Taking Stock: Links between Local Policy and Building Energy Use across the United States

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April 2020

Report U2005

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Contents

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Acknowledgments

This report was made possible through the generous support of the Bloomberg Foundation. The authors gratefully acknowledge the support of external reviewers, internal reviewers, and colleagues. External expert reviewers were Jennifer Gunby, US Green Building Council; Stacy Glatting, Matthew Burgess, Cindy Jacobs, and Michael Zatz, US Environmental Protection Agency; Stefano Baratuche, Princeton University; Eric Mackres, World Resources Institute; Kimi Narita, Natural Resources Defense Council; Megan Day, National Renewable Energy Laboratory; Garrett Fitzgerald, Urban Sustainability Directors Network; Adam Hinge, Sustainable Energy Partnerships; Matt Cox, Greenlink Analytics; and Mike Steinhoff, Kim Lundgren Associates. External review and support do not imply affiliation or endorsement. Internal reviewers were Lauren Ross, Jim Barrett, Chris Perry, David Ribeiro, Shruti Vaidyanathan, Maggie Molina, Therese Langer, and Steven Nadel. The authors also gratefully acknowledge the assistance of Roxana Ayala, Alexander Jarrah, and Nick Henner. Last, we thank Fred Grossberg for developmental editing; Mary Robert Carter for managing the editing process; Mariel Wolfson for supervisory editing; Mary Rudy, Sean O'Brien, and Roxanna Usher for copy editing; Eric Schwass for publication design; and Ben Somberg, Maxine Chikumbo, and Wendy Koch for their help in launching this report.

Executive Summary

KEY TAKEAWAYS

- Between 2013 and 2016, per capita building electricity and natural gas use declined at annual rates of approximately 1% and 4%, respectively, in medium and large US urban municipalities.
- Many municipalities do not share comparable annual data regarding their climate action initiatives or community energy use and greenhouse gas emissions. This lack of data inhibited our ability to determine how several local policies relate to per capita energy use or emissions. Thus, this report serves as a preliminary study of how these factors and energy use relate. Future analyses would benefit from local governments providing more detailed, comparable, and annual data.
- Although our findings are only a first step in analyzing how local policy can relate to energy use, our results should not be overlooked, and two trends stand out. Across local municipalities, per capita building energy use declines were associated with decreases in the share of the population with low incomes and the share of households living in older homes.
- Local governments have an opportunity to reduce per capita energy use by increasing the pace of energy-efficient housing construction projects while designing and implementing carefully targeted initiatives that improve access to energy-efficient affordable housing for low-income households.

BACKGROUND

In recent years, local governments across the United States have been at the forefront of efforts to reduce greenhouse gas (GHG) emissions and mitigate climate change. Many local governments have created initiatives that target reductions in building energy use, which accounts for 39% of global emissions and more than 70% of emissions in large cities. Limited research has investigated whether these initiatives, or the factors they seek to influence, are associated with energy reductions in the United States. This report uses US community-level data to determine statistical relationships between local per capita electricity and natural gas consumption and multiple local factors, several of which are within the control of local governments.

METHODOLOGY AND DATA LIMITATIONS

Our report presents the results of separate analyses examining trends in the per capita electricity and natural gas consumption of the building sector in US municipalities. We first discuss how per capita electricity and natural gas consumption can be related to factors such as demographics, economic activity, and weather. We also provide an overview of research examining relationships between common local-level policies and building energy use. We then present the results of separate regression models that identify relationships between per capita electricity and natural gas use in buildings and multiple relevant factors, including those that local policies influence. We were unable to analyze other forms of energy use using this approach, such as transportation-related energy or fuel oil use, or communities' GHG emissions at the local level, because the necessary data are often unavailable, imprecise, and inconsistently measured for past years. In some cases, these data are available but only for an unrepresentative sample of urban areas. Although we could not statistically analyze local GHG emissions, we did include both local and national estimates of the potential GHG changes associated with our models' statistically significant variables.

FINDINGS

Between 2013 and 2016, per capita building electricity use declined in medium and large urban municipalities at an annual rate of 1%. Per capita building natural gas use declined at an annual rate of 4% over this same period. Compared with the nation overall, electricity use declined at a faster rate at the local level, while natural gas use at the local level declined at a relatively slower rate.

Our model results revealed a statistically significant relationship between per capita building energy use across American municipalities and two local-government-influenced factors. Decreases in the share of households with incomes below 200% of the federal poverty level were associated with decreases in per capita electricity use and increases in the share of households living in newer housing were associated with decreases in per capita consumption of both electricity and natural gas. Data availability affected our results, and we were unable to test for relationships between per capita energy use and several policies and programs. In some cases, relatively few municipalities in our samples had implemented policies, limiting our models' ability to detect relationships. Some initiatives with high energy savings potential, such as building energy performance standards, have only recently been adopted by localities. With time, these policies may also prove to be effective at reducing energy use and GHG emissions.

To better understand the GHG emissions reduction potential of our model's significant variables, we examined how shifts in each may have contributed to observed per capita emission changes in the cities of Los Angeles, Minneapolis, and Washington, DC between 2013 and 2017. Over this period the statistically significant factors identified in our models could have contributed to 32% of the GHG emissions changes in Los Angeles, 59% of shifts in Minneapolis, and 26% of reductions in Washington, DC.

IMPLICATIONS FOR LOCAL GOVERNMENTS

The changing physical and socioeconomic qualities of neighborhoods can help inform how local governments achieve their energy efficiency and climate action goals. We identify two policy opportunities for local governments to accelerate energy savings in ways that are beneficial to current and future residents:

- Mandate or incentivize stringent energy efficiency standards for housing construction projects while streamlining the permit and inspection process and amending zoning codes to allow for the construction of more housing units.

- Carefully design and implement policies and programs in a targeted manner to improve low-income household access to affordable efficient housing and resources that reduce poverty.

Introduction

Local governments in the United States have played an increasingly important leadership role in climate change mitigation and adaptation since the start of this century. In February of 2005, the 141 countries that ratified the Kyoto Protocol became subject to its 2012 goal of a 7% reduction in greenhouse gas (GHG) emissions below 1990 levels, but the United States was not among them. Recognizing this lack of action by the federal government and an urgent need to curb emissions, Seattle Mayor Greg Nickels launched an effort to commit American cities to the protocol's goals under the Mayor's Climate Protection Agreement. In the years that have passed, more than 1,000 mayors have joined the agreement (US Conference of Mayors 2019). Many local governments have also committed to additional agreements with GHG goals such as the Chicago Climate Charter and the We Are Still In campaign (Ribeiro et al. 2019).

In recent years, US municipalities have increased their focus on the sources and uses of energy at the local level as a means of achieving these climate change mitigation goals (Ribeiro et al. 2019). As of 2013, urban areas were responsible for 64% of the world's primary energy use and 70% of carbon dioxide emissions (IEA 2016). The buildings sector is responsible for 39% of global emissions, and it can account for over 70% of emissions in large cities (Abergel, Dean, and Dulac 2017; C40 2018). However it remains unclear whether the actions of local governments are reducing this footprint, or if observed changes in building emissions and energy use are due to factors outside their direct control. Data limitations have made this difficult to determine. Inconsistent approaches to tracking energy use, GHG emissions, and policy implementation make determining the effectiveness of local government actions especially challenging.

Our report analyzes whether the factors that local climate change mitigation policies seek to influence, such as green building certifications or urban density, are related to reductions in per capita energy use in the building sector and associated emissions. In some cases, we have included data regarding implementation of these policies. However, because these data are available only in limited cases, our research mostly examines the factors that policies seek to influence. Our analysis also considers factors affecting energy at the local level such as shifts in demographics, the economy, and weather that are partially or wholly outside the direct control of municipal governments. We have overcome several data limitations by focusing our analysis on building-sector electricity and natural gas consumption as two of several key inputs used to calculate GHG emissions, rather than on the reported emissions themselves. We discuss data challenges we faced and how we overcame these in subsequent sections.

Challenges Measuring Emissions and Energy Use

While many local governments are actively working to reduce community-wide GHG emissions, past research indicates that relatively few are tracking their progress (Ribeiro, Mackres, and Barrett 2014; Aznar et al. 2015; Ribeiro and Samarripas 2018). *The 2019 City Clean Energy Scorecard* examined 75 cities in the largest US metropolitan areas and found that just over 20% had adopted goals to curb city-wide emissions and were tracking their progress toward doing so (Ribeiro et al. 2019). Efforts to track progress toward these goals are complicated because local-level emissions and energy use data are often unavailable, imprecise, and inconsistently measured.[1] Our own analysis of *City Scorecard* data revealed that even those that have conducted several GHG inventories may have used varying methodologies, so results are not directly comparable. Bader and Bleischwitz (2009) examined several of the emissions inventory tools that were used by localities in the early 2000s and found that they typically were neither comparable to one another nor accurate.

To address these issues, the World Resources Institute, the C40 Cities Climate Leadership Group, and ICLEI–Local Governments for Sustainability developed and tested a standard methodology for calculating GHG emissions called the Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (GPC). The protocol was finalized and released in December 2014 (WRI and WBCSD 2015). Since then, an increasing number of cities have adopted the GPC; however our examination of inventories for this report indicated that not all have revised their pre-2014 inventories using the protocol. Thus, analyzing data from past inventories both across years and across cities remains challenging.

Methodology

Because of inconsistencies in local-level GHG emissions inventory methodologies, we focus our research on two consistent data inputs in inventories—electricity and natural gas consumption—rather than on the total emissions reported in those inventories. This report presents the results of separate analyses examining trends in per capita electricity and natural gas use of localities' buildings between 2013 and 2016.[2] We also examine how shifts in these may be related to changes in several independent variables both across localities and across the years 2013 to 2016.

GHG emissions inventories do not always separate commercial and industrial energy use, and we could not distinguish between industrial and commercial shares of energy use for several municipalities in our data. Because of this, and because limited data are available for the factors that relate to nonresidential energy use, we have chosen to analyze the entire buildings sector's per capita energy use rather than attempt to do so for the residential and nonresidential energy subsectors separately. However our analyses do take into consideration the share of each area's energy use that is residential versus nonresidential. We have normalized energy use on a per capita basis using municipalities' daytime populations because nonresidential energy use is included. Daytime population totals include a count of those who commute to a location for work and those that reside in the area and do not work.

All municipalities included in our research have a daytime population of at least 100,000 across the years 2013 to 2016. Our electricity analyses incorporate data from 47 cities and counties, and the natural gas analyses include data from 33 cities and counties. These cities and counties were selected for our research because they provide annual electricity and

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[1] Even when cities publish total emissions data, they may not disclose the energy data that underlie those totals.

[2] We do not examine transportation fuel use because we found it to be largely unavailable. Furthermore, those that do report vehicle fuel consumption tend to use various methodologies to arrive at these totals, and many of these are not comparable. We have also been unable to analyze vehicle miles traveled (VMT) totals for municipalities because these data are not sufficiently available for a representative sample of US localities.

natural gas consumption data that are closely representative of the municipal boundary through either a GHG emissions inventory or a local municipal utility's reporting. Although our report focuses mainly on city-level energy use, we did include energy use data for three counties in our analyses: Durham County, North Carolina; Multnomah County, Oregon; and San Diego County, California. We included these counties to ensure our sample sizes were sufficient to return statistically significant results. We have included only counties that had community-wide electricity and natural gas data and those that contained a primary metropolitan statistical area central city with a daytime population of 100,000 or more across all years of our analyses.

