences in energy consumption between BCCRs and ACCRs. As shown in Figure 1, residences are partitioned into the two groups by their effective year built. The overall estimate can therefore be decomposed further into average differences by effective year built. This is useful for examining potential differences in energy consumption by the age of residences within and between the two groups. Specifically, the model is

$$Y_{ijt} = \boldsymbol{\delta EYB}_i + \boldsymbol{\beta X}_i + v_{jt} + \varepsilon_{ijt}, \tag{2}$$

which differs from (1) because $\boldsymbol{EYB}_i$ is a categorical variable for each effective year built from 1999 through 2005. J&K estimate the same model, and as in the original analysis, I include residences built in 2002 as the omitted category.

Figure (3) illustrates the estimated δ's graphically for electricity, natural gas, and combined energy consumption. There is no trend in electricity consumption by effective year built. This result is consist with no observable, enduring effect of the energy code change on electricity consumption. With natural gas, however, the results are again different. While there is no trend for the BCCRs, consumption is declining for the ACCRs. Yet it appears that it may take a year or so for the decline to begin after the code change, raising the possibility that residences with an effective year built in 2003 (and maybe some in 2004) might still have been subject to the before code change requirements. The results for combined energy consumption, which is effectively a weighted average of electricity and natural gas, more closely resemble those for natural gas. The important take away from the figure is that the trend in energy consumption appears the break around the time of the energy code change, suggesting that the code change had an effect on energy consumption, rather than the estimates simply capturing an age effect.[10]

[10] J&K's Figures 3 and 4 present results for electricity and natural gas using only the first 3 years of consumption data. Those reported here differ by clearly showing no code change effect on electricity, but a more clear effect on natural gas. J&K did not provide separate estimates for combined energy consumption.

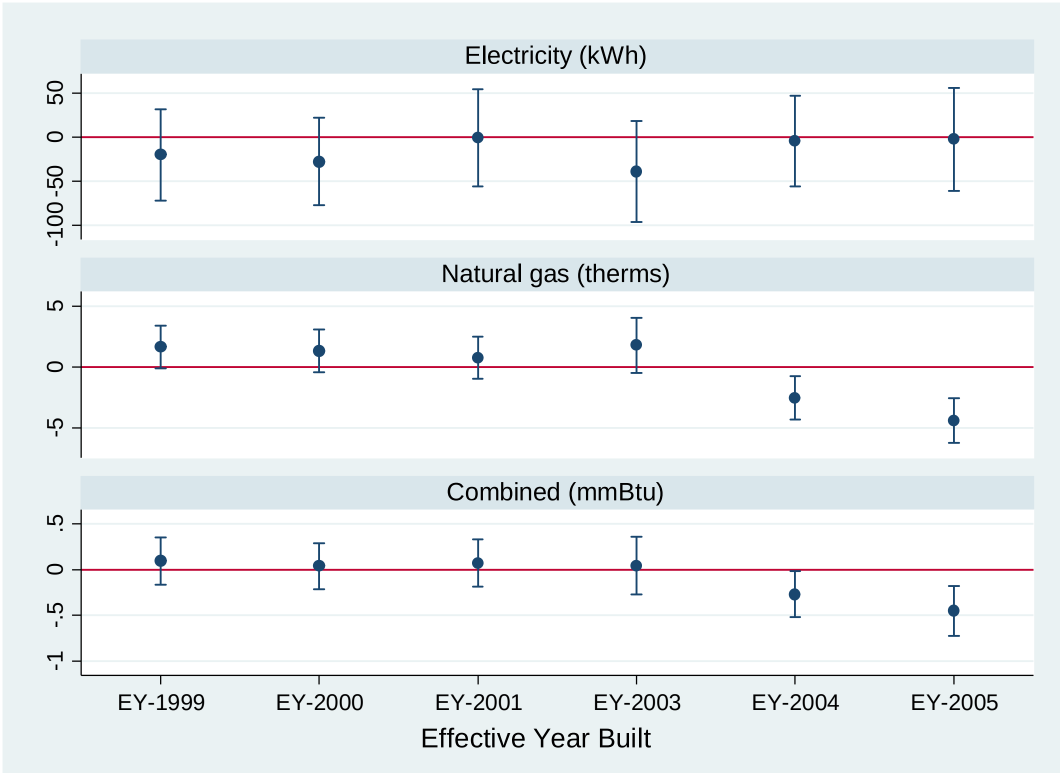

Figure 3: Overall differences in electricity, natural gas, and combined energy consumption among residences by effective year built, relative to those built in 2002, with 95-percent confidence intervals

