Estimating Energy Savings from Energy Renovations in Dutch Residential Buildings

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Abstract

The building sector is one of the largest consumers of energy and a major contributor to greenhouse gas emissions. Improving the energy efficiency of buildings is therefore critical to reducing environmental impacts and achieving the climate targets set by the European Green Deal. In this context, energy renovations, such as insulation upgrades and heating system improvements, are widely promoted as a key strategy. However, there remains considerable uncertainty around the actual energy savings achieved in practice, partly due to performance gaps and behavioral rebound effects. This thesis aims to quantify the real-world impact of energy-efficient renovations on residential gas consumption in the Netherlands, focusing on older dwellings constructed before 1980.

Utilizing data from the WoON 2018 housing survey, which includes detailed data on dwellings and households, the study employs a multiple linear regression model to isolate the effect of renovations on energy use. By comparing the energy consumption of similar renovated and non-renovated dwellings using statistical methods, this study leverages real-world data to estimate the extent to which renovations reduce energy consumption. The research addresses the influence of occupant behavior and other contextual factors, aiming to provide robust estimates of energy savings attributable to renovations.

The results show that a one-unit improvement in thermal quality, roughly equivalent to upgrading three energy label classes, is associated with a 16.4% average reduction in annual gas consumption. Interestingly, the effect of renovations increases with higher thermal quality levels, contrary to the expectation of diminishing returns. In contrast, differences in gas consumption among homes rated between label G and D are not statistically significant. A national policy scenario, in which all dwellings are upgraded to label D, is estimated to reduce total residential gas consumption by only 0.8–1.3%, and by 1.4–2.3% within the sample. A robustness check incorporating thermostat temperature reveals signs of a rebound effect, suggesting that improved efficiency may lead to increased usage or comfort gains that offset part of the savings.

These findings have important implications for energy and climate policy. First, they underscore the need for ambitious renovation standards, as moderate improvements may yield limited savings. Second, they raise concerns about the effectiveness of using label D as a regulatory or subsidy threshold. Finally, the results support more nuanced cost-benefit evaluations and the targeting of deeper retrofits in older buildings to achieve meaningful reductions in energy use. Overall, this study contributes empirical evidence to inform the design and evaluation of renovation policies aimed at transitioning the residential sector toward near-zero energy buildings by 2050.

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Chapter 1

Introduction

The building sector is a significant consumer of energy and a major source of greenhouse gas emissions. In response, the European Green Deal highlights the building sector's central role in meeting climate targets, notably through initiatives such as the Energy Performance of Buildings Directive (EPBD) (European Commission, n.d.). Improving energy efficiency in buildings has become a critical goal not only for reducing environmental impacts but also for improving indoor comfort and living conditions, both in new construction and in the existing building stock.

Focusing on new buildings alone, however, is insufficient. Buildings are long-lasting structures, and opportunities for (deep) energy renovations are often limited, costly, or disruptive. This raises the risk of becoming 'locked in' to inefficient buildings (Grubb et al., 2014).

Since the majority of buildings that will contribute to emissions in 2050 are already built (Giandomenico et al., 2022), it is essential to understand the energy-saving potential of renovations. Addressing the performance of the existing building stock is thus a critical step toward achieving a climate-neutral, nearly zero-energy building standards by 2050.

1.1 Situation in the Netherlands

Each winter, millions of Dutch households rely on natural gas to heat their homes, cook meals, and take hot showers. While this dependence once reflected the abundance of domestic gas reserves, it has become a pressing environmental and geopolitical concern. As part of its climate strategy, the Dutch government is now working to phase out gas for residential heating in favor of more sustainable alternatives such as all-electric systems. Such a transition is only viable if dwellings are sufficiently insulated. Without adequate thermal performance, electric heating becomes inefficient and costly (Milieu Centraal, n.d.-b). Improving insulation is therefore a critical precondition for reducing energy demand and enabling a shift to low-carbon heating technologies.

To support this transition, the Netherlands has implemented policies aligned with the European EPBD. One key instrument is the energy label, which classifies dwellings based on their thermal efficiency and provides residents with guidance on potential improvements. Newly built homes must meet strict energy performance standards (Rijksdienst voor Ondernemend Nederland, 2024), and from 2030 onward, all rental properties will be required to meet minimum efficiency thresholds (Rijksoverheid, 2025). At the core of these efforts lies the enhancement of thermal quality, through better insulation, improved ventilation, and efficient heating systems.