We first analyzed how per capita electricity and natural gas consumption have changed relative to factors such as demographics, economic activity, and weather. These are factors known to be associated with energy use at any geographic level. We then ran separate panel regression models to estimate the relationship between per capita electricity and natural gas use and several factors that local policies often seek to influence, all while controlling for factors that are partially or wholly outside the direct control of local governments. These analyses identify the relationships between per capita energy use and several independent variables that underlie variations across cities and across years. We used a variable selection and regularization method known as the least absolute shrinkage and selection operator (LASSO) to increase the prediction accuracy of our models. This process excluded some variables that were originally included in our data sets. We also excluded any independent variables that were shown to be highly correlated with one another. Table 1 provides a list of all the variables we included in our data sets and their corresponding data sources. Appendix A provides additional details about our methodology.

Table 1. Variable data considered for our analyses

Electricity and natural gas variables	Source
MWh and therms per capita (daytime population)	US Energy Information Administration and GHG inventories
Share of population below 200% federal poverty level (FPL)	US Census Bureau American Community Survey (ACS) 1-year estimates
Housing age index*	US Census Bureau ACS 1-year estimates
Average firm size for county or municipality	US Census Bureau ACS 1-year estimates
Households per square mile	US Census Bureau ACS 1-year estimates and 2010 Census
Local heating and cooling degree days	US National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information
Metropolitan statistical area gross domestic product per capita	US Bureau of Economic Activity
Average household size	US Census Bureau ACS 1-year estimates
Residential unit room index*	US Census Bureau ACS 1-year estimates
Number of years since local government implemented a cool roof requirement for buildings	Cool Roof Rating Council and American Council for an Energy-Efficient Economy's (ACEEE's) 2015 and 2017 *City Energy Efficiency Scorecard*s

Electricity and natural gas variables	Source
Square feet of Leadership in Energy and Environmental Design (LEED) certified building space in municipality per capita (daytime population)**	Green Building Information Gateway
Square feet of ENERGY STAR®-certified building space in municipality per capita (daytime population)**	Green Building Information Gateway
Square feet of energy-benchmarked building space in municipality per capita (daytime population)**	US Environmental Protection Agency (EPA) ENERGY STAR program
Median age	US Census Bureau ACS 1-year estimates
Share of population that is non-Hispanic white	US Census Bureau ACS 1-year estimates
Residential share of total electricity and natural gas use	
Electricity-only variables	**Source**
Utility-reported MWh energy savings per residential customer	US Energy Information Administration

*See Appendix A for a detailed description of how the housing age and residential unit room index were calculated. **We were unable to normalize LEED, ENERGY STAR, and benchmarking data by the total square feet of commercial space in a location because these data were unavailable for all years of our analysis.

Data availability issues have limited our analyses in several ways. Each analysis relies on a separate sample of municipalities because many do not consistently track both community-wide electricity use and natural gas consumption on an annual basis. In some cases, our analyses use data regarding the factors that local government initiatives seek to influence rather than data reflecting the policies and programs themselves. Data tracking the adoption and implementation of some local initiatives are unavailable for many localities. Even after focusing on municipalities that do track policy-related data, we found that comparable data covering all geographies were not always available. Ultimately, we have had to limit the number of policy outcomes considered so that our models contain enough cities to provide statistically significant results.

Building Energy Use Trends

Per capita electricity and natural gas use in buildings declined between 2013 and 2016 for the municipalities included in our research samples. These findings are based on examining the electricity consumption of 47 localities and the natural gas use of 33 municipalities. Table 2 shows how per capita energy use changed for these locations.

Table 2. Changes in local building-sector energy use

Year	Electricity sample (MWh per capita)	Natural gas sample (therms per capita)
2013	9.71	297
2014	9.68	302
2015	9.51	277
2016	9.46	269
Change	–1.0%	–3.7%

The change in each column is determined by first using a Microsoft Excel linear regression function to calculate the slope of a linear trend line that best aligns with graphed values. The slope of the line is then divided by the 2013 value for each variable. The annual changes in per capita energy use we observed were found to be statistically significant using paired sample *t*-tests that returned *p*-values of less than 0.01 for both samples.

While both electricity and natural gas use per capita declined at the local level, natural gas did so at a faster pace than electricity. To put these numbers in perspective, table 3 displays changes in US national building-sector electricity and natural gas use per capita.

Table 3. Changes in US national building-sector energy use

Year	Electricity (MWh per capita)	Natural gas (therms per capita)
2013	11.76	237
2014	11.78	239
2015	11.67	218
2016	11.62	209
Change	–0.4%	–4.4%

The change in each column is determined by first using a Microsoft Excel linear regression function to calculate the slope of a linear trend line that best aligns with graphed values. The slope of the line is then divided by the 2013 value for each variable.

Per capita electricity consumption is declining at a modestly faster pace for the municipalities we analyzed compared with the nation overall. However per capita natural gas consumption is declining at a slightly slower rate locally relative to the nation. In the following sections, we explore possible factors that may be driving these changes and whether local government decisions may have also played a role in these shifts.

Factors Underlying Building Energy Use at all Scales

Many factors affect building energy use. Some of these are largely within the purview of local governments, but others could be affected by governments or nongovernment actors at other geographic scales. Demand for energy can shift with changes in an area's economy or demographics. Energy use also fluctuates with the weather as hot or cold days create demand for heating or cooling. We explore these factors that are partially or wholly outside the direct influence of local governments in the following sections.

First, we explore how our samples compare with US urban areas along these indicators. Definitions of urban areas vary by the defining entity, but they are generally larger than a single city or county. They do not serve as a perfect comparison for the municipalities in our samples, but they provide comparative data at the geographic scale closest to the localities included in our research. Although we could not use these comparisons to make a conclusive judgment regarding the representativeness of our samples, we include them to put our data in context and show that our samples are largely in line with the characteristics of US urban areas. Last, we discuss how each of these factors may be related to per capita electricity and natural gas use.

DEMOGRAPHIC FACTORS

We compared several relevant demographic markers of our samples' municipalities with those of all US urban areas. To draw these comparisons, we used US Census Bureau data from a study completed by Parker et al. (2018) that characterizes US urban areas along several dimensions using 2012–2016 ACS estimates. Table 4 shows these comparisons.

Table 4. Demographic comparison of city samples to all US urban areas

Demographic characteristic	Electricity sample average	Natural gas sample average	All urban areas
Non-Hispanic white share of population	51%	50%	44%
Foreign-born share of population	16%	13%	22%
Mean earnings per worker age 16+	$59,100	$57,218	$49,515
Employed share of those age 25–54	76%	74%	77%
Population that are less than 18 years old	22%	21%	23%
Population that are age 65+	12%	12%	13%
Share of population below 200% FPL	20%	22%	17%

With some exceptions, the demographics of the localities in our samples align relatively closely with those of urban areas overall. The age characteristics of our samples are very similar to those of all US urban areas. Workers in all our samples' municipalities do tend to earn more than those in urban areas overall, but this may be because our data are focused on the central cities or counties of urban areas and exclude outlying areas. This exclusion of urban areas outside central cities or counties may also explain why a slightly larger share of our samples' populations has incomes below 200% of the FPL. Localities in our samples also tend to have proportionally larger white populations and fewer foreign-born residents.

The factors highlighted here align with differences in residential energy use. First, household income is related to energy use. In a study of apartment buildings in five major cities with energy benchmarking and transparency ordinances, Kontokosta, Reina, and Bonczak (2019) found that white and wealthier households tend to have higher energy use intensities (EUIs), a metric of energy use per square foot. The authors also offer potential explanations for these trends. These households use more energy because they can afford to do so. They use more energy for heating in the winter and cooling in the summer. They also use more energy for household appliances and electronics. The researchers also found that lower-income households have higher EUIs. They argue that these households tend to live in less-efficient homes that are older and not as well maintained and have less-efficient appliances.

While both low-income and high-income households may have higher EUI's, data from the 2009 and 2015 Residential Energy Consumption Surveys (RECS) indicate that low-income households still have lower energy use overall (EIA 2013, 2018). However these same surveys indicate that the gap in per household energy use is changing. In 2009, households with incomes of $120,000 or more consumed 57.8 more MMBtus than those earning $40,000 or less.[3] By 2015, this gap had shrunk to 44.6 MMBtus. Although per household energy use decreased across all income brackets between 2009 and 2015, those with incomes below $40,000 saw a decrease of only 14.7% while those with incomes of $120,000 or more saw a decrease of 18.2%. The reason low-income household energy use declines have not kept pace with high-income households may be that the average size of low-income homes increased between 2009 and 2015. Between these years, the average size of homes decreased for all household income brackets except for those earning less than $40,000 and those earning between $60,000 and $79,999, with sharper declines occurring among those earning more than $120,000. Immergluck (2018) explains that low-income and minority neighborhoods experienced high rates of single-family home foreclosures during the Great Recession, and many of these homes have since been turned into rental properties, attracting low-income households as tenants. The energy use of low-income households may be higher than it would otherwise be because more are renting single-family homes as opposed to apartments.

The age distribution of a population and the share of foreign-born residents are also associated with differences in energy use. Estiri and Zagheni (2019) found that household energy use increases with age. Localities with a smaller foreign-born population are likely to have smaller households as the average household size for foreign-born residents between 2012 and 2016 was 3.35 people versus 2.25 people for native-born households (Census Bureau 2019a).[4] This can lead to higher per capita energy use values for these areas, the dependent variables in both our electricity and natural gas analyses.

We have collected data reflecting each municipality's median age, share of the population with incomes below 200% FPL, non-Hispanic white share of the population, and average household size in our models to account for the demographic trends discussed. Although we attempted to include data regarding the share of a population's households with incomes at or above $100,000 as a wealth indicator, we could not do so because of a strong time trend in which the share of these households increased consistently with each year across our samples' municipalities. Efforts to detrend this variable were unsuccessful.

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[3] The RECS data do not use bins that specifically reflect households with incomes of $120,000 or above in the 2015 survey or below $40,000 in the 2009 and 2015 surveys. We created these bins using RECS data to make the comparisons shown here.

[4] Household sizes reflect nationwide data from ACS 2012–2016 five-year estimates.

ECONOMIC FACTORS

Gross domestic product (GDP) tracks overall economic activity in a geographic area, but GDP data have been largely unavailable at the city level and were only recently made available for US counties starting with data representing 2018 (BEA 2019). Therefore we have used metropolitan-area GDP per capita values to characterize each of the localities in our samples.[5] Table 5 shows that the GDP per capita values of our samples, obtained from the US Bureau of Economic Analysis (BEA), mostly align with the GDP per capita of all US metropolitan areas, with the values of our natural gas sample slightly lower in comparison.

Table 5. Changes in metropolitan area per capita GDP

Year	Electricity sample average	Natural gas sample average	US metro areas average
2013	$55,127	$53,056	$55,422
2014	$56,778	$54,482	$57,366
2015	$58,902	$55,996	$59,522
2016	$60,312	$57,226	$60,814
Change	+3.2%	+2.6%	+3.3%

The change in each column is determined by first using a Microsoft Excel linear regression function to calculate the slope of a linear trend line that corresponds to the values of each variable. The slope of the line is then divided by the 2013 value for each variable. *Source:* BEA 2019.

GDP per capita increased for municipalities in our electricity and natural gas samples as per capita energy use declined, in line with recent research. Although a growing business may increase its demand for energy, recent changes in the overall US economy and the increased energy efficiency of buildings and technology have led to relatively flat energy use in the face of GDP growth (Molina, Kiker, and Nowak 2016). While per capita energy use and GDP may be decoupling from one another over time, this trend may not hold between locations, and per capita energy use may be higher in metro areas with higher GDP per capita.

We collected metro area GDP per capita data for each location in our samples, but these data were not selected by the LASSO procedure for incorporation in the final models. [6] As with the share of households with incomes at or above $100,000, these data exhibited a time trend that could not be accounted for in the models. We also included data reflecting each area's average number of employees per firm as recent research has indicated that larger firms have higher energy intensities (Fix 2017). Finally, we did not include utility prices in our models because we could not dismiss the possibility that doing so would create simultaneous equations bias. Such a bias was possible because we could not determine whether prices should be considered an independent or dependent variable in our models, with the latter determined by per capita energy use and other factors. Energy efficiency can lower overall and peak energy demand, thus avoiding the need for new generation,

[5] We have calculated metropolitan-area GDP per capita using each area's GDP and total resident population.