3.3 Yearly Differences

While the energy code change is associated with lower energy consumption overall, as measured with mmBtu, the results in Table 1 clearly indicate that something different is happening over time with electricity compared to natural gas. This motivates closer scrutiny of how the estimated building code effects differ over time. Accordingly, I estimate additional models of the form

$$Y_{ijt} = \boldsymbol{\delta CodeChange}_i \times \boldsymbol{Year}_t + \boldsymbol{\beta X}_i + v_{jt} + \varepsilon_{ijt} \tag{3}$$

where $\boldsymbol{Year}_t$ is a categorical variable for each year in the sample. Estimation of this model yields distinct energy code effects for each year, where the δ's capture differences in the annual averages between BCCRs and ACCRs. I estimate separate models for electricity, natural gas, and mmBtu and report the results graphically.

Figure 4 includes all three sets of results. The δ's are scaled as a percentage difference from average consumption for the corresponding energy measure and year. It is worth keeping

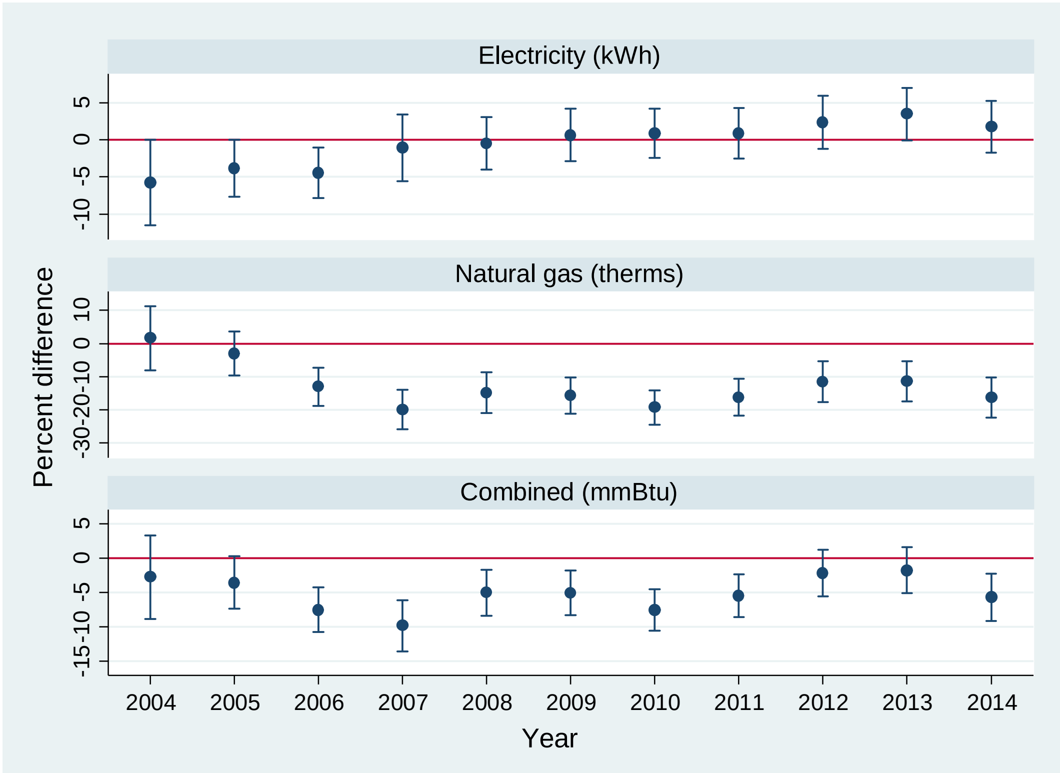

Figure 4: Annual differences in electricity, natural gas, and combined energy consumption between before and after code change residences, with 95-percent confidence intervals

