The Distributional Effects of Building Codes*

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NOT FOR GENERAL CIRCULATION.

Abstract. For almost 40 years, building energy codes have been used to try to improve the energy efficiency of newly constructed and renovated buildings. But recent empirical research has cast doubt on how much they actually affect energy use. Moreover, it is routinely pointed out that pricing the externalities of energy use directly would be a more efficient policy than a building standard. However, energy pricing policies are often regressive, and transfers that would offset this regressivity may be difficult or impossible to implement. At the same time, whether building energy codes themselves are regressive or not is unclear. Using spatial discontinuities in California's building code strictness and information about over 185,000 homes located around such borders, we evaluate the effect of building codes on home characteristics, energy use, and sales prices; we also study building codes' distributional burdens. We find that stricter energy use requirements cause builders to build smaller homes, creating an aggregate reduction in energy use but not leading to a detectable change in consumption on a per-square-foot basis. There is, however, substantial heterogeneity by income.

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I. Introduction

Building energy codes are widely employed throughout the United States. Although they are likely less efficient than pricing the externalities associated with energy use directly, building energy codes may be preferable if there are informational failures, if individuals are myopic, or if energy pricing policies lead to undesirable distributional outcomes. However, whether building energy codes actually reduce residential energy use or lead to better distributional outcomes is unclear. Part of the difficulty in evaluating the effectiveness of building energy codes is that the existing empirical studies focus on changes in building codes over time (Jacobsen and Kotchen 2013; Levinson 2015; Kotchen 2016). As such, they lack a comparison group of homes that were built at same time but don't face the same building energy code.

We adopt a novel approach to this question by exploiting spatial and temporal discontinuities in California's energy building codes. California has 16 distinct climate zones with different energy requirements for each. While the climate in each of these zones may be different on average, the weather conditions on either side of the border are essentially identical. We obtain account-level electricity and natural gas billing data for the years 2009-2015 from four California utilities, which together serve the vast majority of homes in the state. We then restrict our sample to about 185,000 homes that are located in 11 cities spanning multiple climate zones and that are within 3 kilometers of a climate zone border. We use a difference-in-differences approach, comparing cross-border differences in energy use among homes built prior to the introduction of energy building codes (before 1977) to differences among homes built after climate zones were introduced (1982 and later).[3] Importantly, our approach allows us to flexibly control for changes in building practices over time with vintage fixed effects, something previous studies have been unable to do.

We also estimate how the effect of building codes on energy use and housing prices varies by income group. Specifically, we use Census block-group-level income data to look at the heterogeneity of building codes' impact on home characteristics, energy use, and housing prices across different income groups.

[3] Between 1977 and 1982, building requirements varied slightly according to heating and cooling degree days. However, the modern climate zones did not yet exist.

We find that building codes reduce natural gas consumption by about 6% for the average household in our sample; average electricity consumption has a negative but statistically indistinguishable from zero point estimate. However, these averages mask substantial heterogeneity across income groups, and we find that households in the top of the income distribution save substantially more energy on an aggregate and on a per square foot basis, while households at the bottom of the distribution use significantly *more* electricity per square foot.

We also show that the stricter energy codes reduce home size, which in addition to better building materials is a channel through which the codes might reduce energy consumption. We are the first to our knowledge to be able to measure how builder respond to codes along the dimension of home attributes.

Using the same methodology, we also estimate the degree to which the energy code changes are capitalized into housing prices. We find that housing prices decrease on average, but that this effect is due to the reduction in home size discussed above rather than to a decrease in the price per square foot of the home. Furthermore, sales prices actually increase on an absolute and a per square foot basis for households in the lowest quartile of the income distribution, while home prices in the second and third income quartiles fall.

Our paper makes contributions along several dimensions. First, our identification strategy is unique in this literature. With the exception of Aroonruengsawat et al. (2012), the empirical literature on building codes uses only intertemporal variation (Jacobsen and Kotchen 2013; Levinson 2015; Kotchen 2016). Aroonruengsawat et al. (2012) use state-level panel data from the US and find that building energy codes reduce electricity use by as much as 5%. Because their estimation strategy is based largely on differential timing in the introduction of energy codes across states, the accuracy of their results depends crucially on their ability to control for potential confounding factors, such as heterogeneous trends and non-linear relationships between weather and electricity use. By contrast, our estimates rely on a much weaker identification assumption: we only require parallel trends near climate zone borders. We are also able to consider natural gas use, something Aroonruengsawat et al. (2012) do not observe. Unlike any of the existing studies, we also examine capitalization, distributional consequences, and whether building codes affect home characteristics, such as square footage.

The rest of the paper is organized as follows. In Section II, we provide background on energy building codes in the US and California and discuss our data. In Section III, we detail our estimation strategy. Section IV presents and discusses our results, and Section V concludes.

II. Background and data

A. California's energy efficiency building codes

Broadly, building codes are sets of practices that builders must follow. Some building codes target fire safety; others aim to make homes more resistant to hurricanes or more energy efficient. Typically, the imposition of a building code is motivated by either an externality (e.g., an individual will not take into account their neighbor's house catching fire when choosing the level of fire safety) or myopia/informational barriers (e.g., it is difficult to observe how sturdy a building is). We focus on building codes that target energy efficiency. Such building codes have been in part justified by the significant externalities associated with energy use. However, no state currently taxes building energy use, which is a more efficient way to achieve lower energy consumption in the absence of informational or landlord-tenant market failures.

In addition to the market failures mentioned above, a possible justification for eschewing such a tax is that it would disproportionately affect poor households and that redistribution of the tax revenue to offset this effect is not feasible. In other words, while building energy codes are less efficient, they may achieve a more preferable distributional outcome than energy taxes. However, it is unclear whether building codes themselves are progressive or not. For example, savings from building codes requiring greater energy efficiency may be larger for richer households, because their houses tend to be bigger and they may use more energy overall. On the other hand, even if the monetary savings are larger for richer households in absolute terms, the savings relative to income may be much larger for the poor. In addition, how binding and how costly building energy codes are may vary by the likely income category of a house's buyer. If certain buyers already demand highly efficient homes, the additional effect of a building energy code on energy use (and the additional compliance cost) may be zero.

California was one of many states to implement a statewide energy efficiency code in the 1970s (Aroonruengsawat et al. 2012). It officially adopted such a code in 1978, although, some building energy standards that were adopted in the code began to be enforced in late December, 1976 (CEC, 1978). Because we focus on energy use in single-family homes, we restrict the discussion below only to requirements that apply to such dwellings.