1.2 Uncertain Impact of Energy Renovations

Despite strong policy backing and high expectations, the actual energy savings achieved through renovations remain a subject of debate. While engineering models often predict large reductions, real-world studies consistently find more modest outcomes, a discrepancy known as the energy performance gap (Zou et al., 2018). In existing research, the direction of the renovation effect is consistent with theory and expectations, but the magnitude of the effect appears modest. This gap raises important questions about the cost-effectiveness and climate impact of renovation-based policies.

In European policy frameworks, energy renovations are widely promoted as a multi-benefit solution. They are expected to reduce energy bills, enhance indoor comfort, and contribute to climate mitigation. These expectations have been institutionalized through instruments like the Dutch energy labels (internationally known as energy performance certificates).

Economic theory suggests that well-insulated buildings should lead to lower energy bills and reduced emissions, aligning environmental goals with private financial incentives (Grubb et al., 2014). However, the limited uptake of renovations and the modest results seen in empirical data suggest that these benefits may be smaller or less certain in practice. More reliable, data-driven estimates of realized savings are needed to assess whether current policies are delivering meaningful results, and whether they can support the transition to a climate-neutral housing stock. Clear comparisons of energy consumption data can also enhance transparency and raise awareness about the benefits of energy-efficient renovations, motivating more homeowners to invest in these improvements.

The implications of the performance gap are far-reaching. If actual energy savings are substantially lower than projected, the cost per unit of avoided carbon may be higher than assumed, challenging the rationale behind existing renovation subsidies. In a context of limited public budgets and competing climate priorities, accurate estimates of realized savings are essential for identifying the most effective policy mix.

1.3 Research Objective

This thesis aims to empirically determine the real-world impact of energy renovations on residential gas consumption in the Netherlands. In particular, the study focuses on gas-heated dwellings built before 1980, a segment of the housing stock that is especially relevant for renovation policies because of its low baseline energy efficiency.

Using household-level data from the 2018 WoON survey, the research quantifies how improvements in thermal quality affect gas usage. By applying a robust multiple regression framework that controls for key dwelling, household, and behavioral characteristics, the analysis isolates the causal relationship between energy renovations and gas consumption.

Grounding the study in actual data rather than theoretical models, this research contributes to a realistic and reliable understanding of how renovation measures translate into energy savings. In addition, the estimated relationship will be used to analyze the gas savings for the scenario in which all dwellings are upgraded to meet a minimum energetic quality (energy label D). These projections will help assess the cost-effectiveness of such mandates and support evidence-based policy-making in the area of residential energy efficiency.

1.4 Reading Guide

This thesis is structured as follows. Chapter 2 reviews the relevant literature on residential energy use, energy efficiency, and the impacts of renovations. Chapter 3 describes the empirical strategy, including the regression model and the selection of variables. Chapter 4 outlines the data, sample selection, application of survey weights, and the operationalization of variables. Chapter 5 presents the main findings, including both descriptive statistics and regression results. Projected energy savings are also calculated, and robustness checks are performed. Chapter 6 discusses the findings in relation to existing research, and reflects on the limitations of the study. Finally, Chapter 7 concludes with policy implications and suggestions for future research.

Chapter 2

Literature Review

This chapter synthesizes the academic literature related to residential energy efficiency, with a focus on the effectiveness of energy renovations in reducing energy consumption. It outlines theoretical and empirical insights on barriers to energy efficiency, the effectiveness of retrofit policies, the determinants of household energy demand, and the role of information instruments such as energy labels.

2.1 Residential Energy Consumption in the Netherlands

Households in the Netherlands account for a significant amount of the total energy consumption. Residential energy use comprises several key end-uses, including space heating, space cooling, water heating, lighting, cooking, and appliances (International Energy Agency, 2014).

The main residential energy consumption consists of natural gas and electricity. In 2016, natural gas was used mostly for space heating (78%), followed by warm water (20%), and cooking (2%). In 2021, the total residential energy consumption consisted of 71% natural gas, 16% electricity, 3% district heating, and 10% renewable energy (Compendium voor de Leefomgeving, 2023). At the start of 2019, over 90% of dwellings use gas for their main heating system, and only a few percent of dwellings do not use any gas (Centraal Bureau voor de Statistiek, 2021).