in mind that when the estimates are based on annual differences, there is less statistical power, yet the trend in point estimates is of primary concern here. The results for electricity illustrate an upward trend and clearly show how focusing on the first three years of data provides an overestimate of the electricity savings.[11] Indeed, ACCRs appear to consume even more electricity in the more recent years, despite initially consuming less. But the trend clearly differs for natural gas. After the first two years, the ACCRs consume significantly less natural gas, with point estimates ranging between 10- and 20-percent less, and the difference endures over time. Finally, the results for overall energy consumption indicate that ACCRs uniformly consume less energy, but the differences vary from year to year, with point estimates ranging between 2-percent and 10-percent less. In this case, we can see visually how the short-run estimate over three years is actually quite close to the 11-year estimate.

What might explain the pattern of differences for electricity and natural gas over the 11-

[11] Recall that ACCRs are continuously entering the data set in 2004 and 2005. Estimates for these years are therefore based on a smaller set of ACCRs with monthly observations not uniformly spread over months of the year.

year period? With respect to electricity, Levinson (2014) posits that such a pattern might arise because ACCRs are simply newer, and the newness effect might dissipate over time. Although better insulated when newly constructed, residences may quickly lose some of the tight envelope that increases initial efficiency. New heating and cooling systems are more likely to have clean and efficient air filters that are subsequently changed less regularly. It may also take the occupants of new residences time to fully move in and acquire the same set of appliances as those in older residences.

An alternative explanation for the electricity results is that, despite the small differences in the effective year built between BCCRs and ACCRs, occupants of the ACCRs may be different, perhaps younger and more likely to add members to a growing family. Younger families may also have relatively increasing demands for goods that use electricity in ways unaffected by the building code (e.g., televisions and electronics). In this case, however, the relative increase in electricity consumption in ACCRs over time would not mean the code change had no effect. Instead, it would raise questions about the identification assumption underlying the regression models for estimating average differences, a topic to which I return in Section 4.

The natural gas results show a consistent pattern of energy savings from the building code after the first two years. While there may be an initial adjustment period for natural gas consumption in new residences, perhaps because new occupants are learning to use systems, I prefer an explanation that simply discounts estimates for the first two years because all ACCRs are not yet fully included in the data set. That natural gas shows a consistent energy code savings beginning in 2006 is surely consistent and plausible given the focus of the code change on space and water heating, the main drivers of natural gas consumption other than cooking.

3.4 Monthly Differences

A fourth set of models examines differences in electricity and natural gas consumption over months of the year. J&K conducted this analysis to show that ACCRs consumed less electricity in the summer and less natural gas in the winter, because of lower energy demand for air-conditioning and heating, respectively. Here I examine the patterns of monthly consumption with models of the form

$$Y_{ijt} = \boldsymbol{\delta CodeChange}_i \times \boldsymbol{Month}_t + \boldsymbol{\beta X}_i + v_{jt} + \varepsilon_{ijt}, \tag{4}$$

where $\boldsymbol{Month}_t$ is a categorical variable for month of the year. In this case, the δ's provide estimates of the differences in consumption between before and after code change residences for each month of the year.

Figure 5 illustrates the results graphically for electricity and natural gas.[12] I report results using the original 2004-2006 data and the full set of data through 2014. The top panel shows the pattern for electricity described by J&K: using data three years after the code change, there are no differences in electricity consumption between before and after code change residences during the colder and winter months, but the ACCRs consume less electricity during the hotter and summer months when demand for air-conditioning is greater.[13] When using all the data through 2014, the profile of electricity consumption remains the same, yet the difference between before and after code change residences tends to be greater across all months of the year. We have already established in Figure 4 that electricity consumption is increasing over time in the ACCRs compared to the BCCRs, and Figure 5 shows that the increase occurs because of greater baseline demand rather than a seasonal effect.[14] The natural gas results in the bottom panel reveal lower consumption of natural gas in ACCRs in the colder and winter months, indicating greater efficiency with heating. With natural gas, however, there does not appear to be an increasing or decreasing trend over months of the year when using the full set of data, and this is consistent with the ACCRs consuming uniformly less natural gas in Figure 4.