[6] See Appendix A for a detailed discussion of the LASSO procedure.

transmission, and distribution investments that would be passed on to consumers in the form of higher rates (Baatz 2015). The reverse can also be true: an increase in energy demand leads to higher rates.

WEATHER FACTORS

We used degree-day data from NOAA to examine weather shifts at the local level. Degree days reflect energy demand for heating or cooling buildings and are calculated by NOAA (2005) using the following method:

> A mean daily temperature (average of the daily maximum and minimum temperatures) of 65°F is the base for both heating and cooling degree-day computations. Heating degree days are summations of negative differences between the mean daily temperature and the 65°F base; cooling degree days are summations of positive differences from the same base.

Using data from the US Energy Information Administration's (EIA's) 2015 Residential Energy Consumption Survey, we established that the average heating and cooling degree days of our samples are roughly comparable to all US urban areas. In 2015, the average cooling degree days (CDD) for our electricity sample was 1,804 while the average CDD for all urban areas was 1,837. The average heating degree days (HDD) for our natural gas sample was 3,778 while the average HDD for US urban areas was 3,791.

CDD increased for localities in our electricity sample while HDD decreased for municipalities in the natural gas sample. Table 6 shows these shifts.

Table 6. Changes in average CDD and HDD

Year	Electricity sample average CDD	Natural gas sample average HDD
2013	1,601	3,825
2014	1,601	4,052
2015	1,804	3,791
2016	1,835	3,269
Change	+5.7%	–5.0%

The change in each column is determined by first using a Microsoft Excel linear regression function to calculate the slope of a linear trend line that corresponds to the values of each variable. The slope of the line is then divided by the 2013 value for each variable.

We would expect an increase in CDD to coincide with an increase in electricity use as the demand for cooling rises, but this trend is not immediately apparent from our data averages. We would also expect natural gas use to decline as HDD and the demand for heating decrease, and this is reflected across the municipalities in our sample. Decreasing HDD could also potentially provide a partial explanation for the decline in electricity use as some buildings use electricity for heating. While these factors may be related to energy use, it is difficult to say the degree to which CDD and HDD are correlated with per capita energy use without controlling for other important factors.

We included annual CDD data in our electricity model and annual HDD data in our natural gas model. Although electricity is used for heating in some buildings and may be responsive to HDD, we could not include both CDD and HDD in the electricity model as they were highly correlated with one another.[7] We also considered including a variable with the share of households that use electricity for heating, but a preliminary analysis revealed that these survey estimates did not tend to vary much from year to year.

Policies Affecting Local Building Energy Use

Although past research studies such as those by O'Shaughnessy et al. (2016) and ICLEI USA (2018) have attempted to predict the effect that local government policies and programs will have on future energy use or GHG emissions, few have examined the effect that these initiatives have already had on energy use. We review several studies examining factors associated with recorded energy changes in the sections that follow and highlight research on local policies that aim to save energy. The policies and programs we summarize here are those that local governments across the United States have enacted, have a documented record of reducing community-wide energy use, and are associated with available data considered in our analyses. These include building energy codes, green building requirements and incentives, energy benchmarking and transparency ordinances, cool-roof requirements and incentives, zoning codes that encourage higher-density building construction, and utility-sector energy efficiency programs. We do not discuss state policies in detail, but we do reference them in some cases because the division of powers between state and local authorities can vary from place to place.

Although our analysis is broadly focused on determining how multiple factors (including those that local policies seek to influence) may be related to per capita energy use across medium and large US municipalities, many of the studies detailed below analyze the effect that individual policies have had in specific locations. A limitation of our approach in comparison to these prior studies is that our results can describe only relationships between per capita energy use and variables commonly represented in data across many municipalities. Our models cannot detect the effect of a single policy or program being implemented in only one or a few locations. A future study mirroring our methodology may be better able to detect relationships between energy use and policies that are currently only being implemented in a few places, assuming these policies become more common across municipalities.

ENERGY-SAVING BUILDING CODES AND CERTIFICATIONS

Berg et al. (2019) documented the history of building code standards that are designed to reduce energy use. California adopted the first energy code requirements for residential buildings undergoing construction or substantial renovation as part of its 1978 Title 24 Building Standard. Several states followed California's lead by adopting their own energy codes throughout the 1980s. At the same time, regional code development organizations, and eventually the International Code Council, worked to develop the Model Energy Code (MEC) to serve as a guide for states wishing to install their building energy code standards.

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[7] Appendix B includes correlation tables for the variables in our models.

The MEC was later renamed the International Energy Conservation Code (IECC). Most states currently use an IECC residential energy code and a commercial energy code based on ASHRAE 90.1 standards developed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) and the Illuminating Engineering Society (Berg et al. 2019). IECC codes have been revised every three years; ASHRAE standards for commercial buildings have also been revised every three years since the first code was released in 1975 (Kirkwood 2010).

In some states, local governments have the authority to adopt building energy codes that are more stringent than those in place at the state level. To date, no known studies have examined the effect that these local building codes have on energy use relative to state codes; however studies have looked at the effect that more-recent and stringent versions of energy codes have had on energy use relative to older versions. These studies have largely focused on the effects of residential energy codes in states with a long history of code adoption. Isolating the effect of building codes can be difficult because building age is a confounding factor (Levinson 2016). Buildings tend to use less energy in the years immediately following construction than after they have been operating for a long time because newer properties require less maintenance and are more likely to operate efficiently without issues. Studies have found that the effect of building energy codes can be better isolated in older buildings (Deason and Hobbs 2011; Novan, Smith, and Zhou 2017). However assessing the impact of these codes remains challenging even while controlling for differences in building type, household size, and weather. Past research studies have found it challenging to control for factors such as occupant behavior, homeowners that make energy efficiency retrofits, and homes that do not use electricity for heating (Levinson 2016; Nadel 2015; Novan, Smith, and Zhou 2017).

Although most studies on building energy codes have found evidence of energy reductions, all show energy savings lower than those initially projected (Deason and Hobbs 2011; Aroonruengsawat, Auffhammer, and Sanstad 2012; Jacobsen and Kotchen 2013; Kotchen 2015; Levinson 2016). This gap between expected and actual energy savings may be due in part to energy modeling biases that older buildings consume more energy and newer buildings consume less energy than they do (IPEEC 2019). Withers and Vierra (2015) argued that some of the anticipated energy savings from building codes may be offset by higher-than-anticipated heating and cooling demand in buildings and an increased electricity demand from appliances and electronics. Levinson (2016) argued that many of the early studies examining the effect of building energy codes on energy use did not adequately control for the factors listed above. Controlling for these factors, Levinson conducted his own analysis of energy use in California homes both after and before the advent of energy codes in the state's 1978 Title 24 Building Standard. His results show that post-1978 homes use 25% less natural gas and up to 15% less electricity. Post-1978 homes also see natural gas savings during cold days, but Levinson observed that expected electricity savings did not materialize during hot days.

Novan, Smith, and Zhou (2017) conducted a follow-up study suggesting that Levinson's data, which relied on monthly energy use data reported in a statewide survey, were too imprecise to detect energy code electricity savings on hot days. They also cited evidence indicating that pre-1978 homes, acting as a baseline for comparison in Levinson's study, may have been assumed to be less efficient than is accurate, a finding like that discovered by Withers and Vierra (2015). Using Sacramento Municipal Utility District advanced metering infrastructure, these researchers found that homes built just after the advent of California's 1978 energy codes used 8–13% less electricity for cooling than homes built before 1978. These savings were demonstrated while controlling for the same factors as Levinson.

Many local governments require or incentivize builders to go beyond energy code standards. These localities are mandating, subsidizing, or financing newly constructed or renovated properties to become certified using a green building rating system. The most common systems used by local governments include ENERGY STAR standards developed by the EPA or the US Green Building Council's (USGBC's) LEED rating system.

The ENERGY STAR program is a voluntary initiative that helps businesses, governments, and individuals improve energy efficiency (EPA 2019a). To participate in the program, property owners track their buildings' energy use using EPA's online Portfolio Manager tool. This tool reveals how buildings' EUIs compare to similar buildings operating in similar climates. Most buildings also receive a score between 1 and 100 to rate their energy performance. Those that receive a score within the top 25% of scores of similar buildings nationwide and have their performance annually verified by a licensed professional engineer (PE) or registered architect (RA) achieve ENERGY STAR certification. Data collected from Portfolio Manager reveal that properties that are ENERGY STAR certified use 35% less energy and generate 35% fewer GHG emissions than similar noncertified facilities (EPA 2019a).

Many localities incentivize builders to achieve certification under the LEED system introduced by USGBC in 2000 (Tufts 2016). Like ENERGY STAR, LEED is a voluntary initiative that uses a series of performance metrics to guide businesses, governments, and individuals in improving their properties' energy and water efficiency, waste generation, and occupant comfort. To obtain LEED certification, buildings must be built and operated to standards that maximize energy efficiency, reduce negative impacts on the environment, and improve human health and safety. To achieve these goals, building owners must undertake a set of required actions and perform several others from a list of optional interventions. This flexibility can lead some projects to focus less on energy-saving actions relative to others. To help ensure that energy efficiency is a strong focus in all projects, older versions of LEED have been replaced with versions more focused on energy efficiency. Amiri, Ottelin, and Sovari (2019) reviewed past studies examining the energy efficiency of LEED-certified buildings and found that performance of certified newly constructed buildings degrades with time. They also found that whether past studies rely on representative and comparable building samples is sometimes unclear. Last, their review of past research uncovered several studies indicating that higher LEED certification levels can reduce energy use to a greater degree. These findings are consistent with a recent analysis of LEED buildings by Pyke (2019) showing that GHG emissions from building energy use are lower in buildings with higher certification levels.

We encountered several challenges in collecting data representing the stringency of local energy codes and green building certifications. We could not obtain energy code stringency data at the local level for all sample municipalities in the years we analyzed. We did include a housing age index, which is effectively a weighted average of the share of households living in structures built in past decades.[8] Although we include this variable, we cannot exactly determine the underlying reasons for any relationships between housing age and energy use. Such a correlation may be due to the spread and evolution of local energy codes or the fact that newer housing tends to operate more efficiently regardless of the energy code it was constructed to meet. We collected data representing the per capita square footage of both ENERGY STAR– and LEED-certified properties for each municipality over time; however our initial analysis revealed that these two variables are highly correlated with one another and with data representing the per capita square feet of benchmarked building space, making it difficult for our models to determine whether any one of them has a statistically significant relationship with per capita energy use.[9] After running multiple iterations of our models with each of these variables, we have included the per capita square feet of benchmarked building space in our electricity model and the square feet per capita of LEED-certified building space in our natural gas model.[10] We made these decisions because these variables exhibited the lowest overall correlation with other variables and achieved the highest R-squared value, a determination of the model's overall fit in describing the observed variation.

Building Energy Benchmarking and Transparency Policies

Since 2008, 30 cities and 1 county have enacted mandatory energy benchmarking and transparency policies for buildings (IMT 2019). These policies require that owners of certain buildings track and report their energy use annually. Local governments then release this information to the public. Many cities see benchmarking as a first step toward reducing community-wide energy use. Local officials hope that by making this information public, market appraisers and investors will begin to consider such information in their property valuations, encouraging owners and managers to improve the efficiency of their buildings (Hart 2015). Energy benchmarking can also lead owners and managers to improve energy efficiency as a means of lowering operating costs or attracting new tenants.