Between 1978-1982, building requirements differed somewhat depending on local heating and cooling degree days, but the variation was relatively small.[4] Starting in 1982, California introduced 16 "climate zones" (see Figure 1) and specified different energy requirements for each one. Climate zones are enforced at the zip code level and, in many cases, do not cross city boundaries. We obtain each zip code's climate zone from the California Energy Commission (CEC) and use this information along with the homes' latitude and longitude to classify homes into climate zones.[5] In 1995, CEC conducted a thorough review of the climate zones and changed the climate zone of several cities (California Energy Commission 1995). As we discuss below, this re-classification affects relatively few homes in our sample and we omit them from the analysis.[6]

Builders in each climate zone can meet the energy efficiency requirements in two ways. First, they can demonstrate that the building is expected to use less than the allowed energy budget for that climate zone, expressed in thousands of BTUs per square foot of conditioned space per year for space conditioning or thousands of BTUs per dwelling unit per year for water heating ("performance standard"). There are separate energy budgets for heating and cooling. Table 1 lists different energy budget components by climate zone for the years 1982-1983. Whether or not a particular building meets the required energy budget is determined by software that simulates energy use as a function of building characteristics and location. Alternatively, builders can use an "alternative package" of requirements for how the building must be built. The 1982 building code contained 3 such packages for each climate zone; starting in 1983, there have been 5. Tables A1 and A2 in the Online Appendix provide examples of alternative packages for zones 1 and 16. Because the performance standard offers much more flexibility, the

[4] We do not know how heating and cooling degree days were determined for each location during this time period, so we are unable to exploit this variation.
[5] Available from http://www.energy.ca.gov/maps/renewable/BuildingClimateZonesByZIPCode.pdf
[6] In principle, these changes create the perfect natural experiment since the California Energy Commission points out that the reclassification was due to mistakes in the original boundaries. Unfortunately there are not enough homes affected by the change to detect an effect on energy usage, so we omit these homes from our sample rather than try to exploit the change for identification.

vast majority of new home builders choose to use the performance standard.[7] Thus, our measure of building code strictness is based on energy budget differences for neighboring climate zones.

Energy budgets vary by climate zone because some zones have milder climates than others, on average.[8] For example, zone 15 is located in the Southeast of California, far from the ocean, and has a heating budget of only 1.4 thousand BTUs per square foot of conditioned space per year. But because of its hot climate, its cooling budget is 38.9 thousand BTUs per square foot. By contrast, zone 1 is located in the Northwest, which is much colder, and has a heating budget of 11.1. Because it is near the ocean, which prevents summer temperatures from getting too high, its cooling budget is only 0.1. However, there are also zones with both high heating and high cooling energy budgets (e.g., zones 11-14). Thus, whether a particular climate zone is "stricter" than its neighbor sometimes depends on whether we consider the heating or the cooling budget. Because cooling is almost always done with electricity and heating is almost always done with natural gas, we use the cooling budget rankings for analyzing differences in electricity use (measured in kWh) and the heating budget rankings for analyzing natural gas consumption (measured in therms).[9]

Energy budgets change discontinuously at climate zone borders while the climate itself is expected to be continuous.[10] Tables 2 and 3 tabulate the heating and cooling budget differences for each climate zone pair, denoting differences of zones that border each other with a box. To put these differences in perspective, 1,000 BTUs is equivalent to about 0.293 kWh or to about 0.01 therms. The average home in our sample uses 13.5 kWh and 0.67 therms per day and has about 1800 square feet of living space. Thus, for the average home, a binding reduction in the energy budget of 1,000 BTUs per square foot would translate into a 1.3 kWh per day reduction

[7] We contacted plans examiners in three jurisdictions across the state of California (Ryan Pursley from the City of Concord Building Office, Joe Espinsoa from the Palo Alto Building Office, and Leslie Edwards from the Kern County Building Office) and Michael Kunz from Title 24 Express, a company that helps builders certify energy building code compliance. All of them confirmed that new homes almost exclusively utilize the performance method for compliance.

[8] The California Energy Commission uses weather from a 'representative city' in each climate zone to determine the stringency of the standard. A list of the representative city for each zone is available from http://www.energy.ca.gov/maps/renewable/building_climate_zones.html.

[9] It is possible that there are spillovers from the heating budget to kWh and from the cooling budget to therms because of building choices that affect both heating and cooling (e.g., insulation). We are currently investigating this possibility.

[10] We have examined the borders in our sample for indications of discontinuities. With the exception of one border that appears to coincide with a large hill/small mountain range, topographic characteristics appear to be continuous across borders.

in electricity use (over 10% of the mean) and a 0.05 therms per day reduction in natural gas use (about 7% of the mean). Almost all of the border energy budget differences exceed 1,000 BTUs, and some exceed 5,000 BTUs. Cooling budget differences are generally larger than heating budget differences. If energy building codes are binding, the magnitudes of energy budget differences suggest that we should expect substantial differences in energy use for homes on different sides of climate zone borders.

B. Data and estimation sample

Home characteristics and sales prices. We obtain housing characteristics data from CoreLogic. The dataset contains detailed characteristics for over 6 million single-family homes, including the exact premise address and latitude/longitude coordinates, the square footage of the home, number of bedrooms, and the historical housing transaction dates and prices. To ensure that sales prices in our sample represent arms-length transactions, we eliminate sales of less than $10,000.

CoreLogic also reports two measures of a home's vintage: the year it was first built and the year it went through major renovations, if any ("effective year built"). If renovations affect a large enough fraction of a home's square footage, current building standards will generally apply to the entire home. For smaller additions, only the new portion of the home will need to comply, and prescriptive standards are more common in this scenario. Since we do not observe the size or nature of home renovations, we cannot determine which energy building code applies to a home whose effective year built is more recent than its original year of construction. For these reasons, we use the year a home was first built as our vintage measure.

Using the latitude and longitude provided by CoreLogic, we calculate each home's own climate zone and its distance to the nearest climate zone. We then restrict the sample to single-family homes that are within 3 kilometers of a climate zone border, leaving us with almost 2 million homes. Because there was some variation in building requirements by heating and cooling degree days between 1977 and 1981, some of which may have corresponded to modern climate zone boundaries and some of which almost certainly did not, we omit these homes from our analysis. For the same reason, we omit homes located in cities whose climate zone changed in 1995.[11] To maximize the comparability of the treated and control group, we also omit homes

[11] We could in principle leverage this change as part of our empirical analysis. However, our sample contains only about 17,000 homes in these cities that were built between 1946-2008.

built prior to 1946 or after 2008, as there is evidence that new homes use less energy in the first few years of their existence than in the longer run (Levinson 2015; Kotchen 2016). Finally, we restrict our analysis to areas where there is a mix of older (pre-1977) and newer (post-1981) homes on each side of the climate zone border. We perform this last step in the sample selection process by plotting each home in our dataset on a map and visually identifying regions with a roughly equal proportion of pre-1977 and post-1981 homes on either side of the border. This eliminates regions where home are geographically isolated from each other (even though they might be adjacent to the same border), as well as regions where new development primarily occurred on a single side of the climate zone border.

Energy use. We obtain monthly premise-level electricity and natural gas usage data from four major California utilities: San Diego Gas & Electric, PG&E, South California Edison, and South California Gas. Figure 2 shows the geographic areas covered by each of these utilities. Together, they serve almost all of California, with the exception of the very northern part of the state, the Sacramento area, and a few cities that have their own electric and gas utilities. Thus, every climate zone border has the possibility of being represented in our sample although in practice some borders do not have any homes located nearby.

Our energy usage data span the time period of January 2009 through July 2015, allowing us to obtain a fairly precise measure of each premise's expected electricity and natural gas usage. Because our variation is ultimately at the premise-level, we calculate the average daily electricity and natural gas use of each premise over this entire time period.