4 Differences in Weather Responsiveness

An advantage of the analysis in the previous section is that it yields an estimate of the average effect of the building code change on residential energy consumption. A disadvantage of the approach is potential vulnerability to omitted variable bias. If there is some unobserved variable that is correlated with energy consumption and the BCCR-ACCR categorization, for reasons unrelated to the building code change, then the estimates could be biased. As discussed previously, examples include differences in families that purchased homes in Gainesville a few years later, and differences in the stock of appliances in newer residences. Although observable, the age versus vintage effects could still pose problems for similar reasons because they are not separately identified in the previous estimation strategy. This is effectively Levinson's (2014) critique.

[12] I do not report the results for mmBtu because the reason for estimating monthly differences is to gain insight into the seasonal patterns of consumption for the original sources of energy demand, electricity and natural gas. But, of course, similarly formatted results for mmBtu are available upon request.

[13] The results presented here are based on models with zip-code by month-year fixed effects rather than simply month-year fixed effects as shown in J&K's Figures 1 and 2.

[14] Although I do not find evidence for it here, a seasonal effect of comparatively increasing demand for electricity in the summer by ACCRs would be consistent with an air-conditioning rebound effect.

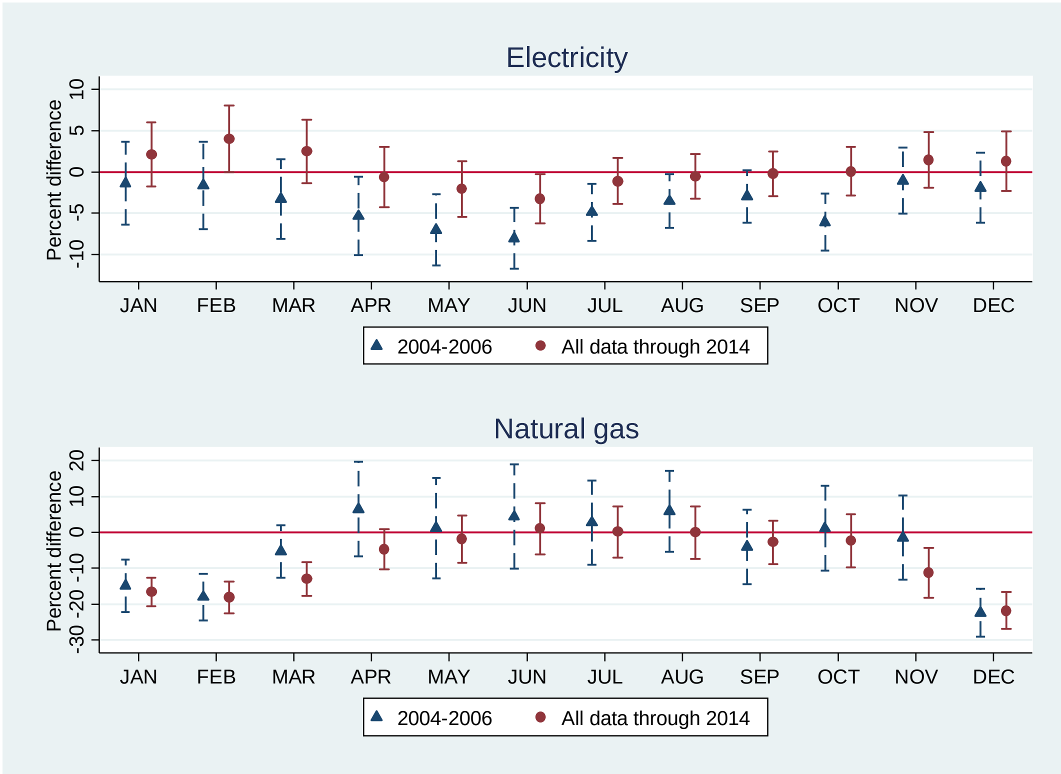

Figure 5: Monthly differences in electricity and natural gas consumption between before and after code change residences, 2004-2006 and all data through 2014, with 95-percent confidence intervals

