

# Energy Choices in Buildings: A Comparative Study of Electricity and Natural Gas Across Different Construction Years

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## Abstract

This report delves into the evolution of energy choices in buildings, specifically examining the preference between electricity and natural gas. It seeks to understand how preferences for these energy sources have evolved over different years, highlighting the dynamic nature of energy utilization in the context of building construction and use.

## 1 Introduction

### 1.1 Background

The use of energy in buildings has evolved significantly over the past century, with electricity and natural gas emerging as the two primary sources. Natural gas has been used in buildings for heating and cooking for many decades, valued for its efficiency and relatively lower environmental impact compared to coal or oil. However, the environmental impact of energy sources has become a crucial consideration. Electricity, particularly when sourced from renewables, is often seen as a cleaner option compared to fossil fuels, including natural gas. Therefore, building codes and regulations have increasingly favored energy-efficient and low-carbon solutions, impacting the relative use of electricity and natural gas in buildings.

## 1.2 The Commercial Building Energy Consumption Survey (CBECS)

The U.S. Department of Energy’s 1977 Organization Act mandated the Energy Information Administration (EIA) to collect and disseminate energy-related data. Under this, EIA conducts comprehensive surveys every four years in the commercial, residential, and manufacturing sectors, known as the Commercial Buildings Energy Consumption Survey (CBECS). Despite concerns about self-reported data accuracy, CBECS pairs building characteristics with energy consumption data, covering a wide range of commercial buildings. While its simplified data collection approach may limit the detailed analysis, CBECS is pivotal for statistical studies, historical performance records, and benchmarking tools like EnergyStar’s Portfolio Manager.

## 2 Data Processing

The initial dataset comprised a large table of 6436 rows and 1249 columns. To facilitate focused analysis, a subset of variables (**NFLOOR**: Number of Floors. **WKHRSC**: Total Hours Open Per Week. **YRCONC**: Year of construction category. **SQFTC**: Square Footage. **OWNTYPE**: Building owner. **PBA**: Principal Building Activity. **MAINHT**: Main heating equipment.) relevant to our study was retained using SAS. In this dataset, variables PBA, YRCONC, OWNTYPE, and MAINHT were identified as categorical variables, while the others were numeric.

Then use R to handle other data problems: The MAINHT variable originally contained numeric codes representing various heating sources. To simplify the analysis and focus on key categories, these codes were consolidated into 2 groups based on the type of heating source: 1, Electric; 2, Natural gas. NFLOOR with more than 14 floors were not reported using actual floor counts but rather coded as 994 for buildings with 15-25 floors and 995 for buildings with more than 25 floors, we will consider them as NA, and remove all the NA above.

## 3 Statistical Approach

In our research, a Generalized Linear Model (GLM) was adopted to fit the data. This statistical method enabled us to model the relationship between the year of construction and the choice of energy source, taking into account various predictor variables and their interactions.

The model fitting was followed by proportion analysis using the EMMEANS (Estimated Marginal Means) library. The fundamental principle of using EMMEANS lies in its ability to provide more profound insights into the modeled relationships. EMMEANS calculates the estimated marginal means (also known as least-squares

means) for specified factors in the model. These means are particularly useful for understanding the impact of each level of a categorical variable while controlling for other factors in the model.

## 4 Results

The analysis of heating energy source preferences in different buildings was conducted using the estimated marginal means (EMMs) obtained from the ‘emmeans’ package in R. Key insights are derived by examining the emmean values, which are presented on a logit scale. In our coding scheme, ‘1’ represents natural gas and ‘0’ represents electric heating. If emmean is High Positive emmean Values, these indicate a strong preference for natural gas as the heating source over electric heating. The higher the emmean value, the stronger the preference for natural gas. On the contrary, low Positive or Negative emmean Indicates a lower preference or a preference for the alternative heating source.

Referring to Table 1 in the appendix, we observe a range of emmean values, moving from 1.442 to 0.501. This trend indicates a significant shift in heating energy source preferences from natural gas to electric. The decrease in emmean values suggests that over the categories or conditions being analyzed, there is a gradual but noticeable movement towards a preference for electric heating over natural gas.

## 5 Conclusion

As we examine the trend across different construction eras, a clear pattern emerges: with the advancement towards modern times, there is a notable increase in the preference for electricity in the overall energy mix used in buildings. The increasing dominance of electricity in the energy mix of modern buildings is a multifaceted phenomenon, driven by advancements in technology, economic shifts, environmental concerns, and changing social norms. This trend is likely to continue, with electricity playing an increasingly central role in the energy strategies for new building constructions and renovations. As we move forward, it’s crucial for policy makers, architects, and builders to recognize and adapt to these changes, ensuring that the future of building energy is sustainable, efficient, and aligned with the global goals of reducing environmental impact.

## 6 Appendix

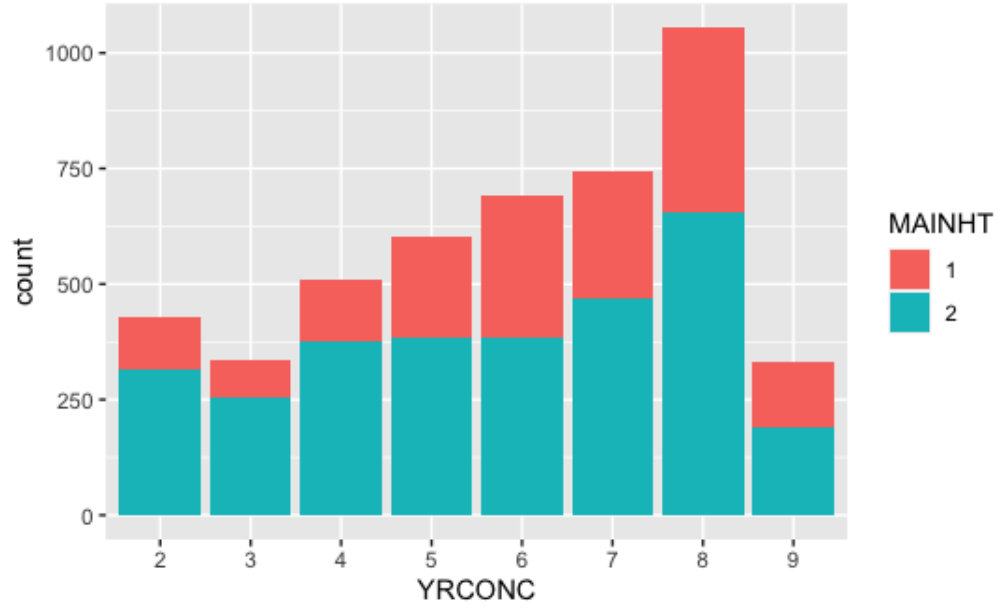


Figure 1: Number of Building use different mainheat in different year.

YRCONC	emmean	SE	df	asymp.LCL	asymp.UCL
2	1.442	0.168	Inf	1.114	1.771
3	1.390	0.181	Inf	1.035	1.745
4	1.317	0.159	Inf	1.005	1.629
5	0.868	0.149	Inf	0.575	1.161
6	0.551	0.146	Inf	0.266	0.837
7	0.743	0.146	Inf	0.457	1.030
8	0.670	0.139	Inf	0.397	0.943
9	0.501	0.167	Inf	0.174	0.827

Table 1: EMMEANS results.