We use the address provided by the utility to try to match each home in the 3-kilometer CoreLogic sample described above to its energy use. To minimize false matches, which could introduce measurement error in our measure of building code strictness, we only retain cases where addresses match perfectly (including the street number, street name, city, and zip code) or where the only difference in the addresses is an abbreviated street suffix (e.g., "Ave" instead of "Avenue", "Rd" instead of "Road", etc.).[12] We then drop a few homes that match to more than one utility providing the same type of energy. Our final sample contains 647,434 single-family homes near climate zone borders, 577,115 of which have electricity usage information and

[12] In addition, we found that attempting to match more homes by accounting for misspellings and other errors did not significantly increase the number of matches, at least for homes in the San Diego Gas and Electric utility area.

519,856 of which have natural gas usage information. We then further restrict the sample to about 185,000 homes located in 11 cities that span two or more climate zones, 136,000 of which have natural gas usage information and 155,000 of which have electricity usage information. Figure 3 shows a map of these homes.

Household demographics. Finally, to categorize the income of each household, we use the American Community Survey for 2010, which is publicly available from the US Census. The data are at the block group level (the smallest geographic unit for which income is publically available) and contains information on education, race, and income. For each home in the sample, we calculate an inverse distance weighted average of these demographic characteristics from the centroids of the 3 nearest block groups. Currently, we are only using the income information in the analysis.

Summary statistics. Panel A in Table 4 presents the summary statistics for all the homes around climate zone borders. As mentioned above, the average home uses 13.5 kWh and 0.67 therms per day. Even after eliminating homes built before 1946, the average year built in our sample is fairly low (1967), suggesting that we have many control homes that were not subject to building codes when they were first constructed. The average home in our sample has 1,814 square feet of living space, 3.36 bedrooms, and 2.31 bathrooms. There is substantial variation in sales prices, but on average the most recent transaction for homes in the sample is $355,207. Even normalizing the sales price by the square footage results in a standard deviation that is more than three times the mean. Finally, occupants of the homes in our sample make about $35,900 per person per year.

Panel B of Table 4 shows minimum and maximum per-capita income in each income quartile. If the income numbers appear low for California, remember that we are measuring per-capita income rather than household income. At the low end of the distribution, occupants of homes in our samples earn between $1,800 and $21,753 per person per year. The range of the second quartile is the smallest, spanning $21,756 to $32,002. Quartile 3 ranges from $32,008 to $43,255, and we see the large right tail of the income distribution in the top income quartile, which includes households where occupants earn between $43,264 and $316,856 per person per year.

III. Empirical strategy

A. Estimating equation

Although climate zone borders are largely determined by the local weather, to reduce the administrative burdens, climate zones are enforced at the zip code level. While this gives us more confidence that weather does not change discontinuously across climate zones, it also raises the possibility that there are other discontinuities at the border. We do two things to control for these. First, rather than simply comparing post-1982 homes on different sides of a climate zone border, we adopt a difference-in-differences approach. Specifically, we compare cross-border differences between homes built prior to 1977 to cross-border differences between homes built in or after 1982. Our identifying assumption is that, conditional on the fixed effects we discuss below, differences between cross-border homes that are *not* driven by energy building codes are on average the same for pre-1977 and post-1981 homes. Second, in our primary specification, we restrict the sample of homes to eleven cities that straddle two or more climate zones where we can be more confident that the identification assumption holds and where we can also control for city-by-vintage fixed effects.[13] Although this specification only uses one third of our data, we show that the results are qualitatively similar (although not statistically significant) for the full sample of homes. As a further means of controlling for confounding factors, we also restrict the sample to three cities – Los Angeles, San Diego, and Vallejo – where the heating and cooling budget differences move in the same directions across the climate zone borders. Finally we provide a formal test of the parallel trends assumption in the next subsection.

To quantify the effect of the building code regime on home characteristics, energy usage, or housing prices, we estimate the following equation:

$$Y_i = \beta Post_i * Strict_i + \alpha_y + \alpha_z + \varepsilon_i, \tag{1}$$

where Y_i is a home characteristic, the average daily energy use (electricity or natural gas), or most recent sale price of dwelling i. The variable $Strict_i$ is an indicator for dwelling i's building code being stricter than the nearest climate zone, while $Post_i$ is an indicator for the dwelling being built after 1981. In some specifications, instead of $Strict_i$ we use the continuous variable $BudgetDiff_i$, which measures the budget difference (in thousands of BTUs) of home i's climate

[13] These eleven cities are Carson, Garden Grove, Long Beach, Los Angeles, Palmdale, San Bernardino, San Diego, Santa Barbara, Santa Clarita, Torrance, and Vallejo.

zone relative to the neighboring climate zone. If building codes significantly reduce energy usage and our identification assumption holds, we expect β to be significant and negative when using the $Post_i * Strict_i$ variable and significant and positive when using the $Post_i * BudgetDiff_i$ variable.

We control for the fact that there may be a secular trend in the energy efficiency of new homes with vintage (year built) fixed effects, α_y. In our primary eleven-city specification, we allow the time fixed effects α_y to vary at the city level. To control for any spatial differences that are common to all homes in a particular area, we include a set of zip code fixed effects, α_z. Regressions where the dependent variable is the sale price also include month-by-year fixed effects for when the sale took place. Standard errors are clustered by zip code throughout.

To estimate the heterogeneity in the impact of building codes by income quartile, we allow β to vary by the household's estimated income quartile:

$$Y_i = \sum_{q=1}^{4} \beta_q (Post_i * Strict_i * 1[Inc_i = q]) + \alpha_{yq} + \alpha_{zq} + \varepsilon_i, \tag{2}$$

where $1[Inc_i = q]$ is an indicator equal to 1 if household i's estimated income falls into quartile q, where quartiles are defined relative to other households in our sample. In addition, we control for quartile-specific year built and zip code fixed effects.

B. Testing the parallel trends assumption

As discussed above, climate zones in many cases respect city borders by design. A natural concern is that cities on either side of the border may have different trends in energy usage (with respect to house vintage) by chance. In that case, we could mistakenly attribute post-1981 differences in electricity usage to building codes. Luckily, we have a large number of homes in our 11-city sample that were built prior to 1977, so we can directly test whether there are any differential trends that could not have been caused by building codes (absent differential sorting into older homes).

Figure 4 provides a visual check of the parallel trends assumption and provides a preview of the treatment effect that we will discuss in the next section. Each plot shows the residuals we obtain when we omit the $Post_i * Strict_i$ variable from our main specification in Equation 1 for the strict and lax side of each border, averaged by year built and weighted by the number of observations. In all four panels, notice that the trend in the dependent variable prior to the introduction of the building codes in 1977 is close to zero for both sides of the yet-to-be-introduced climate zone border, and the trends diverge after the introduction of the introduction of climate zones in the 1982 building code.

In addition to the visual check of the parallel trends assumption, we perform a formal statistical test by estimating the model

$$Y_i = \sum_{t=1947}^{1976} \beta_t (YearBuilt_i = t) * Strict_i + \alpha_y + \alpha_z + \varepsilon_i, \tag{3}$$

and omitting the $(YearBuilt_i = 1946) * Strict_i$. In this model, the coefficients β_t give the difference-in-differences estimates of the change in the dependent variable between 1946 and each subsequent year in the sample (Autor 2003). We fail to reject the parallel trends assumption using a Wald test for the null hypothesis that the average of the pre-1977 β-coefficients is non-zero. Test statistics are available upon request.