To address these concerns, I estimate models to test for differences in the way BCCRs and ACCRs adjust energy consumption in response to weather shocks. The approach is essentially a difference-in-differences strategy that takes account of unobservable, time-invariant heterogeneity with the inclusion of residence fixed effects. While J&K estimate similarly specified fixed effects models for electricity and natural gas consumption separately, I focus here on the combined measure of mmBtu.[15] The combined measure is preferable because, as mentioned previously, it yields an overall effect that accounts for potential substitution between electricity and natural gas.

[15] Though not reported here, I also estimated separate models for electricity and natural gas. The specifications are identical to those in J&K's analysis but with the expanded data set through 2014. The main results continue to hold, whereby ACCRs are less responsive in electricity due to ACDD and less responsive in natural gas due to AHDD. These results are available upon request.

The first model takes the form

$$Y_{it} = \boldsymbol{\delta CodeChange}_i \times [ACDD_t, AHDD_t] + \boldsymbol{\beta}[ACDD_t, AHDD_t] + \boldsymbol{Month}_t + \boldsymbol{Year}_t + \mu_i + \varepsilon_{it}, \tag{5}$$

where the dependent variable is monthly mmBtu consumption, the code change indicator is interacted with the weather variables, $\boldsymbol{Month}_t$ is a set of month of year dummies, $\boldsymbol{Year}_t$ is a set of year dummies, and μ_i is a residence fixed effect. The model provides estimates of the how temperature variation affects monthly energy consumption in the BCCRs (the βs), and how the estimates differ in the ACCRs (the δs).

Two other specifications provides alternative estimates of the difference-in-differences—that is, the δs—but control for the direct weather effects more flexibly. One specification is

$$Y_{it} = \boldsymbol{\delta CodeChange}_i \times [ACDD_t, AHDD_t] + v_t + \mu_i + \varepsilon_{it}, \tag{6}$$

where v_t represents month-year fixed effects. Note that the weather variables do not enter on their own because with one weather station, they are not separately identified from the month-year fixed effects. The other specification is the same expect for the inclusion of zip-code by month-year fixed effects, v_{jt}, as specified in previous models.

Table 2 reports the results of all three models using all of the data through 2014. The results of specification (5), reported in the first column, show the unsurprising result that greater ACDD and AHDD in a month increases energy consumption. This is reflected in the positive and statistically significant estimates of β_{ACDD} and β_{AHDD}, as well as a the linear combinations $\beta_{ACDD} + \delta_{ACDD}$ and $\beta_{AHDD} + \delta_{AHDD}$. The results also show that the before and after code change residences respond differently, as indicated by the negative and statistically significant estimates of δ_{ACDD} and δ_{AHDD}. Specifically, the ACCRs increase energy consumption by less than the BCCRs, and this is consistent with the ACCRs being more energy efficient. The same results hold with similar magnitudes and statistical significance for the more flexible models in columns (2) and (3).[16]

To get a sense for the magnitude of how much BCCRs and ACCRs differ in their responsiveness, it is useful to focus on the results in column (1). Specifically, the ratios of

[16] Studying California residences over decades, Chong (2012) and Levinson (2014) find evidence that more recently constructed houses subject to more stringent building codes increase electricity consumption more in response to hotter weather. Chong (2012) explains his results for Riverside, California as increased air-conditioning ownership having outweighed other energy-saving impacts. While Levinson (2014) is able to control for air-conditioning ownership over a broader geographic area, the same explanation could underlie his results because his models control for average air-conditioning effects without allowing electricity responsiveness to vary differently among residences with and without air-conditioning.