2.1.1 Gas-Powered Heating Systems

There are two gas-powered heating systems commonly used: gas heaters and central heating boilers. Gas heaters offer local heating, only heating up the air around the heater itself, without a distribution system (Martinopoulos et al., 2018). In central heating systems, water is heated by the boiler and distributed throughout the whole house. Over eighty percent of dwellings in the Netherlands are heated by central heating systems (Centraal Bureau voor de Statistiek, 2024). According to Milieu Centraal (n.d.-a), gas heaters are less efficient than central heating boilers, leading to a higher gas consumption and more emissions.

2.2 Barriers to Energy Efficiency Investments

Improving energy efficiency, defined broadly as achieving the same or better comfort (e.g., indoor temperature) with less energy input, is widely seen as a cost-effective climate mitigation measure. In the building sector, this typically involves retrofits that enhance thermal performance. A wide range of thermal energy renovation measures and concepts exists, which are often classified based on their scope and depth.

A common distinction is made between shallow and deep energy retrofits (Fasna & Gunatilake, 2019; Zhivov & Lohse, 2020). Shallow retrofits typically include relatively low-cost, limited interventions, such as replacing windows or improving insulation in specific areas. These upgrades can yield modest energy savings, often corresponding to a shift of one or two energy label classes. In contrast, deep retrofits involve comprehensive renovations that aim to significantly reduce a building's energy demand, such as full envelope insulation, and are typically associated with a jump of multiple energy label classes.

Renovation measures can also be defined as a change in at least one dwelling property (e.g., heating system, ventilation, window quality) from one category to a 'better' one (Filippidou et al., 2019). Policy frameworks like the European Green Deal emphasize renovation as a key strategy, citing both environmental and social benefits such as lower energy bills and improved living conditions (European Commission, n.d.).

According to an analysis by McKinsey & Company (2009), thermally renovating domestic buildings should have a net negative cost, meaning that the financial savings from reduced energy use are expected to outweigh the upfront investment over time, resulting in overall net savings. However, the uptake of renovations remains limited. As Grubb et al. (2014) describe, buildings are long-lived and often resistant to change, especially when renovations are costly, disruptive, or poorly incentivized. This creates the risk of being 'locked in' to an inefficient building stock unless targeted action is taken.

Some barriers that help to explain the underinvestment in energy efficient renovations include (upfront) financial costs, market failures, and behavioral factors (Solà et al., 2020). An example of a potential market failure is split incentives, where the landlord has to facilitate the renovations while they may not get the benefit themselves (Grubb et al., 2014). In the Netherlands this might not be fully applicable, as energetically better performing dwellings receive a premium, and thus do benefit the landlord (Brounen & Kok, 2011). An example of a behavioral factor is that consumers take a relatively short-term view, and are risk-averse (Grubb et al., 2014). When there are uncertain returns (unknown payback time) on spending their resources on renovations, combined with the discomfort of having them implemented, they are inclined to stick to the status quo (Li et al., 2019).

Policies are being designed to address these failures and try to promote investing in energy-efficiency upgrades (Solà et al., 2020). To address financial barriers, fiscal measures can be taken, such as providing subsidies and low-interest loans. Energy performance certificates can help to increase access to trustworthy information regarding energetic renovations, reducing some of the risk. Reliable estimated energy savings can drive people to undertake renovations (Guerra-Santin et al., 2021).

2.2.1 Energy Labels

The European Energy Performance of Buildings Directive (EPBD) mandates that member states establish energy performance standards and a certification scheme for existing buildings. The Netherlands implemented its energy labelling scheme in 2008. The Dutch energy label is based on a theoretical energy consumption calculation (Majcen et al., 2013a). This refers to an estimated amount of energy a dwelling would use under standardized conditions, rather than the actual energy consumed by occupants. In other words, it predicts energy use based on the physical characteristics of the dwelling, not on real-life usage patterns or household behavior.

The calculation method for the energy index, described in ISSO 82.3 (NEN 7120), is based on a steady-state method.[1] It considers building characteristics such as insulation levels, ventilation method, and the efficiency of the heating system. To ensure consistency across dwellings, the calculation also applies standardized assumptions for occupant behavior, such as internal temperature settings, shower frequency, and occupancy density (e.g., number of residents per square meter) (Centraal Bureau voor de Statistiek, 2016). As a result, the energy index reflects a theoretical estimate of energy performance under typical conditions, based on simplified and standardized representations of energy use in homes (Hoogervorst, 2024).