IV. Results

A. Home characteristics

First, we consider the possibility that more stringent building codes affect the observable characteristics of homes constructed after the code begins to be enforced, such as the square footage or number of bedrooms. The results for square footage are shown in Table 5A. In the first row of each panel, we use a binary measure of strictness that uses the sum of the heating and cooling budgets to determine the overall budget. In each of the binary specifications, we estimate an economically meaningful decrease in home size, but the point estimates are not statistically distinguishable from zero. To increase the power of our estimates, we use the difference in the heating and cooling budgets as a continuous measure of code strictness. This specification doesn't attenuate the effect of the code when small differences in the dependent variable correspond to small differences in the code strictness. When we measure code strictness with the continuous budget difference, we find consistently positive and significant impacts of a larger energy budget (which corresponds to a *less* strict building code). Specifically, for every 1,000 BTU increase in the total energy budget in our primary specification in Panel A, we see a 0.38%

increase in living square footage. Evaluated at the mean budget difference of nearly 10,000 BTUs, this corresponds to roughly a 4% decrease in home size. In our three-city sample in Panel B, the effect is an even larger 0.47% increase in living square footage for each 1,000 BTU change in the code stringency.

Table 5B shows the effect of the building code on the number of bedrooms. All of the specifications show a statistically significant change in the number of bedrooms. Using the binary measure of strictness, we find a 5% decrease in the eleven-city sample and a 9.5% decrease in the three-city sample.

The overall patterns from the previous two tables show a decrease in home size as a result of stricter building codes, but interesting patterns emerge when we look at changes in home characteristics for households in different income brackets in Tables 6A and 6B. Beginning with the building codes' effect on square footage in Table 6A, we see that on a percentage basis the reduction in home size (8.7%) is concentrated among households in the second income quartile. While we can't distinguish the point estimates in the highest quartile from zero, the wealthiest households seem to have the largest absolute reduction in home size (619 square feet). Just as we saw for the total change in home size, the number of bedrooms in top income homes seems mostly unaffected by the building code. However, we see a large change of more than 13% in the third income quartile and very little change in the bottom income quartile. Results for our three-city sample and full sample as well as results for the heating and cooling definitions of strictness are largely similar and can be found in tables A3 to A6 of the appendix.

B. Energy usage

Overall, it appears that stricter energy building codes led builders to construct smaller homes. To test for both unconditional and conditional changes in energy use, we consider both aggregate energy use and energy use per square foot.

Table 7 shows the effect of a more stringent energy building code on natural gas usage. In our primary sample, we see a marginally significant reduction of 6.2% on the strict side of a border. The effect is slightly stronger, 7.2%, when we restrict our sample to homes in the three cities where the heating and cooling strictness definitions agree. The results are qualitatively and quantitatively similar when we use the full sample of all homes within three kilometers of a climate zone border (available upon request). In terms of our continuous measure, we estimate a 0.33% increase in natural gas usage per 1,000 BTU increase in the heat energy budget. Restricting the sample to Vallejo, Los Angeles, and San Diego homes results in a 1.5% per 1,000 BTU reduction in natural gas usage. These differences become smaller and cease to be significant when natural gas usage is measured on a per square foot basis.

Table 8 shows the corresponding estimates broken down by income quartile. Here, we see significant decreases of over 20% in natural gas use only for the third quantile when using the binary "strict" measure. The second quintile saves close to 10%, but the top and bottom quartiles don't show a statistically significant change in natural gas consumption. The budget difference measure tells the same story, although the estimates for the second income quintile cease to be statistically significant. When we consider energy usage per square foot, we actually see an *increase* in natural gas usage per square foot for the second income quintile. This result underscores the importance of accounting for changes in home size as part of the total effect of the building codes on energy usage.

Table 9 shows the same estimates for electricity usage, measured in log(kilowatt hours per day) and log(kilowatt hours per day per square foot). In the preferred sample, we see no change in consumption on the side with the stricter cooling budget. However, when we restrict our sample to the three cities where the heating and cooling budgets agree, we see a meaningful (but statistically indistinguishable from zero) 6.2% decrease in consumption on the strict side; the continuous measure shows a marginally significant reduction of .36% kWh per 1,000 BTU difference in the energy budget. In both samples, the energy intensity of each square foot actually seems to increase under the stricter code, but the results are not statistically significant.

The averages in Table 9 mask a substantial amount of heterogeneity in usage changes by income quartile. While the change in overall consumption by quintile are largely insignificant, there are substantial decreases in the energy intensity per square foot of living space in the top two income quintiles and substantial *increases* in the bottom two quintiles.

C. Housing prices

Finally, we consider the effect of stricter building codes on housing prices in Table 11. As we discussed in the models where square-footage and bedrooms were the dependent variables, the binary measure of strictness is noisier and hence less powerful than the continuous measure. Multiplying the continuous point estimate by the mean budget difference of about 10,000 BTUs, we see that home prices on the strict side of the border fall on average by about 5% in the continuous specification and by 3.8% in the binary specification. The three-city sample produces slightly larger estimates of 11% for the binary measure and 8.6% (5.75% / 10,000 BTUs x 15,000 BTUs) for the continuous measure of strictness. However, when we normalize price by square footage, our estimates become largely insignificant, suggesting that the effect of building codes on home prices is operating solely through their effect on the size of the home.

There is a substantial amount of variation in the way that prices capitalize the building code changes across income groups. In Table 12, we see that home prices in the lowest income quintile actually *increase* as a result of the stricter codes, while prices in each of the other income quartiles fall. The continuous measure of strictness implies a 5.6% increase in the sales prices of homes owned by households in the lowest quartile of the income distribution and a 1.5% decrease in the price of homes at the top of the income distribution. Furthermore, the price per square foot also increases in the lowest income quintile, a result that we could have inferred from the decrease in home size and the increase in sales price for these homes.

D. Distributional implications of results

Recall the following findings about the income heterogeneity of stricter building codes' impacts: (a) the characteristics of low- and high-income homes are statistically unaffected (although our point estimates for the latter are large), while the size and number of bedrooms falls for middle-income (quartiles 2 and 3) households; (b) gas usage is unchanged for the low- and high-income homes, either on an aggregate or per-square-foot basis, whereas the findings for middle-income households are mixed; (c) on a per-square-foot basis, electricity usage rises for low-income and 2^{nd} quartile households and decreases for 3^{rd} quartile and high-income households; and (d) both on a per-square-foot and aggregate basis, housing prices increase for low-income households, fall for middle-income households, and are unchanged for the highest income households.

Thus, while the electricity use of high-income households falls, this does not appear to translate meaningfully into changes in their housing prices. A simple explanation for this is that energy costs are likely to be much smaller than the sale price for the highest-income households; thus, even if energy savings are fully capitalized into the housing price, this may not lead to a detectable change in an expensive home's sale price.

For the third quartile, we see stricter building codes leading to reductions in energy use coupled with *reductions* in the sale price, both on an aggregate and per-square-foot basis. Although building codes do not significantly reduce the size of this group's homes, they do reduce the number of bedrooms, which could account for the reduction in the sale price.

The second income quartile sees the largest reduction in house size and number of bedrooms (in relative terms), coupled with a decrease in gas use and increase in electricity use on a per-square-foot basis. Unsurprisingly, it sees the largest decrease in housing prices.