Studies of energy benchmarking policies reveal that these initiatives do lead to energy savings. Mims et al. (2017) examined existing city reporting and independent research studies to determine that benchmarked buildings reduced their energy use intensity between 1.6% and 14% over a two- to four-year period following policy implementation. Antonoff (2018) added to these findings with a study of the cities of Chicago, Minneapolis, New York, and San Francisco. These cities achieved energy savings of 1.3–4.3% in benchmarked buildings over a three- to six-year period following the adoption of their requirements. Energy reductions can vary from city to city due to differences in policies, climate, and local building stock characteristics such as property size, use, and age.

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[8] See Appendix A for a detailed description of how the housing age index was calculated.

[9] See Appendix B for correlation matrices for each mode. We normalized ENERGY STAR and LEED square feet using each municipality's daytime population.

[10] These variables were not found to be statistically significant in any iteration of the models.

With the help of EPA staff, we collected data representing the per capita square feet of benchmarked property space in a locality; however we have only included the variable in our electricity model for the reasons described in the previous section.

COOL-ROOF REQUIREMENTS

Urban areas often experience higher temperatures in the summer compared with surrounding rural areas because they have more buildings, parking lots, and streets. Compared with vegetated spaces, these surfaces have less capacity to retain water that can cool the air through evapotranspiration. These surfaces also tend to be darker and consequently have a lower albedo—a measure of how much a surface reflects the sun's light and radiation. Therefore buildings with and surrounded by darker-colored impermeable surfaces have a higher demand for cooling during the summer and use more electricity. To mitigate this effect, many localities have begun to incentivize or require building owners to lower the albedo of their roof surface or install a vegetated green roof. The US Department of Energy (DOE 2011) estimated that cool roofs can reduce electricity used for cooling by 15% in a single-story building. This translates to annual cost savings of up to $0.20 per square foot in a commercial building and up to $0.05 per square foot in a residential home. Jeong, Millstein, and Levinson (2019) suggested that temperature reductions from cool roofs may ultimately be higher in places with a higher share of land occupied by nonresidential properties. This could indicate that energy savings associated with cool roofs would also likely vary by area land-use patterns. Cool roofs not only reduce the electricity demand of specific buildings but also have the capacity to reduce an urban area's peak demand in summer months (EPA 2019b). Our models include data that track the number of years since a cool-roof requirement was implemented at the local level. Because relatively few residential local policies are in place, this variable includes data for both residential and nonresidential cool-roof requirements. The Cool Roof Rating Council (2019) tracks the adoption and implementation of local cool-roof ordinances. These ordinances have also been tracked through past editions of ACEEE's *City Energy Efficiency Scorecard*.

ENERGY-EFFICIENT LAND-USE PLANNING

In recent years, several studies have established a link between building energy use and urban density. Resch et al. (2016) explained that a series of researchers have attributed lower energy use arising from density to the construction of multiunit, multistory buildings:

> The energy needed for heating and cooling per floor area, all else equal, can … be shown to be lower in tall buildings than in low structures due to a lower envelope area to floor area ratio. The heat loss to the ground and through the roof is divided by an increasingly larger floor area as the building reaches higher, while the surface wall area per story remains the same (801).

Resch et al. confirmed this finding in their own analysis of urban buildings in several European countries. Danielski, Fröling, and Joelsson (2012) examined how an apartment building's envelope-to-volume area, what they refer to as its shape factor, can have an especially notable effect on heating demand. They found that increasing the compactness of a building and reducing its shape factor by 0.7 could reduce heat demand by 11–21%, with greater savings realized in buildings with lower thermal envelopes. However these savings were more pronounced in colder climates, with diminishing savings for low-thermal-envelope buildings constructed in climates with average temperatures above 14°C (57°F) and for high-thermal-envelope buildings in places with average temperatures above 11°C (52°F).

Land-use decisions that determine urban density can become locked in for many years to come. In considering the effect that these decisions have, Guneralp et al. (2017) found that the energy use intensity of buildings in growing cities is largely determined by choices about the density of development on unused or underused land.

We collected data from the US Census Bureau for the number of households per square mile in each locality. We have also included data regarding each area's average household size and a variable that represents the number of rooms in homes to help account for other elements of urban density.

UTILITY-SECTOR ENERGY EFFICIENCY PROGRAMS

Many utilities are required by state or local governments to provide their customers with energy efficiency incentives or no-cost upgrades. These programs saved customers almost 259 million MWh in 2018, the equivalent of roughly 7% of total electricity consumption (Berg et al. 2019).[11] These energy savings can translate into more than $90 billion in annual electricity cost savings (Molina, Kiker, and Nowak 2016). These programs not only help customers save energy and costs but also allow utilities to avoid capital investments in new power plants. ACEEE estimated in 2016 that efficiency has helped avoid energy demand that would have led to building the equivalent of 313 large power plants since 1990 (Molina, Kiker, and Nowak 2016).

For investor-owned utilities (IOUs), energy efficiency directives come from state legislatures and utility regulatory commissions. Local government regulatory boards issue similar orders for municipal utilities. These programs are funded through a combination of customers' utility rates and public benefit funds. While utility energy efficiency program expenditures reached a low point in 1998, spending has increased in the years since. Molina, Kiker, and Nowak (2016) documented that expenditures climbed from $1.6 billion in 2006 to $7 billion in 2014. Spending increases have slowed in recent years, with utilities spending $8 billion in 2018 (Berg et al. 2019).

Some of the municipalities in our samples are served by IOUs, and others are served by municipal utilities. IOU service territories are typically much larger than municipal boundaries, and energy efficiency reporting typically reflects activities outside core urban areas. To address these issues, we have included a normalized savings variable expressed as MWh savings per residential customer to account for savings from electric utility energy efficiency programs. We normalized total savings by the number of residential customers because the variable closely reflects our electricity model's dependent variable of MWh per

[11] This total reflects 2018 annual incremental savings and savings still being realized from measures installed in past years.

capita. Electricity savings data also reflect the primary utility serving a locality.[12] We could not include natural gas program savings data because these were not available for all municipalities in our natural gas sample.

Research Findings

We used two models to analyze relationships between the various factors we have discussed and per capita electricity and natural gas use. We conducted two panel regressions to identify which variables exhibit a statistically significant relationship with per capita energy use both over time and across cities. Although our models can identify correlations between the dependent variable and independent variables across a wide swath of municipalities, they cannot establish causality. Furthermore, our results should not be taken to imply that variables found to not be statistically significant are not related to energy use. These variables may be correlated with per capita energy use within the context of specific municipalities with certain characteristics but not across all US municipalities. Data representing these variables may also not be precise enough to appear statistically significant in our models. Finally, policies with the potential to affect these variables may have not been in place long enough for their effects to be detectable.

COMMUNITY-WIDE ELECTRICITY ANALYSIS

Our first panel regression analysis examines the relationship between 13 independent variables and a locality's MWh of electricity consumed per capita.[13] Table 7 provides the results of this analysis with statistically significant variables marked with asterisks.

Table 7. Robust fixed-effects panel regression results for community MWh per capita

Variable	Coefficient	Standard error	*T*-statistic	*P*>*t*
Share of population below 200% FPL*	2.44588	0.84657	2.89000	0.00600
Housing age index*	1.18754	0.25797	4.60000	0.00000
Average firm size for county of municipality	−0.01667	0.01381	−1.21000	0.23400
Households per sq. mile	−0.00034	0.00048	-0.71000	0.48400
MWh savings per residential customer	0.18607	0.20689	0.90000	0.37300
Cooling degree days*	0.00019	0.00008	2.27000	0.02800
Average household size	0.25950	0.53016	0.49000	0.62700
Residential room index	0.10523	0.09539	1.10000	0.27600
Years since cool roof ordinance implemented	−0.01571	0.02892	−0.54000	0.58900
Benchmarked building sq. ft. per capita	0.00043	0.00067	0.64000	0.52300
Median age	0.00109	0.02780	0.04000	0.96900

[12] In cities served by more than one electric utility, we used data from the primary utility identified in ACEEE's *The 2019 City Clean Energy Scorecard*.

[13] This report's previous sections and Appendix A provide a detailed account of how variables were selected for our analysis.

Variable	Coefficient	Standard error	*T*-statistic	*P>t*
Non-Hispanic white share of population	0.78619	1.71664	0.46000	0.64900
Residential share of total electricity use*	6.16802	3.67957	1.68000	0.10000
Constant	−1.02566	3.97352	−0.26000	0.79700

$R^2 = 0.4110$

Four variables in our analysis proved to be statistically significant predictors of MWh per capita: the share of a population with incomes below 200% FPL, the housing age index, cooling degree days, and municipalities' residential share of total electricity use.[14] All of these variables were positively correlated with MWh per capita. For simplicity, we discuss per capita energy changes associated with these variables in kWh rather than MWh in this section.

As we have discussed, those with low incomes are more likely to live in less-efficient housing with a higher energy use intensity. The average size of low-income homes has also increased in the years following the Great Recession, creating added energy demand for heating and cooling. A 1% average annual increase in the share of a population with these incomes is associated with an average annual increase in per capita electricity consumption of roughly 25 kWh.

The housing age index has several component parts, but our model indicates that a community's overall per capita electricity use increases as the share of a community's households living in older homes increases.[15] As previous research indicates, this could be because older homes were built before the advent of energy codes or under less-stringent energy codes, but it could also be due to the decline in the overall energy performance of homes as they age without interventions to increase energy efficiency. Table 8 details how a 1% increase in the share of households living in homes constructed in past decades would affect per capita electricity use, assuming the share of households living in properties constructed in other decades remains constant.

Table 8. Increase in annual per capita electricity associated with a 1% increase in the share of households living in each of the previous decades

Decade of housing structure construction	Increase in average annual kWh per capita
1939 or earlier	95
1940–1949	83
1950–1959	71
1960–1969	59
1970–1979	48

[14] See Appendix A for a discussion of how we calculated the housing age index.

[15] See Appendix A for a detailed description of how the housing age index was calculated.

Decade of housing structure construction	Increase in average annual kWh per capita
1980–1989	36
1990–1999	24
2000–2009	12

CDD is positively correlated with per capita electricity use as would be expected because warmer days create a demand for electricity for cooling. An increase in CDD of 100 would correspond to an increase of 19 kWh in average annual per capita electricity use.

Last, a 1% increase in the share of electricity consumed by the residential sector coincides with an increase of 62 kWh per capita. This relationship may exist because the residential sector is more likely to use electricity for both cooling and heating while the commercial sector overwhelmingly uses natural gas for heating. According to 2016 ACS estimates, 48% of homes use natural gas as their primary fuel for space heating, but an even higher share of commercial buildings relies on natural gas for heating (Census Bureau 2019a). EIA's 2012 Commercial Building Energy Consumption Survey (CBECS) found that more than 80% of commercial buildings use natural gas as their primary fuel for space heating (EIA 2016).

COMMUNITY-WIDE NATURAL GAS ANALYSIS

Our second panel regression analysis focused on the relationships between 11 independent variables and a locality's therms of natural gas consumed per capita.[16] Table 9 provides the results of this analysis, with statistically significant variables marked with asterisks.

Table 9. Robust fixed-effects panel regression results for community therms per capita

Variable	Coefficient	Standard error	*T*-statistic	*P>t*
Share of population below 200% FPL	98.69504	70.96828	1.39000	0.17400
Housing age index*	70.23130	28.83627	2.44000	0.02100
Average firm size for county of municipality	2.27341	2.53587	0.90000	0.37700
Households per sq. mile	−0.05758	0.04553	−1.26000	0.21500
HDD*	0.02114	0.00664	3.18000	0.00300
Average household size	−16.61730	66.20688	−0.25000	0.80300
Residential unit room index	15.29672	29.07126	0.53000	0.60200
Years since cool-roof ordinance implemented	1.64039	2.08874	0.79000	0.43800
Total LEED building stock sq. ft. per capita	−0.45711	0.84457	−0.54000	0.59200
Median age	−9.64066	164.71890	−0.06000	0.95400
Residential share of total natural gas use	5.80224	100.04240	0.06000	0.95400

[16] This report's previous sections and Appendix A provide a detailed account of how variables were selected for our analysis.