Table 2: Difference-in-differences estimates of energy consumption due to weather variability, 2004-2014

	mmBtu		
	(1)	(2)	(3)
Code Change × ACDD (δ_{ACDD})	-0.014***	-0.013***	-0.009**
	(0.004)	(0.004)	(0.004)
Code Change × AHDD (δ_{AHDD})	-0.118***	-0.112***	-0.093***
	(0.011)	(0.011)	(0.010)
ACDD (β_{ACDD})	0.115***	–	–
	(0.004)		
AHDD (β_{AHDD})	0.403***	–	–
	(0.007)		
Month dummies	Yes	No	No
Year dummies	Yes	No	No
Month-year dummies	No	Yes	No
Zip-code × month-year dummies	No	No	Yes
Residence fixed-effects	Yes	Yes	Yes
R-squared (within)	0.273	0.286	0.331
Observations	254,467	254,467	245,467

Notes: Standard errors are clustered at the residence level. One, two, and three asterisks indicate significance at the 90-, 95-, and 99-percent levels, respectively.

coefficients $\delta_{ACDD}/\beta_{ACDD} = -0.123$ and $\delta_{AHDD}/\beta_{AHDD} = -0.292$ have useful interpretations.[17] The first implies that a unit increase in the monthly ACDD causes the ACCRs to increase energy consumption by 12 percent less on average than the BCCRs. The second implies that a unit increase in the monthly AHDD causes the ACCRs to increase energy consumption by 29 percent less on average than the BCCRs. These magnitudes suggest that the building code change had a substantial effect on tempering energy consumption in response to more extreme temperatures.

Because we have seen important differences in how the building code affects energy consumption over time, it is worth considering how the estimated differences in responsiveness to weather shocks might change over time. The final model that I estimate expands on specification (5) as follows:

$$\begin{aligned} Y_{it} &= \boldsymbol{\delta CodeChange}_i \times [ACDD_t, AHDD_t] \times \boldsymbol{Year}_t \\ &+\boldsymbol{\beta}[ACDD_t, AHDD_t] \times \boldsymbol{Year}_t + \boldsymbol{Month}_t + \boldsymbol{Year}_t + \mu_i + \varepsilon_{it}, \end{aligned} \tag{7}$$

where $\boldsymbol{Year}_t$ is interacted with the weather variables to estimate the coefficients of interest separately for each year. Then, after estimating the model, I derive the ratio δ_{kt}/β_{kt} for $k = ACDD, AHDD$ and $t = 2004...2014$ along the the 95-percent confidence intervals (see footnote 17 for details) and report the results graphically in Figure 6.

Despite the very different empirical strategy from that in Section 3, there is a now familiar pattern to the results. Soon after the building code change, ACCRs increase energy consumption significantly less is response to more ACDD, and this suggests greater efficiency with air-conditioning.[18] But the difference between before and after code change residences appears to dissipate over time, until there is no evidence of an energy code affect about 8 years later. This pattern is clearly consistent with a relative newness effect in ACCRs that is not enduring. In contrast, the difference in responsiveness to AHDD appears roughly constant over the 11 years and is always statistically different from zero, with point estimates ranging between 20 and 30 percent. This result suggests that the energy code had real effects on the efficiency of residences for heating, and this tracks the previous findings for natural gas.

[17] These ratios are nonlinear combinations of two coefficients. Test statistics are derived using the delta method, and both ratios are statistically different from zero at the 99-percent level. The 95-percent confidence intervals for the ACDD and AHDD ratios are (-0.186, -0.059) and (-0.340, -0.243), respectively.

[18] The large confidence interval for the point estimate in 2007 is most likely do to having fewer observations to estimate an effect for that year. Recall the missing data mentioned in footnote 6.