Finally, one explanation for the housing price increases for low-income households coupled with the increase in energy use is the rebound effect: building codes make low-income homes more energy-efficient and occupants respond by using more energy. We can test this hypothesis by using monthly data to see whether the gradient of energy use with respect to temperature of pre- versus post-1981 low-income homes differs across the climate zone borders. Unfortunately, we did not have time to do this yet.

If this explanation is correct, whether or not building codes are welfare-improving for low-income households is not straightforward. Without knowing the counterfactual energy usage absent any rebound effect, we cannot determine how low-income households should value the building codes. However, it is worth mentioning that low-income households are often credit-constrained and/or face very high borrowing rates. To the extent that mortgage rates are lower than borrowing rates from other sources, bundling energy efficiency costs into the home price may relax low-income households' borrowing constraints and improve welfare even if there is no myopia.

E. Future work

In the near future, we hope to leverage the monthly nature of our data. Specifically, we could likely obtain more precision by including location-by-month-by-year fixed effects and removing energy use fluctuations due to weather shocks. With the monthly data, we can also estimate how/whether energy building codes affect the energy use gradient with respect to cooling and heating degree days, overall and for high-/low-income households. We are also investigating several explanations for the relatively small differences in energy use across climate zone borders, including the possibility that California's building energy codes are not binding. We will also consider whether building codes affect remodeling choices by looking at "effective year built" as the outcome.

V. Conclusion

We adopt a novel approach to estimating the causal effect of building codes on energy usage by using spatial discontinuities in the code's strictness across California's 16 climate zones and a sample of 11 cities that span one or more climate zone. Comparing cross-border differences in the energy use of homes built before the introduction of a state-wide building code in 1977 to differences in the energy use of homes built after the introduction of modern climate zones in 1982, we find strong evidence that building codes led builders to change their building practices, resulting in smaller homes with fewer bedrooms. There is some evidence that homes built after climate zones' introduction on the strict side of the border use less natural gas, but the differences disappear once we account for the reduced size of the home. Distributionally, we see the largest reductions in energy usage among high-income households, while the lowest-income households actually *increase* their energy use. Home prices for the latter group increase, suggesting the presence of a rebound effect and/or some difficult-to-observe characteristic change caused by building codes.