Large databases containing energy index data exist in the Netherlands, and can often be combined with actual energy consumption data. Rovers and Tigchelaar (2022) investigated the insulation grade in Dutch dwellings. They found that the insulation grade decreased consistently with lower energy labels (i.e., higher energy index), as expected. In this thesis, renovations are defined as all actions that reduce the energy index, a variable that empirically reflects improvements in the underlying thermal quality of the dwelling.

The energy label category, ranging from A++ (best) to G (worst), is determined by the energy index, as shown in Table 2.1 (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (BZK) & Centraal Bureau voor de Statistiek (CBS), 2019b). The energy index (or label) is an indication of the expected energy consumption of the dwelling. In the context of this research, energy labels represent the energetic quality of the dwelling. By comparing similar dwellings with different energy labels, the study aims to assess the impact of energy renovations. Findings will show how improvements in energy index (or labels) influence energy consumption in the dwelling.

[1] In 2021, the standard to determine the energy label was updated. However, the data used for this thesis uses the previous version, which is described here.

Table 2.1: Conversion from Energy Index to Energy Label

Energy Label	Energy Index
A++	$\leq$ 0.60
A+	0.61 - 0.80
A	0.81 - 1.20
B	1.21 - 1.40
C	1.41 - 1.80
D	1.81 - 2.10
E	2.11 - 2.40
F	2.41 - 2.70
G	$>$2.70

2.3 Key Determinants of Residential Gas Consumption

Actual energy consumption, particularly gas consumption for heating, is determined by a combination of factors. Besides factors contained within the energy label calculation, other factors also play a role. Typically, they can be distinguished as being either dwelling or household characteristics.

Brounen et al. (2012) distinguish between technical and demographic variables. Their results indicate that gas consumption is determined by both kind of variables. They also included a regression model containing a variable representing the insulation quality, suggesting there are diminishing renovation effects. Upgrading from the worst insulation level to one better, leads to approximately 3% less gas per capita use, while upgrading dwellings that are already somewhat insulated lead to smaller gas reductions. Significant factors are dwelling size, number of rooms, dwelling type, period of construction, maintenance, insulation quality, gender, number of residents, age, income, and family composition.

In a large-scale Dutch study comparing theoretical and actual gas consumption, Majcen et al. (2013b) conducted separate regression analyses to examine the determinants of each. They found that variables such as floor area, ownership status, income, and house value were significant predictors of actual gas consumption, but were largely insignificant or had only a minor influence on theoretical consumption. This reflects the fact that theoretical values are deterministically calculated based on standardized assumptions, which exclude occupant behavior and socio-economic characteristics.

Regarding energy behavior, younger people shower more often and for longer periods of time, and use the bath (if present) more often than older residents (Rovers & Tigchelaar, 2022). Furthermore, older residents prefer a higher indoor temperature, leading to higher energy consumption (Wei et al., 2014).

2.4 Effectiveness of Retrofitting Programs and Policy Design

Many papers are written about the energy performance gap, the discrepancy between theoretical and actual energy consumption (Zou et al., 2018). Studies have identified a range of reasons for this gap such as technical limitations and (p)rebound effects. Technical limitations refer to situations where the implementation of (renovation) measures is suboptimal, resulting in construction defects or deficiencies in execution. The rebound effect occurs when people increase their energy consumption following efficiency improvements, due to lower energy costs, thereby potentially offsetting part of the (theoretical) energy savings (Sorrell et al., 2009). The prebound effect is the opposite, where people consume less energy than predicted in low-efficiency dwellings because of high energy costs, leading them to consciously limit their energy use (Sunikka-Blank & Galvin, 2012).

In the Netherlands, comparison of actual and theoretical gas consumption per energy label consistently shows that energy-efficient buildings (labels A-B) consume more gas than theoretically expected, while buildings labeled as inefficient (C-G) consume less gas than expected (Majcen et al., 2013a; Van Den Brom et al., 2018; Visscher, 2017).

Van Den Brom et al. (2018) studied nearly 90,000 thermally renovated Dutch rental dwellings, finding that actual energy savings were consistently lower than expected. Especially energy savings for buildings with low energy efficiency before renovation were not well predicted, which is partly attributed to behavioral changes post-renovation. The rebound and prebound effect are found for the Dutch (social) housing stock (Majcen et al., 2015; Van Den Brom et al., 2019). These effects result in actual savings being less than predicted.