Variable	Coefficient	Standard error	*T*-statistic	*P>t*
Constant	−156.31440	306.16690	−0.51000	0.61300

R^2 = 0.4305

The housing age index and heating degree days were shown to be statistically significant predictors of therms per capita.[17] Both the housing age index and heating degree days were positively related to therms per capita.

As with electricity, a community's per capita natural gas use is positively correlated with the age of its housing stock. Those living in older homes consume more energy on a per capita basis. Table 10 details how a 1% increase in the share of households living in homes constructed in past decades would affect per capita natural gas use, assuming the share of households living in properties constructed in other decades remains constant.

Table 10. Increase in annual per capita natural gas associated with a 1% increase in the share of households living in each of the previous decades

Decade of housing structure construction	Increase in average annual therms per capita
1939 or earlier	5.6
1940–1949	4.9
1950–1959	4.2
1960–1969	3.5
1970–1979	2.8
1980–1989	2.1
1990–1999	1.4
2000–2009	0.7

Therms per capita are, as expected, positively correlated with HDD. As temperatures drop, the demand for natural gas for heating increases. As we have discussed, most nonresidential properties use natural gas for heating. Although a lower share of residential properties uses natural gas for heating, it is still the most common heating fuel for homes (Census Bureau 2019a). Our results show that an increase of 100 HDD would be associated with an average annual increase of 2.1 therms per capita in municipalities.

Further Discussion

Aside from weather-related factors, the statistically significant variables in our models are most closely related to residential energy use. This could be because residential variables such as the age of housing stock and the share of a population's incomes below 200% FPL are indicators of community-wide trends that extend beyond the residential sector. Housing stock age may also closely align with the age of an area's nonresidential buildings. Poverty

[17] See Appendix A for a discussion of how we calculated the housing age index.

could be indicative of the capital available for energy efficiency investments across a community. Perhaps these variables are statistically significant because we have access to more detailed and consistent data for the residential sector through the ACS. Finally, residential energy tends to be more uniform across cities while the economy of localities, and thus their nonresidential buildings, can vary substantially.

Several issues with our samples' data may explain our results regarding commercial variables. Cool-roof policies were tracked using data representing the number of years since the policy was implemented. However most of the locations in our sample do not have these policies in place, meaning that their records contained zero values for these factors. Similarly, some municipalities have energy efficiency MWh savings per residential utility customer that are zero or close to zero. Furthermore, we would have liked to normalize the square feet of LEED-certified and energy-benchmarked properties by the total area of commercial and multifamily properties in each location. However we did not have access to these data over multiple years and chose to normalize the square feet of certified or benchmarked space by each location's daytime population.

Implications for Local Greenhouse Gas Emissions

The per capita electricity and natural gas changes associated with the statistically significant variables in our models also affect GHG emissions. To illustrate this link, we used our samples' local-level data and converted the observed annual average changes in our models' statistically significant variables to expected per capita carbon dioxide (CO_2) savings using the coefficients from our models' results and national emissions conversion factors. This step provides an estimate of the annual average emissions savings that localities across the country may have witnessed between 2013 and 2016. We could not determine how local shifts in these variables contributed to shifts in US national emissions because we do not know the share of national emissions that are attributable to urban localities. Although we cannot provide these estimates, we use emissions data from three cities to illustrate how changes in these variables could have contributed to changes in overall emissions at a local level. Some cities have released detailed annual GHG emissions inventories for past years using the GPC, and we have used these from the cities of Los Angeles, Minneapolis, and Washington, DC to explore how past local changes in our models' significant variables may have contributed to observed shifts in each city's per capita emissions. Inventory data are drawn from CDP (2019) and from prior *City Scorecard* data requests (Riberio et al. 2019).

Converting per capita therms to CO_2 is straightforward because natural gas to CO_2 conversion factors are the same irrespective of location or time. Table 11 provides estimates of per capita kg CO_2 changes associated with the average annual local changes observed in our natural gas model's statistically significant variable data.

Table 11. Estimated per capita CO_2 shifts resulting from observed average annual changes in our natural gas model's statistically significant variables

Average annual change in variable	Per capita kg CO_2 change
0.04 housing age index decrease	–4.1
193 HDD decrease	–5.9

We have converted per capita therms to kg of CO_2 using conversion factors from EPA (2020).

The average annual changes across our sample's municipalities in the housing age index and HDD both coincided with decreases in per capita natural gas and its associated CO_2 emissions. Decreases in HDD were associated with the largest reductions in per capita CO_2 followed by decreases in the housing age index.

Converting electricity to CO_2 is more challenging as conversion factors vary over time and place. These differ because different utilities generate electricity using fuels that vary in terms of their carbon intensity. Communities that receive a greater share of their electricity from sources that generate little or no carbon emissions will have a lower conversion factor. To provide a national estimate for municipalities, we multiplied 2018 US national electricity-to-CO_2 conversion factors by the average annual changes in our model's statistically significant variable data and their corresponding model coefficients. Table 12 displays these estimates.

Table 12. Estimated per capita CO_2 shifts resulting from observed average annual changes in our electricity model's statistically significant variables

Average annual change in variable	Per capita kg CO_2 change
0.05 housing age index decrease	–28.1
1% decrease in people with incomes below 200% FPL	–11.6
91 CDD increase	+8.2
0.05% increase in residential share of electricity	+1.5

Per capita MWh have been converted to kg of CO_2 using conversion factors from EIA (2019).

The observed average annual changes in our electricity model's statistically significant variables coincided with larger decreases than increases in per capita electricity and associated CO_2. Decreases in both the housing age index and the share of people with incomes below 200% FPL were larger than per capita emissions increases associated with increasing CDD and the residential share of total electricity. The largest potential decreases in per capita emissions were associated with the observed average changes in the housing age index.

We used 2013–2017 GHG inventory data for the cities of Los Angeles, Minneapolis, and Washington, DC to show how past changes in our models' statistically significant variables may have contributed to observed emissions reductions. We chose these cities for this analysis because they not only have reliable annual data available but also are making progress toward achieving ambitious climate change mitigation goals in different regions of the country. Ribeiro et al. (2019) found that all three cities have reduced their per capita GHG emissions in recent years, and both Los Angeles and Minneapolis are on track to achieve their near-term emissions goals while Washington, DC is on track to be within 25% of its near-term goal.

In estimating how shifts in housing age and poverty may have contributed to these cities' recent declines in per capita GHG emissions, we have multiplied the shifts in our models' statistically significant variables for each city by the coefficients in our models and then by the respective emissions conversion factors included in each city's inventories. Estimated per capita emissions reductions associated with our models' statistically significant variables reflect combined shifts in both electricity and natural gas and are presented in metric tons of CO_2 equivalent ($MtCO_2e$) as these are standard units of measure in GPC inventories. CO_2 equivalent considers the combined effect of multiple GHGs, not just CO_2. Table 13 displays the results of these calculations and the share of total reductions in city-wide per capita GHG emissions that could have been associated with our models' significant variables.

Table 13. Potential 2013–2017 per capita $MtCO_2e$ changes associated with each location's shifts in our models' statistically significant variables

Per capita GHG changes	Los Angeles	Minneapolis	Washington, DC
City-wide emissions	−0.33	−1.21	−0.97
200% FPL	−0.09	−0.05	−0.04
Housing age	−0.13	−0.51	−0.23
CDD	+0.06	−0.01	+0.01
HDD	−0.02	−0.16	−0.07
Residential share of electricity	+0.07	+0.02	+0.09
Net change related to identified local factors	−0.10	−0.71	−0.25
Share of city-wide emissions change	32%	59%	26%

City-wide per capita emissions changes are representative of all sectors.

Although we cannot establish causality between changes in the above factors and per capita GHG emissions, these estimates provide a way of understanding the relative potential contribution each may have already made to reducing city-level per capita emissions. After accounting for the net changes related to the significant variables identified by our models, we found that these factors could explain 59% of the per capita emissions change in Minneapolis, 32% of the change in Los Angeles, and 26% of the change in Washington, DC. The unexplained per capita emissions reductions in these three cities may be due to energy-saving policies and programs that could not be adequately captured in our study's data.

As we will discuss in more detail in subsequent sections of this report, local governments have clear opportunities to affect two of the statistically significant variables identified by our models: the share of households living in older housing and the share of the population with low incomes. Of the two, the estimates above reveal that declines in housing age index scores have potentially contributed the most to declines in past years' per capita emissions. However the contribution of each factor varies by city. For example, decreases in poverty in Los Angeles potentially contributed nearly as much to per capita emissions reductions as did changes in the city's housing age index.

Neighborhood Change, Energy Use, and Greenhouse Gas Emissions

Our analysis cannot account for all the individual factors that underlie shifts in per capita energy use and GHG emissions, but our results do indicate that the changing physical and socioeconomic qualities of neighborhoods may be playing an important role in city efforts to achieve energy savings and climate change mitigation goals. In the following sections, we provide a detailed examination of how these shifts have occurred throughout urban neighborhoods.

TRENDS IN LOCAL HOUSING CONSTRUCTION AND LOW-INCOME HOUSEHOLD MOBILITY

The degree to which neighborhoods are seeing new housing construction and renovations plays an important role.[18] These projects offer more households an opportunity to live in energy-efficient homes that reduce their energy use and carbon footprint. As we have discussed, new homes may consume less energy because recently constructed housing must comply with energy efficiency codes and standards or because such homes operate more efficiently as both the new structure and systems require less maintenance.

While housing construction projects are leading to reductions in per capita energy use, data indicate that the pace of these projects is slow. Renovation projects tend to occur in only 0.5–1% of buildings annually (Sroufe, Stevenson, and Eckenrode 2019). Most housing construction projects are likely to involve the creation of new homes, and the pace of these projects has slowed in recent years. Data tracked by the US Census Bureau (2019b) reveal that the average number of months between a single-family project's permit application submission and completion increased by 8% from 6.2 to 6.7 months between 2000 and 2018. Over this same span, the time between a multifamily project's permit application submission and completion increased by 47% from 9.8 to 14.4 months.[19]

Past research indicates that the availability and affordability of new homes affects a locality's low-income residents in multiple ways. Construction of new homes can improve housing affordability on a regional scale over several years by increasing supply to meet demand, but middle- and high-income households are still the most likely to immediately move into those new homes (Rosenthal 2014; Zuk and Chapple 2016; Mast 2019). Subsidies can accelerate the creation of new affordable housing, but these subsidies have declined in recent years, and the housing market is largely unable to construct new affordable housing without them (NLIHC 2018). Due to housing affordability and other resource constraints,

[18] Our housing age index can account only for the age of structures based on when they were first constructed, but it is logical to assume that substantial renovations would exhibit a relationship to per capita energy use that is like that of new construction.

[19] *Multifamily* is defined here as a residential structure with two or more units.

many with incomes below 200% FPL occupy older housing stock with aged appliances and equipment that may be inefficient. This can lead to higher energy cost burdens and ultimately housing instability for those with low incomes (Drehobl and Ross 2016). Research by the Institute on Metropolitan Opportunity (2019) indicates that since 2000, these low-income household moves are also adding to poverty concentration in most central cities as these households occupy an increasing share of neighborhoods experiencing economic decline. In many cities, this is also occurring alongside the displacement of low-income households from economically improving neighborhoods with increasing housing costs.