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FIGURES

Figure 1. Building climate zones in California

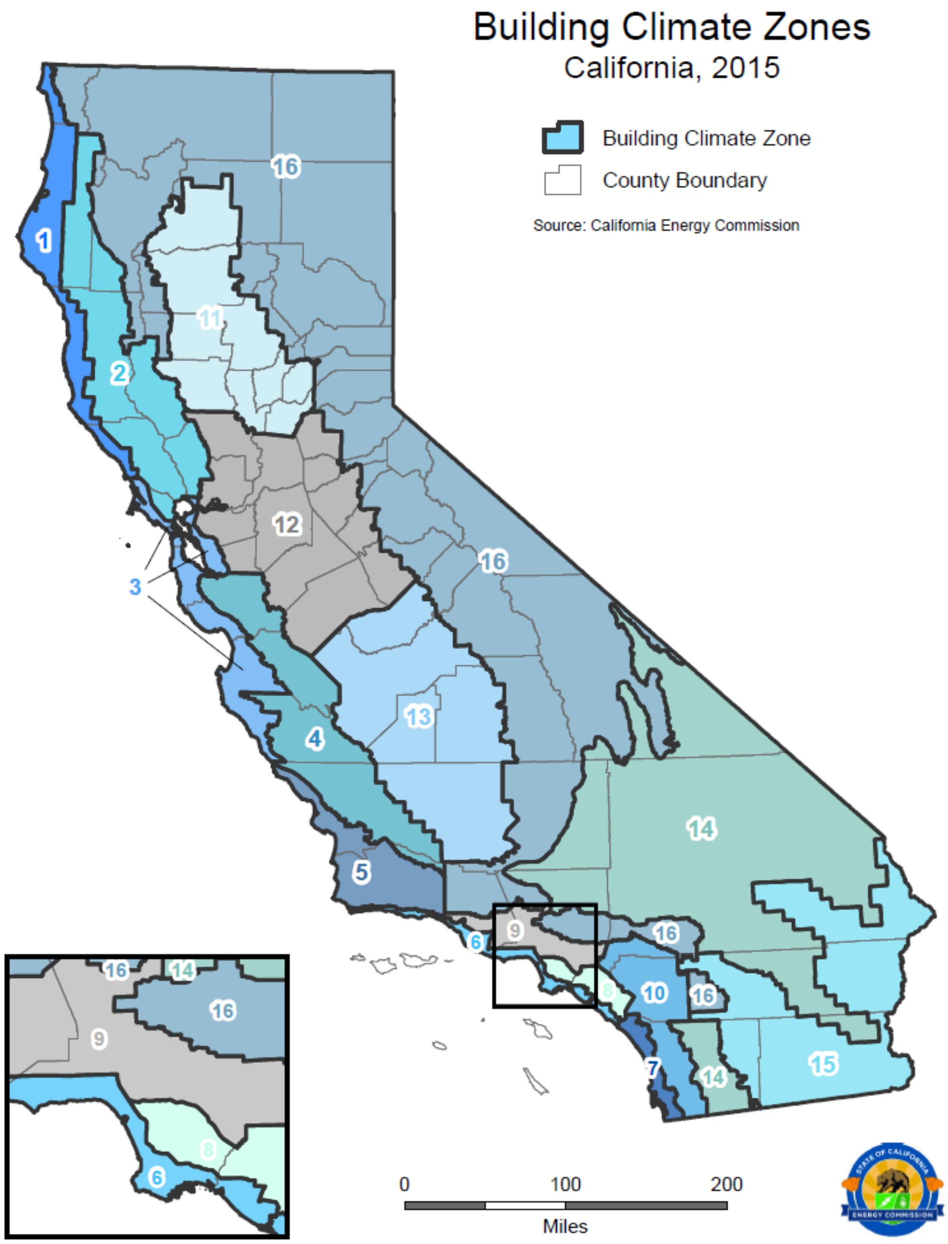


Figure 2. Territories of major electric and gas utilities in California

Figure 3. Locations of in-sample homes

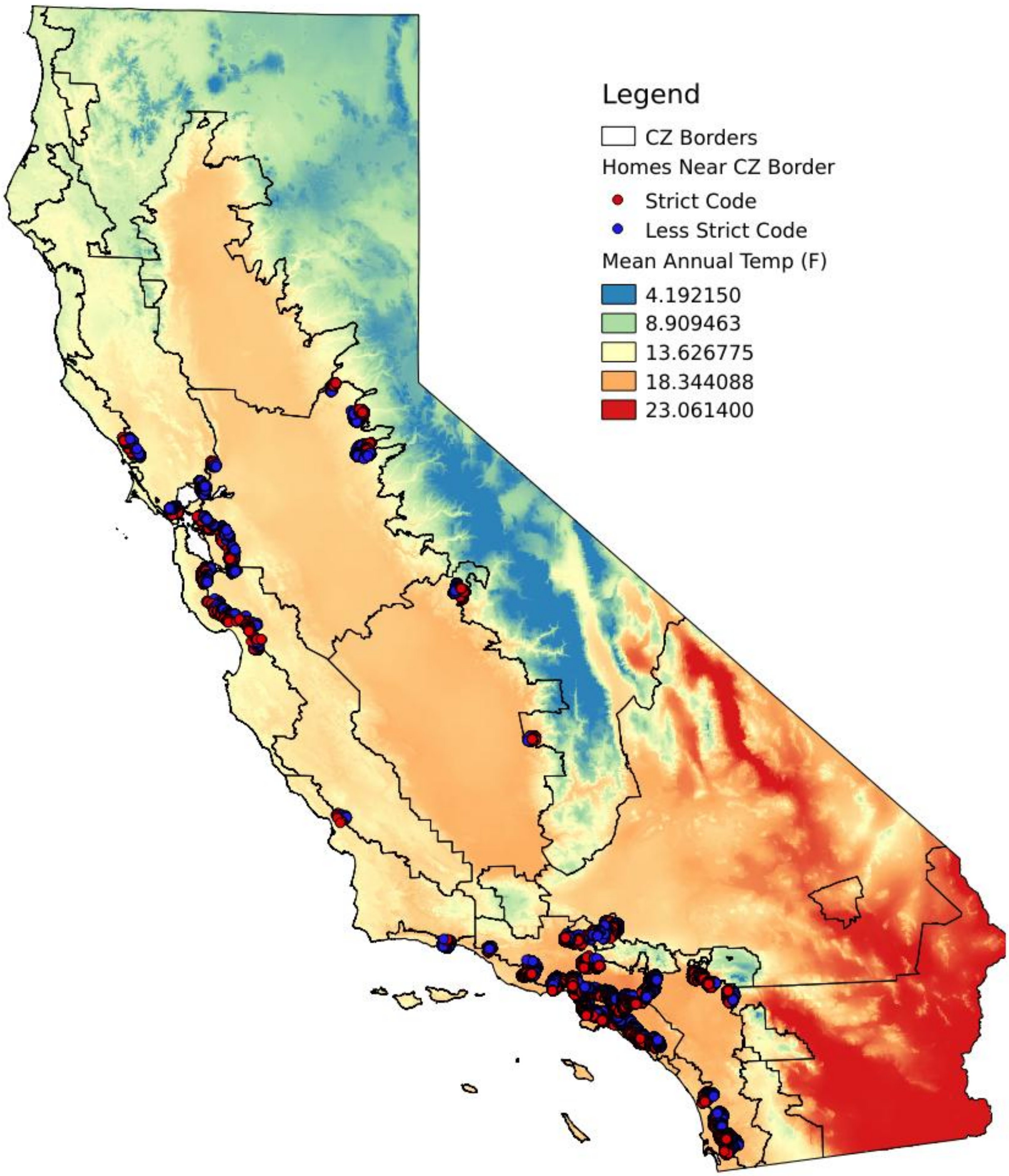
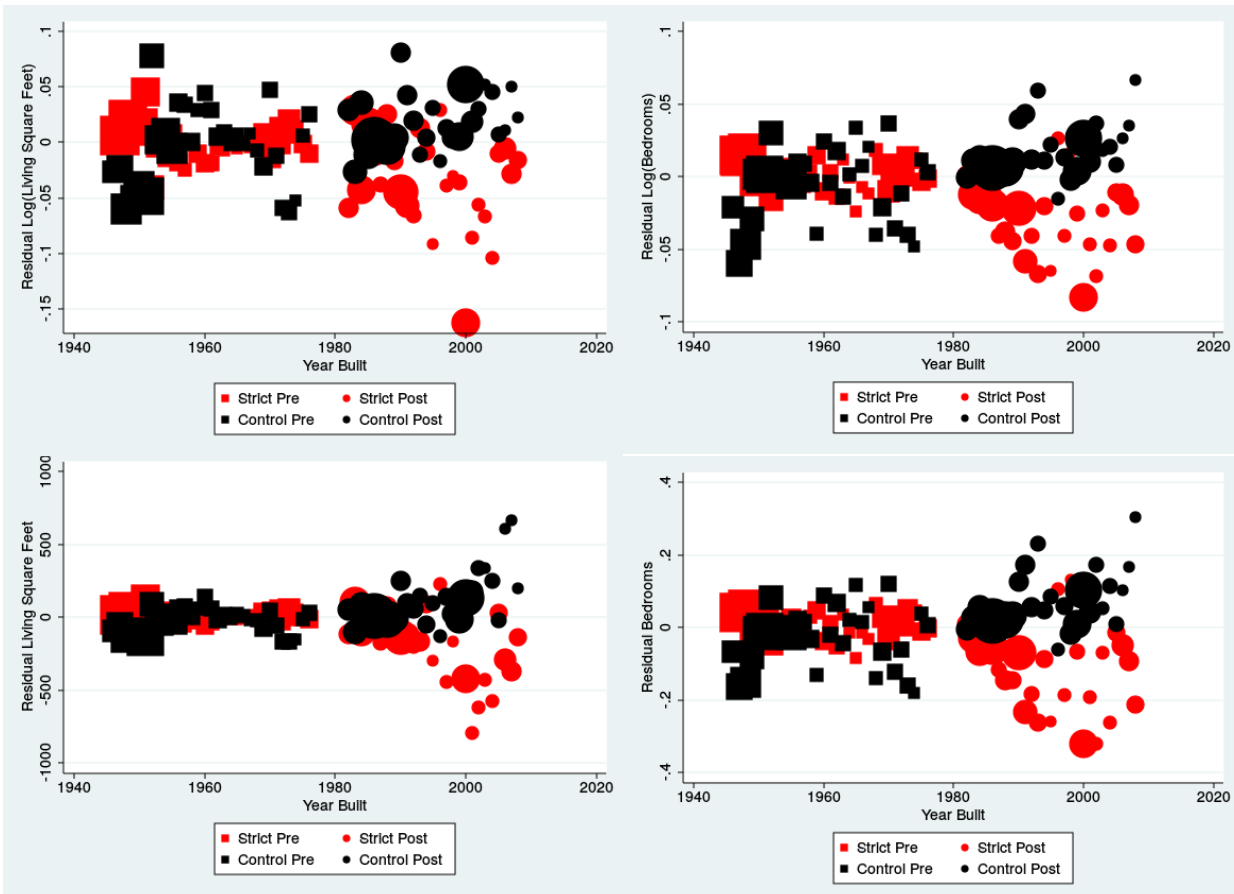


Figure 4. Trends in living square feet and number of bedrooms for older and newer homes on strict versus lax side of a border



TABLES

Table 1: Single family homes performance standards by climate zone, 1982-1983

Zone	Heating budget	Cooling budget	Water heating budget
1	11.1	0.1	22,200
2	14.5	8.7	20,800
3	12.3	2.8	20,800
4	9.9	5.7	20,600
5	10.3	3.5	20,600
6	5.2	11.5	19,400
7	2.7	3.9	19,400
8	3.5	13.6	19,400
9	6.9	17.8	19,400
10	5.6	20.9	19,400
11	16.5	22	20,400
12	15.8	14.2	20,600
13	12.4	23	20,400
14	10.7	27	20,900
15	1.4	38.9	18,700
16	20.8	8.9	22,900

Notes: Heating and cooling budgets are in thousands of BTUs per square foot of conditioned space per year. Water heating budgets are in thousands of BTUs per dwelling unit per year.