A report by the Netherlands Environmental Assessment Agency (PBL) analyzed gas consumption across 6.2 million dwellings (Van Den Wijngaart & Van Polen, 2020). The study estimated that renovations lead to approximately a 10% reduction in gas consumption when dwellings with poor energy labels are upgraded to label D, and around a 20% reduction when they are upgraded to label B. To derive these estimates, the authors used linear regression models to predict gas consumption per energy label, controlling for dwelling type and total floor area. After fitting these models, they assumed that when a dwelling is renovated, its gas consumption shifts to the predicted value associated with the target energy label.

Araya Mejías et al. (2021) analyzed energy savings in 25 British and Italian dwellings, finding significant deviations from expected savings, which are attributed to the habits and behavior of the occupants. The UK's actual energy savings were 14% (74% lower than estimated), while Italy's were 38% (29% lower than estimated). Similarly, Liang et al. (2018) reported energy savings of only 8% for residential buildings, about 40% lower than engineering model predictions.

There is also research into the effects of residential energy efficiency retrofit programs. Giandomenico et al. (2022) provide a systematic review of government supported retrofitting programs, and find mostly marginal savings, dependent on the methodology of the analysis. For more strict research designs (e.g., randomized control trials instead of observational data), more modest estimates are found. The average reduction in energy consumption due to renovations was roughly 7%.

Above studies show that the majority of energy renovations, on average, result in lower energy savings than initially expected. Hoogervorst (2024) mentions that there is relatively little well-founded information on the energy savings achieved in practice from insulating existing dwellings. The theoretical energy consumption is used by policymakers to determine energy saving targets, develop policies, monitor the housing stock, determine rent limits, and assign subsidies (Filippidou et al., 2017). Therefore, correctly calculating these actual savings is considered essential for quantifying the (potential) success of energy efficiency projects.

2.5 Knowledge Gap

There are multiple studies on gas reductions due to renovations. Some studies explicitly aim to identify causal effects on energy efficiency measures (Fowlie et al., 2018; Liang et al., 2018). These studies emphasize the importance of isolating the impact of renovations from confounding factors. For instance, Fowlie et al. (2018) argue for building a credible body of evidence on the actual returns of energy efficiency investments.

However, many other papers do not have this explicit goal. Instead, they focus on explaining or quantifying the energy performance gap, the difference between theoretical and actual energy consumption, without addressing whether the estimates reflect causal impacts. For example, the paper by Majcen et al. (2013a) compares the average actual and theoretical gas consumption of dwellings with different energy labels in the Netherlands. They find that homes with label A consume on average 28% less gas than homes with label G, while the theoretical models predict a 70% reduction. Although this difference is informative, it is not a causal estimate, as it does not account for confounding factors such as dwelling size, occupant behavior, or socio-economic characteristics. Their analysis is based on differences in mean consumption and does not control for other variables that might influence energy use. This illustrates the knowledge gap: many widely cited estimates of energy savings are based on correlations rather than well-identified causal effects.

The academic literature lacks studies on energy renovations in the Netherlands that adopt an explicit causal approach. By explicitly setting the goal to estimate a causal effect, and adapting the model design accordingly, effect estimates become more credible. This thesis will differ from existing research by explicitly discussing the causal interpretation of the estimated renovation effect. Furthermore, this thesis will analyze the non-linearity of the renovation effect. To the author's knowledge, non-linear effects have not been explicitly examined and discussed in Dutch empirical research.

Many papers about residential energy consumption in the Netherlands use databases including only social housing. For this thesis, the WoON survey, a national residential survey, is used that also includes owner-occupied and privately rented dwellings. It includes building, household and behavioral characteristics, that all influence energy consumption. Often, the data from these three categories is not readily available or only on an aggregated level. For the WoON survey this data is available on a household level.

Because energy labels are valid for multiple years after they are issued, they are not necessarily representative of the actual state of the dwelling. Renovations could have taken place without a new energy label being issued or the execution of the personal recording of the home by an energy advisor may be flawed. Another benefit of this dataset is that the energy labels are up to date, since the home recording is a part of the survey. The credibility of the energy index measurements is also very high due to the survey design.

In conclusion, the knowledge gap identified is that there are not many empirical studies estimating the causal effect of energy renovations. The literature on energy renovations in the Netherlands does not appear to include studies that employ an explicit causal design or explicitly discuss non-linearity of the renovation effect. Moreover, many studies on Dutch residential energy consumption focus solely on social housing and include only a limited set of variables, which restricts the generalizability of their findings. Finally, while some papers do estimate potential energy savings under various scenarios, these are typically based on correlational or theoretical analyses rather than causal inference.