These factors are all critical in understanding the relationships between per capita energy consumption and the share of households with incomes below 200% FPL, our model's other predictor of declining per capita electricity use. While national and state-level economic shifts and policies can reduce poverty, local governments also play an important role. Previous research indicates that intergenerational mobility, changes in a family's social status from one generation to the next, improves in cities that provide low-income families with access to homes with affordable rents, mortgages, and energy bills that are also located in what we will refer to as opportunity neighborhoods. These are neighborhoods with lower levels of income and racial segregation, less income inequality, better schools, lower violent crime rates, and a larger share of two-parent households (Chetty and Hendren 2015). Today's poverty reductions in cities are in part the result of former low-income children having grown up in opportunity neighborhoods that were affordable for their parents. Some reductions in city poverty are also due to displacement from economically improving but unaffordable neighborhoods or factors that extend beyond the direct influence of local governments. While several factors can shift the share of a city's population with low incomes, local governments that improve low-income households' access to energy efficiency over the coming years can weaken the relationship between low incomes and higher per capita energy use.

Neighborhood Change in Los Angeles, Minneapolis, and Washington, DC

We see nationwide trends in housing construction and low-income household mobility reflected in the three cities we used to illustrate the per capita GHG emissions reduction potential of our models' statistically significant variables. Table 14 shows how per capita GHG emissions, our housing age index, and the share of a population with incomes below 200% FPL changed for the three cities we examined.

Table 14. Comparison of 2013–2017 changes in per capita GHG emissions, the housing age index, and the population below 200% FPL in Los Angeles, Minneapolis, and Washington, DC

City	Per capita GHG reduction	Housing age index decline	Population below 200% FPL decline
Los Angeles	5.5%	2.3%	8.4%
Minneapolis	15.9%	5.0%	5.5%
Washington, DC	14.2%	3.7%	4.8%

Between 2013 and 2017, Washington, DC and Minneapolis experienced similar shifts in per capita GHG emissions, the housing age index, and poverty while Los Angeles saw smaller declines in per capita emissions and the housing age index but larger declines in poverty.

Table 15 shows that declines across each city's housing age index are mostly due to substantially fewer people living in homes built before 1950 and substantially more living in homes built since 2010.

Table 15. 2013–2017 shifts in city shares of households living in homes constructed in different decades

Decade of home construction	Los Angeles	Minneapolis	Washington, DC
1939 or earlier	−0.5%	−3.6%	−1.5%
1940–1949	−0.7%	−1.7%	−1.9%
1950–1959	−0.3%	0.0%	−0.4%
1960–1969	−0.6%	+0.9%	+0.9%
1970–1979	−0.1%	+0.6%	−1.6%
1980–1989	+0.6%	−0.1%	+0.6%
1990–1999	+0.0%	+0.2%	−0.2%
2000–2009	−1.4%	−1.0%	−1.2%
2010 or later	+1.9%	+4.8%	+5.1%

Minneapolis's share of households living in homes built before 1950 declined by 5.4% while the share of those living in homes built since 2010 increased 4.8%. The city's declining share of households living in homes constructed before 1950 is not just a consequence of those households occupying a smaller share of the city's total households as the population has grown. Fewer Minneapolis households are now living in these older homes. Between 2013 and 2017, the total number of the city's households living in homes built before 1950 declined by a net of 5,305 (Census Bureau 2019a). Washington, DC saw a similar but somewhat smaller decrease in both the share and number of households living in homes built before 1950. The share of households living in these homes decreased 3.4%; the total decreased by 4,478 households (Census Bureau 2019a). The city also witnessed a relatively substantial decline in households living in homes built between 1970 and 1979. The share of households in these homes declined by 1.6%, and the number decreased by 2,526 households (Census Bureau 2019a).

Unlike Minneapolis and Washington, DC, Los Angeles's 1.2% decline in the share of households living in homes built before 1950 was not due to fewer people living in these homes but because those households now occupy a smaller share of the city's total households. The number of households living in homes built before 1950 increased by 20,007 between 2013 and 2017 (Census Bureau 2019a). Although the city is seeing construction of new housing units, something that both the region and California need to keep housing costs affordable, the number of planned units in Los Angeles County has not been on pace to keep up with demand through 2025 (Monkkonen and Friedman 2019). This can keep newly constructed housing costs unaffordable for those with lower incomes and lead to an increase in the number of households residing in older homes. This leads to newer homes being occupied by mostly higher-income households.

Taken together, these trends across the three cities indicate that larger declines in our housing age index may be due to not only the construction of new and more-efficient housing but also the ability of households currently living in older housing to move to newer homes. As we have established, household mobility can be especially important for low-income families' intergenerational mobility and long-term city-wide reductions in poverty. However this is not the only means by which poverty is reduced in cities. Poverty reduction can also happen as low-income households are displaced from unaffordable neighborhoods to areas outside a central city. Data reveal that Los Angeles, Minneapolis, and Washington, DC have witnessed differing degrees of intergenerational mobility and displacement in recent years.

Institute on Metropolitan Opportunity data (2019) indicate that Washington, DC's construction of new and more-efficient housing has coincided with a greater degree of low-income household displacement than in other cities. Of the nation's central cities, "Washington, DC has experienced the nation's worst gentrification trend, with nearly 36% of its entire population living in an area where strong displacement is underway" (Institute on Metropolitan Opportunity 2019, 19). Signs of intergenerational mobility in the city are minimal: only 4.9% of low-income children who grew up in Washington, DC neighborhoods and are now in their mid-30s (and still living in the region) have household incomes in the top 20% of nationwide household incomes (Opportunity Insights 2020). These individuals had an average 2014–2015 household income of only $26,000, roughly one-fifth of the 2015 average household income of $121,072 for the surrounding metropolitan areas (Census Bureau 2019a).

By contrast, only 6% of Minneapolis's population live in neighborhoods experiencing displacement, indicating that gentrification has played a smaller role in the decline of people living below 200% FPL in that city (Institute on Metropolitan Opportunity 2019). The decline in the share of Minneapolitans with low incomes is more likely due to intergenerational mobility. Thirteen percent of low-income children who grew up in Hennepin County neighborhoods (the county that contains Minneapolis) and are now adults in their mid-30s (and still living in the region) have household incomes in the top 20% of nationwide household incomes (Opportunity Insights 2020). The average household income for these individuals was $34,000. This is slightly more than one-third of the 2015 average household income of $92,395 for the surrounding metropolitan areas (Census Bureau 2019a).

Compared with Washington, DC and Minneapolis, Los Angeles saw a larger decrease in the share of people with incomes below 200% FPL. Neighborhood displacement of low-income households is high in Los Angeles. Twenty percent of the city's population live in areas that have witnessed low-income displacement, placing it in a tie as the central city with the fourth-highest displacement in the country (Institute on Metropolitan Opportunity 2019). However displacement alone is unlikely to explain the substantial decrease in poverty. Los Angeles is very similar to Minneapolis in terms of intergenerational mobility. Twelve percent of low-income children who grew up in Los Angeles County neighborhoods (the county that contains the City of Los Angeles) and are now adults in their mid-30s (and still living in the region) have household incomes in the top 20% of nationwide household incomes (Opportunity Insights 2020). Like Minneapolis, the average household income for these individuals was $34,000. This is also slightly more than one-third of the 2015 average household income of $90,892 for the surrounding metropolitan area (Census Bureau 2019a).

Opportunities for Local Government Policies and Programs

Our analysis reveals that, in urban municipalities, decreases in the share of a population with low incomes and the share of households living in older homes are associated with declines in per capita energy use. Local government policies and programs can affect these factors. Prior studies indicate that how these policies are adopted and implemented will determine whether they are effective in influencing energy use. Below we outline several opportunities for local governments to adopt policies and programs that hold the potential to reduce per capita energy use and associated GHG emissions.

Although our research shows potential for local governments to reduce per capita energy use, municipal leaders should not interpret our results as the final word in what actions will or will not help them achieve their climate change mitigation or energy conservation goals. Many of the municipalities in our samples had little or no activity in benchmarking buildings for energy use, using green-building rating systems to certify properties, adopting cool-roof requirements, or achieving energy savings from energy efficiency programs. This limited our models' ability to determine relationships between these activities and per capita energy use. Furthermore, we cannot assess the effectiveness of policies that have been adopted since 2016, such as building energy performance standards or labeling requirements.

Increase the Energy Efficiency and Pace of Housing Construction Projects

Our analysis reveals that housing age is correlated with both electricity and natural gas consumption per capita. Locations with a larger share of households occupying older homes see increased per capita energy use. As we have discussed, past research indicates that this relationship has two possible explanations. It could be due to homes being constructed or renovated to meet progressively more-stringent energy codes. It could also be due to the diminishing efficiency of a home's structure, insulation, and equipment over time and in the absence of maintenance or upgrades. Local governments can address all these concerns by mandating or incentivizing housing construction projects to meet stringent energy efficiency standards. They can also increase the pace of these projects by improving the process efficiency of permit reviews and site inspections and amend zoning codes to allow for the construction of more housing units.

First, local governments with the power to adopt more-stringent energy codes than states can encourage energy-efficient home construction or rehabilitation projects.[20] Ribeiro et al. (2019) asserted that cities should be concerned with not only the stringency of code updates, but also their enforcement. Even if local governments do not have the authority to adopt more-stringent codes, they typically have the power to implement more-stringent

[20] It is important to note that not all cities have the authority to adopt building energy codes or codes that are more stringent. Home-rule states are those that largely allow municipalities to govern themselves as they find appropriate and necessary, provided local laws do not conflict with those at the state or federal level. Ribeiro et al. (2019) explained that cities in these states can generally adopt local energy codes, but this is not always the case. Some home-rule states, like Ohio, expressly reserve the power to pass energy codes for the state government. Municipalities in Dillon's Rule states are permitted to exercise only powers expressly granted them by their state governments. Some Dillon's Rule states may expressly grant cities and counties the power to adopt local building energy codes, but many do not.

enforcement of state-adopted codes. Typically, enforcement is woven throughout a city or county's permitting process. Procedures to verify that a property complies with code provisions can vary in terms of their rigor:

- *Lenient*. Construction project engineers or architects certify that their plans are compliant.
- *Stricter*. Local government code officials review submitted plans for compliance.
- *Strictest*. Projects must receive onsite inspections for construction work and performance once the project is complete.

Funding for energy code compliance is often limited in local governments, and project reviews are frequently some of the first procedures to be scaled back in the event of a budget shortfall. DOE's Building Energy Codes Program and some state energy offices are available to provide municipalities and construction project staff with tools and advice to help compensate for these challenges.

Some local governments may also want to consider instituting requirements or incentives for housing construction projects to be certified using a green-building ratings system. Typically, cities have instituted these requirements for multifamily buildings. For example, San Francisco requires that new low- or high-rise residential buildings achieve certification under either California's GreenPoint Rated program or LEED Silver. Residential buildings that are at least 25,000 square feet and undergoing major alterations are required to certify as GreenPoint Rated or LEED Gold (San Francisco 2017). Incentives encouraging projects to meet green building standards can also take the form of low-interest loans, tax abatements, reduced permit fees, construction density bonuses, or grants. In some cases, these offerings may be structured to complement similar incentives offered by local utility energy efficiency programs (Ribeiro et al. 2019).

Local governments must also ensure that their permit and inspection process is efficient so that the number of annually completed housing construction projects increases. Increasing the number of housing projects that can move quickly from the submission of a permit application to project start and completion increase options for households to occupy more energy-efficient housing.