Table 2: Heating budget differences between climate zones, 1982-1983

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	3.4														
3	1.2	-2.2													
4	-1.2	-4.6	-2.4												
5	-0.8	-4.2	-2	0.4											
6	-5.9	-9.3	-7.1	-4.7	-5.1										
7	-8.4	-11.8	-9.6	-7.2	-7.6	-2.5									
8	-7.6	-11	-8.8	-6.4	-6.8	-1.7	0.8								
9	-4.2	-7.6	-5.4	-3	-3.4	1.7	4.2	3.4							
10	-5.5	-8.9	-6.7	-4.3	-4.7	0.4	2.9	2.1	-1.3						
11	5.4	2	4.2	6.6	6.2	11.3	13.8	13	9.6	10.9					
12	4.7	1.3	3.5	5.9	5.5	10.6	13.1	12.3	8.9	10.2	-0.7				
13	1.3	-2.1	0.1	2.5	2.1	7.2	9.7	8.9	5.5	6.8	-4.1	-3.4			
14	-0.4	-3.8	-1.6	0.8	0.4	5.5	8	7.2	3.8	5.1	-5.8	-5.1	-1.7		
15	-9.7	-13.1	-10.9	-8.5	-8.9	-3.8	-1.3	-2.1	-5.5	-4.2	-15.1	-14.4	-11	-9.3	
16	9.7	6.3	8.5	10.9	10.5	15.6	18.1	17.3	13.9	15.2	4.3	5	8.4	10.1	19.4

Notes: table shows the heating budget of the climate zone in the given row minus the heating budget of the zone in the given column. Boxes indicate zones that border each other.

Table 3: Cooling budget differences bewteen climate zones, 1982-1983

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	8.6														
3	2.7	-5.9													
4	5.6	-3	2.9												
5	3.4	-5.2	0.7	-2.2											
6	11.4	2.8	8.7	5.8	8										
7	3.8	-4.8	1.1	-1.8	0.4	-7.6									
8	13.5	4.9	10.8	7.9	10.1	2.1	9.7								
9	17.7	9.1	15	12.1	14.3	6.3	13.9	4.2							
10	20.8	12.2	18.1	15.2	17.4	9.4	17	7.3	3.1						
11	21.9	13.3	19.2	16.3	18.5	10.5	18.1	8.4	4.2	1.1					
12	14.1	5.5	11.4	8.5	10.7	2.7	10.3	0.6	-3.6	-6.7	-7.8				
13	22.9	14.3	20.2	17.3	19.5	11.5	19.1	9.4	5.2	2.1	1	8.8			
14	26.9	18.3	24.2	21.3	23.5	15.5	23.1	13.4	9.2	6.1	5	12.8	4		
15	38.8	30.2	36.1	33.2	35.4	27.4	35	25.3	21.1	18	16.9	24.7	15.9	11.9	
16	8.8	0.2	6.1	3.2	5.4	-2.6	5	-4.7	-8.9	-12	-13.1	-5.3	-14.1	-18.1	-30

Notes: table shows the cooling budget of the climate zone in the given row minus the cooling budget of the zone in the given column. Boxes indicate zones that border each other.

Table 4: Summary statistics

Panel A: Dependent Variables and Key Covariates			
	Mean	**SD**	**N**
Therms per day	0.674	0.86	647,434
kWh per day	13.49	11.289	647,434
Square feet	1814	870	632,668
Year built	1967	16.248	647,436
Bedrooms	3.36	1.35	647,436
Most Recent Sales Price ($)	355,207.7	1,083,561	457,705
Sales Price / Square Foot ($)	185.2804	626.2679	444,608
Per capita income ($)	35,852	20,401	647,434

Panel B: Per Capita Income by Quartile			
	Min Income	**Max Income**	**N**
Quartile 1	1,806	21,753	168,764
Quartile 2	21,756	32,002	174,775
Quartile 3	32,008	43,255	174,221
Quartile 4	43,264	316,856	174,061

Table 5A. The effects of stricter building codes on home size

	log(Square Feet)		Square Feet	
Panel A: homes near borders within city limits				
Strict x YB Post	-0.0439		-236.3	
	(0.0392)		(208.8)	
Budget Diff x YB Post		0.00381**		12.02*
		(0.00160)		(6.734)
Dependent Var Mean	7.371	7.371	1,714.461	1,714.461
Mean Budget Difference		10.196		10.196
Observations	178,601	178,601	178,601	178,601
Panel B: Vallejo, Los Angeles, and San Diego border homes only				
Strict x YB Post	-0.101		-435.5	
	(0.0632)		(380.5)	
Budget Diff x YB Post		0.00465***		13.64*
		(0.00170)		(7.650)
Dependent Var Mean	7.498	7.498	1,999.848	1,999.848
Mean Budget Difference		14.889		14.889
Observations	55,522	55,522	55,522	55,522
Year Built x City FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Results for the full sample of homes within 3km of a climate zone border are qualatively similar and avaialable upon request.

Table 5B. The effects of stricter building codes on number of bedrooms

	log(Bedrooms)		Bedrooms	
Panel A: homes near borders within city limits				
Strict x YB Post	-0.0538***		-0.204***	
	(0.0183)		(0.0678)	
Budget Diff x YB Post		0.00297***		0.0110***
		(0.00103)		(0.00336)
Dependent Var Mean	1.162	1.162	3.299	3.299
Mean Budget Difference		9.94		9.94
Observations	185,078	185,078	185,226	185,226
Panel B: Vallejo, Los Angeles, and San Diego border homes only				
Strict x YB Post	-0.0952***		-0.357***	
	(0.0288)		(0.109)	
Budget Diff x YB Post		0.00332***		0.0121***
		(0.00118)		(0.00381)
Dependent Var Mean	1.19	1.19	3.409	3.409
Mean Budget Difference		14.885		14.885
Observations	55,520	55,520	55,540	55,540
Year Built x City FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6A. The effects of stricter building codes on home size. Sample of homes near borders within city limits.

	log(Square Feet)		Square Feet	
Q1_post_YB_strict	-0.000210		-52.86	
	(0.0339)		(54.41)	
Q2_post_YB_strict	-0.0873***		-225.6***	
	(0.0242)		(57.16)	
Q3_post_YB_strict	0.00607		-52.06	
	(0.0416)		(81.21)	
Q4_post_YB_strict	-0.0376		-618.6	
	(0.0891)		(678.8)	
Q1_post_YB_diff_budget		0.000639		4.423
		(0.00273)		(4.433)
Q2_post_YB_diff_budget		0.00444***		9.947***
		(0.00106)		(2.471)
Q3_post_YB_diff_budget		0.000103		2.192
		(0.00145)		(2.865)
Q4_post_YB_diff_budget		0.00347		21.30
		(0.00279)		(21.83)
Dependent Var Mean	7.371	7.371	1713.951	1713.951
Mean Budget Difference		10.212		10.212
Year Built x City x Quartile FE	Yes	Yes	Yes	Yes
Zip Code x Quartile FE	Yes	Yes	Yes	Yes
Observations	178,415	178,415	178,415	178,415

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6B. The effects of stricter building codes on number of bedrooms. Sample homes of near borders within city limits.