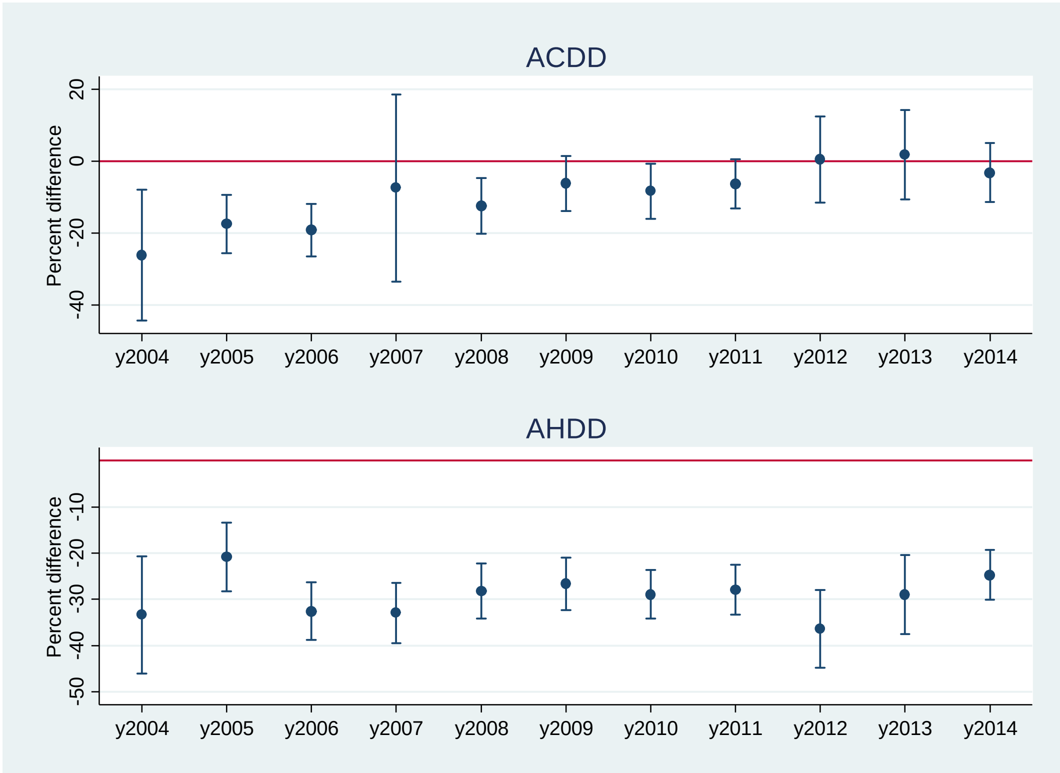

Figure 6: Annual difference-in-differences in energy consumption responsiveness between before and after code change residences due to weather variability, with 95-percent confidence intervals

5 Conclusion

This paper considers the question of whether building energy codes actually save energy. Using more than a decade's worth of billing data for residences in Gainesville, Florida, the answer is "yes," but the results differ for electricity and natural gas. Despite what appears to be an initial code change effect that reduces electricity consumption, the difference between before and after code change residences disappears after a few years. In contrast, the code change has a significant and enduring effect on natural gas consumption, causing a reduction of more than 10 percent. Both the electricity and natural gas results are consistent with the way before and after code change residences respond to weather shocks. In particular, ACCRs increase natural gas consumption by nearly 30 percent *less* than BCCRs in response to marginally colder weather.

Comparison of results from the present paper to those in J&K's original study yields two important methodological insights. First, future studies that take advantage of the discontinuity design of comparing before and after code change residences should wait several years after the code change before using billing data for analysis. The reason appears to be Levinson's (2014) critique about confounding age and vintage effects. Second, evaluation of building codes should not focus exclusively on electricity consumption, which has been the case in most previous studies. Energy codes seek to improve the efficiency of space heating, space cooling, and water heating. While natural gas is used primarily for these purposes, a growing share of residential electricity consumption is for others uses, including appliances, electronics, and televisions.

Finally, the results of this study have broader implications for the evaluation of energy efficiency policies. While a growing number of studies find that engineering forecasts significantly overestimate realized savings of efficiency investments, this does not appear to be the case with Florida's building code. Forecasts predicted that the 2002 code change would translate into a 2-percent increase in residential energy efficiency. The revised estimate here is very close to the forecast: a 2.9-percent savings in overall energy use. Nevertheless, this savings does not necessarily imply that building codes are an efficient or even desirable policy. Following the same approach outlined by J&K, the revised estimates imply social and private payback rates of about 10 and 16 years (up from 4 to 6), respectively. Whether Florida homeowners would find this private payback rate desirable, and how the social net benefits from building codes might compare to other policy instruments to promote energy efficiency are open and important questions for future research.

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