Although the time required for a locality's permit review and inspection process can vary depending on several factors, Ribeiro et al. (2019) identified several city strategies that can encourage projects to improve their energy use and reduce the time for permit review. For example, several cities offer an expedited permitting process for projects that conform with a green building standard of some kind. Seattle (2020) provides an example of using multiple approaches for expediting green building projects. The city offers expedited permitting to all construction projects that work to achieve certification under the more-stringent levels of Built Green, LEED, Living Building Challenge, and Passive House Institute US standards. Seattle also offers a priority facilitated permit process with city staff providing technical assistance for master use projects working to achieve the Living Building Pilot or more-stringent standards. Finally, the city has created a group of subject-matter experts with the power to review energy-efficient project proposals that do not conform to technical codes.

Local governments can also increase the number of newly constructed housing units by revising their zoning codes to encourage the development of multifamily housing. In many American cities, single-family zoning can occupy three-quarters or more of residential land (Badger and Bui 2019). Some cities are taking action to reverse this. The National Community of Practice on Local Housing Policy (2019) documents how local governments are using their zoning codes to increase housing density. One option for localities to pursue is allowing construction of more-dense developments in current residential zones. For example, both Oregon and Minneapolis have recently eliminated single-family zoning and are encouraging the creation of duplexes, triplexes, and fourplexes in these areas. Local governments could also choose to allow residential development in locations where it has been prohibited. Fairfax, Virginia, pursued this path in rezoning commercial areas and zones around Metro transit stations to allow for denser housing developments.

Design and Implement Carefully Targeted Initiatives That Improve Low-Income Household Access to Energy-Efficient Affordable Housing

Localities with a higher share of household incomes below 200% FPL experience higher per capita energy use. As we have discussed, local government actions have likely played a role in reducing poverty in cities over past years. In some cases, this may have taken the form of policies and programs that support the creation and preservation of affordable energy-efficient housing while also increasing access to neighborhoods and resources that promote upward economic mobility. In other cases, local decisions may have reduced poverty through displacement of low-income households. Local governments should carefully design and implement policies and programs in a targeted manner to improve low-income household access to affordable efficient housing and resources that reduce poverty.

We analyzed data from *The 2019 City Clean Energy Scorecard* to understand strategies that cities are using to increase access to energy-efficient and affordable housing and appliances for low-income households. These approaches largely conform to one of three strategies:

- *Building-focused programs*. City-created programs focus on increasing the efficiency and affordability of specific types (income-restricted, specific size of multifamily buildings, etc.) of residential buildings that are often underserved by other efficiency programs.
- *Place-based programs*. Cities identify specific neighborhoods or zones with a large concentration of low-income households and provide financial support to property owners to make energy efficiency improvements while preserving housing affordability.
- *Comprehensive housing policies*. Cities assess all local government actions to determine opportunities for improving housing efficiency and affordability.

All three strategies are carefully targeted using different approaches and can weaken the relationship between poverty and per capita energy use. The first of these three strategies considers only building type in design and implementation. The remaining two approaches consider neighborhoods in addition to characteristics of targeted buildings.

One example of a building-focused program is the Rental Rehabilitation Loan Program administered by the City of Phoenix, Arizona. The program offers low-interest loans to fund

75% of energy efficiency, health, and safety upgrades in multifamily buildings with 12 or fewer units and with 51% of tenants having incomes below 80% of the area median. Property owners must agree to maintain affordable rents after completion of a retrofit project (Phoenix 2017). Although a building-focused program such as this one has the potential to ensure that low-income renters of participating buildings can have both affordable rents and affordable energy bills, whether such a program may also contribute to declines in the city's share of households living in poverty is not clear. However such programs may have the potential to decouple the relationship between poverty and per capita energy use by ensuring that energy efficiency is not limited to higher-income households.

Milwaukee's Targeted Investment Neighborhoods offers an example of a place-based program. The program is administered by the Neighborhood Improvement Development Corporation (NIDC), a nonprofit corporation created and funded by the city. Like Phoenix, NDIC's Targeted Investment Neighborhoods program offers funding for energy efficiency, health, and safety improvements in buildings. Unlike Phoenix, the program is available to both low-income homeowners and owners of affordable rental properties in a mix of payback, deferred, and forgivable loans. Loans of up to $30,000 and $14,999 are available to homeowners and rental property owners, respectively (Milwaukee 2019). Also unlike Phoenix, the program is limited to specific communities to "sustain and increase owner-occupancy, provide high quality affordable rental housing, strengthen property values, and improve the physical appearance and quality of life of neighborhoods" (Milwaukee 2019). Whether the neighborhoods being targeted are receiving investments or already have resources to improve upward economic mobility is not clear. However a program designed in this way would appear to have the potential to improve energy and overall housing affordability while also reducing poverty in the long run.

Dallas, Texas, adopted a comprehensive housing policy in 2018. Formation of the policy was driven by goals of creating and maintaining affordable housing throughout the city, increasing fair-housing choices, and overcoming both segregation and poverty concentration. City staff conducted a market-value assessment and conducted eight town hall meetings to inform the policy's creation. The result was a plan that classified the city's neighborhoods into three types. This typology is used to direct housing and community development investments (Dallas 2019):

- *Stabilization market areas* are those places with a high risk of displacing current low-income residents with further development. Because housing costs are elevated in these places, the city is encouraging the creation of higher-density developments, subsidized affordable housing, and accessory dwelling units.
- *Redevelopment market areas* are those that will see a substantial investment from developers in the coming year. Because construction is accelerating, but not yet moving at a rapid pace, the city is focusing on incentivizing mixed-income housing in new developments.
- *Emerging market areas* are neighborhoods with little development or investment that need "intensive environmental enhancements, public infrastructure assessments and corrective plans, code enforcement, code lien foreclosure, nuisance property abatement, establishment of a crime watch or crime reduction strategies, and

neighborhood resource development." Investments are being targeted for these purposes.

The policy encourages using the Community Development Block Grant (CDBG) program and Home Investment Partnerships (HOME) for energy efficiency upgrades in affordable housing projects. The policy also requires that any project utilizing HOME funds must install ENERGY STAR appliances in housing units (Dallas 2019). A comprehensive housing policy such as this may improve energy and overall housing affordability for low-income residents in a highly targeted fashion that potentially reduces the risk of low-income displacement from neighborhoods.

Commonalities exist across these examples. First, these city programs and policies ensure that funding for energy efficiency improvements is prioritized for low-income single-family homeowners and multifamily property owners that are willing to commit to preserving affordable rents for low-income residents. Second, cities are working to couple their offerings with those of existing programs administered by utilities, nonprofit organizations, and the state or federal government. For example, a city-led program may offer funding to complete home health and safety repairs that are required but not always fully funded by utility energy efficiency programs. Another example is city programs that offer affordable housing providers with financing to make energy efficiency improvements.

For the most part, cities have reported few outcomes from these initiatives. Future research will be necessary to fully assess possible outcomes and trade-offs between the different approaches.

Conclusions

Our research indicates that per capita electricity and natural gas use in buildings decreased at the local level between 2013 and 2016, and these reductions were related to two changes occurring in residential neighborhoods: residents moved into recently constructed housing and the number of those with low incomes declined. Local governments play a role in these changes. Municipalities that increase the energy efficiency and pace of housing construction projects and carefully design and implement targeted policies and programs to improve low-income household access to affordable efficient housing and resources that reduce poverty can reduce per capita energy use and associated GHG emissions.

Our research reveals important information about relationships among local government decisions, neighborhood change, building energy use, and associated GHG emissions. However our analysis was limited by the low availability of detailed, comparable, and annual local data. Providing more and higher-quality local data would improve analyses such as these and provide local governments with additional guidance. Future studies would benefit from including data reflecting a greater variety of the initiatives that localities are undertaking. Researchers would also benefit from municipalities sharing standardized data tracking the spending, compliance or participation rates, and specific activities associated with initiatives that target reductions in building energy use or GHG emissions. Energy-saving policies and programs should also be evaluated more often to ensure that the data associated with these initiatives are accurate, reliable, and precise. Finally, future studies should be able to provide a more complete picture of local policies' effects on energy use and GHG emissions as more cities perform annual GHG emissions inventories using rigorous standardized methods.

Our analysis provides municipal governments with a sense for the per capita energy and GHG emissions reductions that are possible across their localities. However context is important. Some policies that have not been widely adopted across many municipalities have still been shown effective in the locations where they are being implemented. For example, Meng, Hsu, and Han (2017) found that New York City's benchmarking and transparency ordinance was associated with a statistically significant 6% reduction in building EUI after three years of implementation and a 14% reduction after four years. Rigorous evaluations of specific policies like this one are still relatively rare at the local level, but these serve as a highly effective method for determining energy savings and GHG emissions reductions from a single policy or program. Local governments can verify that their actions are having the intended effect by conducting more of these analyses. Broadly focused research like our study will also be strengthened as more evaluations of these policies are completed.

Evolving policies and programs may ultimately prove to be effective in certain or most localities. For example, several cities are adopting or considering building performance policies that set specific energy efficiency standards for properties. Washington, DC, recently adopted such standards for buildings over 10,000 square feet. A preliminary analysis of the policy's energy savings potential revealed that having these properties make improvements to achieve the median Washington, DC, ENERGY STAR score would reduce city-wide energy use by over 20% and save 1.05 million tons of GHG emissions per year (C40 2019). With time, emerging policies such as these may prove to be highly effective at reducing per capita energy use and GHG emissions. We encourage local governments to track and share detailed data on these initiatives so that future research can better determine their effectiveness.

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Appendix A. Detailed Methodology

ASSESSING SAMPLE REPRESENTATIVENESS AND MODEL SPECIFICATION

The process of collecting data for this research was difficult because many local governments do not consistently report community-wide energy use or GHG emissions. As we have noted, many municipalities have reported GHG data that are not perfectly comparable across localities or across years due to different measurement criteria and or problems related to imperfect correspondence between municipal boundaries and utility-reported data. For these reasons, we chose to focus our analysis only on cities and counties that have municipal utilities with service territories that closely conform with these localities' boundaries and those municipalities that have published city-wide energy data through GHG inventories or state reports. We also focused on cities and counties with a daytime population of 100,000 or more. Table A1 provides a list of cities and counties included in each analysis.

Table A1. List of municipalities included in each analysis

Electricity analysis	Natural gas analysis
Anaheim, CA	Baltimore, MD
Austin, TX	Boston, MA
Baltimore, MD	Clarksville, TN
Boston, MA	Cleveland, OH
Burbank, CA	Clearwater, FL
Chattanooga, TN	Colorado Springs, CO
Cleveland, OH	Corpus Christi, TX
Colorado Springs, CO	Denver, CO
Denver, CO	Duluth, MN
Durham County, NC	Durham County, NC
Fayetteville, NC	Gainesville, FL
Fort Collins, CO	Greenville, NC
Garland, TX	Huntsville, AL
Glendale, CA	Indianapolis, IN
Huntsville, AL	Knoxville, TN
Jacksonville, FL	Las Cruces, NM
Kansas City, KS	Long Beach, CA
Knoxville, TN	Los Angeles, CA
Lafayette, LA	Memphis, TN
Lansing, MI	Mesa, AZ
Lincoln, NE	Minneapolis, MN
Los Angeles, CA	Multnomah County, OR
Lubbock, TX	New Orleans, LA

Electricity analysis	Natural gas analysis
Memphis, TN	New York, NY
Minneapolis, MN	Philadelphia, PA
Multnomah County, OR	Richmond, VA
Naperville, IL	Rochester, MN
New Orleans, LA	Salt Lake City, UT
New York, NY	San Antonio, TX
Omaha, NE	San Diego County, CA
Orlando, FL	Springfield, MO
Pasadena, CA	Tallahassee, FL
Philadelphia, PA	Washington, DC
Provo, UT	
Richmond, VA	
Riverside, CA	
Rochester, MN	
Sacramento, CA	
Salt Lake City, UT	
San Antonio, TX	
San Diego County, CA	
Seattle, WA	
Springfield, IL	
Springfield, MO	
Tacoma, WA	
Tallahassee, FL	
Washington, DC	

Variable Selection

We took several steps to include the best set of variables in our models to avoid omitting or overfitting variables while achieving sufficient degrees of freedom, increasing the number of variables in the model that are free to vary.