	log(Bedrooms)		Bedrooms	
Q1_post_YB_strict	0.00674		0.00686	
	(0.0265)		(0.0866)	
Q2_post_YB_strict	-0.0578		-0.238*	
	(0.0362)		(0.134)	
Q3_post_YB_strict	-0.133**		-0.435***	
	(0.0560)		(0.160)	
Q4_post_YB_strict	-0.0446		-0.196	
	(0.0340)		(0.142)	
Q1_post_YB_diff_budget		0.000393		0.00262
		(0.00212)		(0.00690)
Q2_post_YB_diff_budget		0.00301***		0.0116***
		(0.000659)		(0.00241)
Q3_post_YB_diff_budget		0.00418*		0.0137*
		(0.00242)		(0.00698)
Q4_post_YB_diff_budget		0.00147		0.00628
		(0.00179)		(0.00701)
Dependent Var Mean	1.162	1.162	3.298	3.298
Mean Budget Difference		9.955		9.955
Year Built x City x Quartile FE	Yes	Yes	Yes	Yes
Zip Code x Quartile FE	Yes	Yes	Yes	Yes
Observations	184,890	184,890	185,038	185,038

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. The effects of stricter building codes on natural gas use

	log(therms per day)		log(therms per square foot per day)	
Panel A: homes near borders within city limits				
$Post \times StrictHeat$	-0.0620*		0.0303	
	(0.0356)		(0.0290)	
$Post \times DiffBudgetHeat$		0.00335		-0.00229
		(0.00287)		(0.00174)
Observations	136,268	136,268	129,939	129,939
Panel B: Vallejo, Los Angeles, and San Diego border homes only				
$Post \times StrictHeat$	-0.0724*		0.0259	
	(0.0417)		(0.0324)	
$Post \times DiffBudgetHeat$		0.0153***		-0.00399
		(0.00553)		(0.00627)
Observations	58,934	58,934	58,916	58,916

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include city-by-vintage (year built) and zip code fixed effects.

Table 8. Effect of Stricter Building Code on Heating. Sample of homes near borders within city limits.

	log(therms per day)		log(therms per square foot per day)	
$Q1 \times Post \times StrictHeat$	-0.0504		-0.00877	
	(0.0410)		(0.0221)	
$Q2 \times Post \times StrictHeat$	-0.0906**		0.128*	
	(0.0436)		(0.0748)	
$Q3 \times Post \times StrictHeat$	-0.207***		-0.145**	
	(0.0638)		(0.0600)	
$Q4 \times Post \times StrictHeat$	0.00735		0.0330	
	(0.0556)		(0.0520)	
$Q1 \times Post \times DiffBudgetHeat$		0.00161		-0.000601
		(0.00207)		(0.000594)
$Q2 \times Post \times DiffBudgetHeat$		0.00714		-0.0337***
		(0.0103)		(0.00697)
$Q3 \times Post \times DiffBudgetHeat$		0.0302***		0.0193*
		(0.00944)		(0.0109)
$Q4 \times Post \times DiffBudgetHeat$		-0.000747		-0.00102
		(0.00724)		(0.0108)
Observations	136,143	136,143	129,812	129,812

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include income quartile-by-vintage (year built) and income quartile-by-zip code fixed effects.

Table 9. The effects of stricter building codes on electricity use

Panel A: homes near borders within city limits				
$Post \times StrictCool$	0.00638		0.0487	
	(0.0305)		(0.0325)	
$Post \times DiffBudgetCool$		0.0000007		-0.00153
		(0.00138)		(0.00115)
Observations	154,980	154,980	148,513	148,513
Panel B: Vallejo, Los Angeles, and San Diego border homes only				
$Post \times StrictCool$	-0.0623		0.0699	
	(0.0562)		(0.0504)	
$Post \times DiffBudgetCool$		0.00364*		-0.00150
		(0.00186)		(0.00240)
Observations	33,251	33,251	33,249	33,249

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include city-by-vintage (year built) and zip code fixed effects.

Table 10. Effect of Stricter Building Code on cooling. Sample of homes near borders within city limits.

	log(kWh per day)		log(kWh per square foot per day)	
$Q1 \times Post \times StrictCool$	0.0382		0.0275	
	(0.0327)		(0.0174)	
$Q2 \times Post \times StrictCool$	0.0166		0.134**	
	(0.0353)		(0.0649)	
$Q3 \times Post \times StrictCool$	-0.0958		-0.165***	
	(0.0705)		(0.0414)	
$Q4 \times Post \times StrictCool$	-0.0418		-0.103*	
	(0.0725)		(0.0530)	
$Q1 \times Post \times DiffBudgetCool$		-0.00172		-0.000945**
		(0.00105)		(0.000453)
$Q2 \times Post \times DiffBudgetCool$		-0.00164		-0.0103***
		(0.00256)		(0.00196)
$Q3 \times Post \times DiffBudgetCool$		0.00439*		0.00573***
		(0.00229)		(0.00119)
$Q4 \times Post \times DiffBudgetCool$		0.00403*		0.00345**
		(0.00224)		(0.00170)
Observations	154,834	154,834	148,357	148,357

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include income quartile-by-vintage (year built) and income quartile-by-zip code fixed effects.

Table 11. The effects of stricter building codes on sales price

	log(Price)		log(Price / Square Foot)	
Panel A: homes near borders within city limits				
Strict x YB Post	-0.0383		-0.00208	
	(0.0531)		(0.0375)	
Budget Diff x YB Post		0.00507**		0.00167
		(0.00194)		(0.00110)
Dependent Var Mean	12.281	12.281	4.874	4.874
Mean Budget Difference		9.713		9.713
Observations	119,100	119,100	116,623	116,623
Panel B: Vallejo, Los Angeles, and San Diego border homes only				
Strict x YB Post	-0.109		-0.00600	
	(0.0769)		(0.0345)	
Budget Diff x YB Post		0.00575***		0.00143
		(0.00205)		(0.00100)
Dependent Var Mean	12.605	12.605	5.0840	5.0840
Mean Budget Difference		15.127		15.127
Observations	34,105	34,105	34,092	34,092
Year Built x City FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes
Sale YYMM FE	Yes	Yes	Yes	Yes

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. The effects of stricter building codes on sales price. Sample of homes near borders within city limits.

	log(Price)		log(Price / Square Foot)	
Q1_post_YB_strict	0.0636		0.0695	
	(0.0484)		(0.0518)	
Q2_post_YB_strict	-0.0971		-0.0393	
	(0.133)		(0.120)	
Q3_post_YB_strict	-0.0465		-0.0508	
	(0.0356)		(0.0321)	
Q4_post_YB_strict	0.0404		0.0832	
	(0.0972)		(0.0752)	
Q1_post_YB_diff_budget		-0.00566**		-0.00611**
		(0.00216)		(0.00269)
Q2_post_YB_diff_budget		0.0150***		0.0110***
		(0.00501)		(0.00382)
Q3_post_YB_diff_budget		0.00211*		0.00251**
		(0.00120)		(0.00102)
Q4_post_YB_diff_budget		0.00148		-0.00221
		(0.00373)		(0.00275)
Dependent Var Mean	12.281	12.281	4.875	4.875
Mean Budget Difference		9.736		9.736
Year Built x City x Quartile FE	Yes	Yes	Yes	Yes
Zip Code x Quartile FE	Yes	Yes	Yes	Yes
Sale YYMM FE	Yes	Yes	Yes	Yes
Observations	118,879	118,879	116,417	116,417

Standard errors (clustered by zip code) in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.