First, we used past research to guide our data collection. We collected data for only those variables that were supported in published research. Table A2 lists these variables and their sources.

Table A2. Variable data considered for our analyses

Electricity and natural gas variables	Source
MWh and therms per capita (daytime population)	EIA and GHG inventories

Electricity and natural gas variables	Source
Share of population below 200% federal poverty level	US Census Bureau ACS 1-year estimates
Housing age index	US Census Bureau ACS 1-year estimates
Average firm size for county of municipality	US Census Bureau ACS 1-year estimates
Households per square mile	US Census Bureau ACS 1-year estimates and 2010 Census
Local heating and cooling degree days	NOAA National Centers for Environmental Information
Metropolitan statistical area gross domestic product per capita	US Bureau of Economic Analysis
Average household size	US Census Bureau ACS 1-year estimates
Residential unit room index	US Census Bureau ACS 1-year estimates
Number of years since local government implemented a cool-roof requirement for buildings	Cool Roof Rating Council and ACEEE's 2015 and 2017 *City Energy Efficiency Scorecard*s
Square feet of LEED-certified building space in municipality per capita (daytime population)	Green Building Information Gateway
Square feet of ENERGY STAR–certified building space in municipality per capita (daytime population)	Green Building Information Gateway
Square feet of energy-benchmarked building space in municipality per capita (daytime population)	EPA ENERGY STAR program
Median age	US Census Bureau ACS 1-year estimates
Share of population that is non-Hispanic white	US Census Bureau ACS 1-year estimates
Residential share of total electricity and natural gas use	
Electricity-only variables	**Source**
Utility-reported MWh energy savings per residential customer	EIA

We calculated two indices using data from the ACS regarding the number of housing units by structure age and number of housing units by total rooms. To calculate our housing age index, we transformed the share of housing units in structures built in past decades by a multiplier representing each decade. To illustrate, we multiplied the share of housing units in structures built since 2010 by one, the share of housing units built between 2000 and 2009 by two, and so on until we multiplied the share of housing units built in 1939 or earlier by nine. We then added these values together. We took a similar approach to calculate the residential unit room index, multiplying different shares of housing units with certain room numbers by their number of rooms. For example, the unit share with one room was multiplied by one and those with nine or more rooms were multiplied by nine. We added these values together to arrive at our index number. The values of both indices represent an entire municipality and were not normalized using population.

We used the LASSO variable selection method to "right size" our models. This method allowed us to select the fewest policy-related and non-policy independent variables that best predicted our dependent values of energy use. LASSO is one example of a variable selection method that uses some form of sequentially adding or deleting variables while assessing the effect these changes have on the model.[21] We applied LASSO in preparing our data sets only after running a regression with the key policy and non-policy independent variables previously thought to have connections with the target variables to select the set of independent variables that best predicted our dependent variables.

ENERGY USE ANALYSES

We analyzed trends in electricity and natural gas use in cities or counties with a daytime population of 100,000 or more using data from annual GHG inventories or municipal utility reporting. These analyses focus on the years 2013 to 2016. Annual electricity data are available for 47 US municipalities over this span, and annual natural gas data are available for 33 localities. Predictor variables include continuous data for local policy, economic activity, utility initiatives, weather, building stock, and demographic changes.

As a first step, we conducted simple correlation analyses to determine Pearson correlation coefficients between electricity and natural gas use and predictor variables. This aided us in identifying bivariate correlations across the data sets. We then conducted two sets of panel data analyses. One set includes cities that report annual community-wide electricity use, and the other includes cities that report annual community-wide natural gas use. These data sets are not mutually exclusive.

The panel data models show which factors that are endogenous and exogenous relative to local government actions tend to be associated with changes in electricity and natural gas use. The regression controlled for several socioeconomic, demographic, and climatic features. Finally, we quantified the effect that statistically significant policy variables have in terms of both energy use and GHG emissions.

We completed three panel regression models in our panel analyses: pooled ordinary least squares (POLS), random effect (RE), and fixed effects (FE). Each of these approaches reflects different assumptions:

- POLS assumes that the modeled data capture all relevant characteristics of the analyzed individuals (cities).
- RE assumes that the modeled data have no omitted variables or that omitted variables are uncorrelated with the model's variables. RE also allows time-invariant characteristics of individuals (cities) to be considered as explanatory variables.

[21] LASSO is a powerful method that performs two main tasks: regularization and feature selection. The method puts a constraint on the sum of the absolute values of the model parameters, meaning the sum must be less than a fixed value (upper bound). To do this, the method applies a shrinking (regularization) process based on the value of a tuning parameter lambda where it penalizes the coefficients of the regression variables, shrinking some of them to zero. Variables that still have a nonzero coefficient after the shrinking process are selected to be part of the model. We used the LASSO method with a nonpenalization criterion for selected variables (the dependent variables and policy-related variables) and a tuning parameter lambda that was optimally selected after cross validation to minimize the mean-squared prediction error of the regression.

- FE assumes that modeled data may have omitted variables or that omitted variables are correlated with the model's variables. FE cannot measure the effect of time-invariant characteristics of individuals (cities).

Conducting these three analyses generated widely different results. To select the most reliable model, we first performed the Breusch and Pagan Lagrange Multiplier (B-P/LM) model-specification test for random effects to decide between an RE regression and a simple POLS regression. Our null hypothesis in the B-P/LM test was that variances across entities would be zero. The test showed a p-value of 0.000 for both data panels, indicating that the assumptions necessary for the implementation of the POLS regression are not fulfilled.

To decide between the FE or RE model, we first ran a Hausman's test where the null hypothesis was that the unique errors of the entities would not be correlated with the regressors. However, as the standard form of the Hausman test was not well defined for both panel data, we proceeded to perform a robust Hausman's test as described by Wooldridge (2002). The robust Hausman's test is asymptotically equivalent to the standard form of the test and has a conceptually similar null hypothesis. The robust Hausman test showed p-values of 0.0016 for the electricity panel data and 0.0271 for the natural gas panel data, indicating that the panel data should be analyzed using an FE regression model.

Analysis Limitations

In experimental research, unmeasured differences between subjects are often controlled for via random assignment to treatment and control groups. Of course, random assignment is usually not possible, and this is the case when examining the implementation of municipal climate policies across the United States. Consequently, we acknowledge that we could not account for all possible variables in our analysis and that the data of some variables may be imprecise.

Appendix B. Data Set Correlation Matrices

Variables	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14	v15	v16	v17	v18
v1	1.00																	
v2	0.12	1.00																
v3	-0.27	0.30	1.00															
v4	0.13	0.13	0.30	1.00														
v5	-0.27	-0.02	0.46	0.14	1.00													
v6	0.17	0.21	-0.34	0.01	-0.31	1.00												
v7	-0.22	-0.36	0.36	0.23	0.34	-0.18	1.00											
v8	-0.33	0.05	-0.19	-0.20	-0.21	0.21	-0.08	1.00										
v9	0.25	-0.16	-0.39	0.00	-0.43	-0.16	-0.31	-0.04	1.00									
v10	-0.25	-0.14	-0.11	-0.21	-0.04	0.38	0.24	0.39	-0.40	1.00								
v11	-0.24	-0.20	0.48	0.22	0.36	-0.24	0.32	-0.28	-0.45	-0.03	1.00							
v12	-0.19	-0.12	0.43	0.38	0.52	-0.24	0.36	-0.35	-0.43	-0.16	0.77	1.00						
v13	-0.16	-0.22	0.37	0.21	0.40	-0.25	0.37	-0.33	-0.40	-0.07	0.91	0.80	1.00					
v14	0.02	-0.42	0.25	0.08	0.16	-0.08	0.48	-0.21	-0.04	0.25	0.09	0.07	0.13	1.00				
v15	0.19	-0.31	-0.28	-0.23	0.04	-0.44	-0.25	-0.35	0.39	-0.42	-0.10	-0.13	-0.09	-0.06	1.00			
v16	0.49	0.06	-0.54	-0.22	-0.29	0.48	-0.32	0.03	0.25	0.17	-0.53	-0.43	-0.47	0.03	-0.01	1.00		
v17	-0.03	-0.07	0.25	0.29	0.18	-0.75	-0.07	-0.33	0.43	-0.63	0.16	0.24	0.13	-0.11	0.50	-0.41	1.00	
v18	-0.14	-0.35	0.18	0.08	0.17	-0.43	0.29	-0.11	-0.20	-0.03	0.48	0.43	0.50	0.11	0.11	-0.49	0.24	1.00

Figure B1. Correlation matrix for electricity variables considered for analysis

Table B1. Electricity variable ID and name

Variable ID	Variable name
v1	Total MWh per capita (using daytime population)
v2	Share of population below 200% FPL
v3	Housing age index
v4	Average firm size for county of municipality
v5	Households per sq. mile
v6	CDD
v7	Metro GDP per capita
v8	Average household size
v9	Residential room index

Variable ID	Variable name
v10	Years since cool-roof ordinance implemented
v11	Total ENERGY STAR building stock sq. ft. per capita
v12	Benchmarked building sq. ft. per capita
v13	Total LEED building stock sq. ft. per capita
v14	Median age
v15	Non-Hispanic white share of population
v16	Residential share of total electricity use
v17	HDD
v18	MWh savings per residential customer

Variables	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14	v15	v16
v1	1.00															
v2	0.22	1.00														
v3	0.38	0.17	1.00													
v4	0.30	-0.15	0.33	1.00												
v5	0.09	0.01	0.46	0.18	1.00											
v6	0.71	-0.18	0.35	0.42	0.16	1.00										
v7	-0.08	-0.23	0.50	0.43	0.35	-0.03	1.00									
v8	-0.36	-0.17	-0.16	-0.08	0.04	-0.29	0.11	1.00								
v9	0.40	-0.17	-0.29	0.07	-0.47	0.38	-0.35	-0.18	1.00							
v10	-0.35	-0.04	-0.09	-0.20	-0.01	-0.49	0.25	0.42	-0.46	1.00						
v11	0.04	-0.21	0.52	0.35	0.30	0.25	0.35	-0.21	-0.35	-0.07	1.00					
v12	0.25	-0.13	0.60	0.47	0.45	0.36	0.44	-0.25	-0.34	-0.15	0.79	1.00				
v13	0.03	-0.23	0.43	0.30	0.30	0.24	0.40	-0.32	-0.29	-0.17	0.90	0.82	1.00			
v14	0.05	-0.37	0.25	0.08	0.12	-0.04	0.29	0.07	0.08	0.06	0.01	0.05	-0.02	1.00		
v15	0.19	-0.26	-0.29	-0.13	0.02	0.40	-0.45	-0.40	0.36	-0.48	-0.20	-0.17	-0.10	0.03	1.00	
v16	-0.21	-0.20	0.22	0.06	0.17	0.00	0.28	0.13	-0.07	0.10	0.24	0.10	0.14	0.20	-0.05	1.00

Figure B2. Correlation matrix for natural gas variables considered for analysis

Table B2. Electricity variable ID and name

Variable ID	Variable name
v1	Total therms per capita (using daytime population)
v2	Share of population below 200% FPL
v3	Housing age index
v4	Average firm size for county of municipality
v5	Households per sq. mile
v6	HDD
v7	Metro GDP per capita
v8	Average household size
v9	Residential room index
v10	Years since cool-roof ordinance implemented
v11	Total ENERGY STAR building stock sq. ft. per capita
v12	Benchmarked building sq. ft. per capita
v13	Total LEED building stock sq. ft. per capita
v14	Median age
v15	Non-Hispanic white share of population
v16	Residential share of total natural gas use