2.6 Research Question

This thesis aims fill the identified knowledge gap by providing empirical evidence on the effectiveness of energy renovations in Dutch residential buildings, with a particular focus on estimating their causal impact on energy consumption. The study contributes to the literature by adopting an explicit causal framework, analyzing the potential non-linearity of renovation effects, and thoroughly discussing and analyzing the reliability of its findings. To guide this analysis, the central research question is:

How do energy renovations influence the energy consumption of Dutch residential buildings?

Evaluating the actual performance of energy renovations requires robust methodologies using actual measured data. Reliable data is available in the WoON national housing survey. However, causal identification is challenging. Self-selection into renovations or efficient homes may bias estimates. Some households may value energy savings more, leading them both to renovate and to reduce consumption behaviorally, inflating measured effects. This study uses a multivariate regression approach to address these issues, while acknowledging that it cannot be fully ruled out that some important factors may still be missing from the data.

Statistical models such as linear regression are widely applied to model the relationship between energy consumption (specifically gas for heating) and various influencing factors, and to quantify savings. Linear regression is suited to identify a causal effect using the type of data available (Wooldridge, 2020). The underlying hypothesis is that energy renovations have a quantifiable (non-zero) effect on gas consumption.

The central argument is that improved thermal quality leads to measurable reductions in gas consumption, even after accounting for structural, demographic, and behavioral factors. While causality is inherently difficult to establish using cross-sectional data, the approach taken here focuses on isolating the variation in gas consumption that can plausibly be attributed to differences in thermal quality. The underlying assumption is that, conditional on observed variables, differences in gas use between otherwise similar households can be attributed to differences in thermal quality.

To answer this research question, first, the thermal quality distribution will be analyzed. The variation of gas consumption due to thermal quality will be examined. Then, using a regression model that controls for relevant factors, the causal effect of thermal quality on gas consumption will be estimated, i.e., the effect of renovations. Finally, energy savings will be projected using a scenario based on current policy goals, using the estimated causal effect.

Chapter 3

Methodology

This research adopts a statistical approach to assess the impact of energy renovations on residential gas consumption in older Dutch dwellings. The analysis focuses on the relationship between thermal improvements, captured through the energy index, and gas consumption. By utilizing regression models, the research aims to estimate energy savings in homes that underwent renovations compared to similar dwellings that did not. To process and analyze the data, the statistical software R is used, which offers extensive support for statistical methods.

3.1 Linear Regression

Linear regression is a statistical technique used to mathematically model the relationships between variables. Statistics often explore and summarize relationships between variables by identifying trends, patterns, and correlations. Statistics can also be used for prediction, for which linear regression is a suited technique. For example, energy consumption might be predicted based on household characteristics and dwelling features. Using a linear regression model, outcomes for unknown or unseen data points can be estimated by analyzing patterns in existing data.

Linear regression is not only a tool for prediction but also for uncovering causal relationships, determining whether changes in one variable (e.g., energy efficiency of a dwelling) cause changes in another (e.g., gas consumption). However, establishing causality is more complex than identifying correlations. To ensure the estimated effect can be interpreted as a causal effect, it is important to think carefully about which variables are included in the model. This will be explained in Section 3.2.

A linear regression model typically looks similar to Equation 3.1. The equation prescribes the relationship between the dependent variable Y and the predictor (or independent) variables $\vec{X}$. When this model is fitted to data, coefficients $\vec{\beta}$ are estimated for each independent variable, quantifying their effect on the dependent variable. $\vec{X}$ and $\vec{\beta}$ are respectively the vector containing all independent variables and the vector containing their (estimated) coefficients. These coefficients are accompanied by significance levels p, indicating the statistical significance.

Regression coefficients are interpreted ceteris paribus, meaning that the estimated effect of a variable reflects changes while holding all other factors constant. There is one coefficient, the intercept β_0, that is not related to the effect of independent variables, but rather represents the average value of the dependent variable when all the independent variables are zero. Finally, there is an error term ϵ that captures the deviation of the observed values from the predicted values. It accounts for the variability in Y that cannot be explained by the predictor variables. That is, it represents the influence of all other factors that affect Y but are not included in the model.

The sum of squared error terms is minimized during the regression analysis to find the best-fitting line. Smaller error terms indicate a better fit of the model to the data. Generally, the regression results also show the R-squared (R^2), a goodness-of-fit measure of how well the independent variables explain the dependent variable. R-squared ranges from 0, where none of the variation in Y is explained by the $\vec{X}$, to 1, where all of the variation is explained, and Y is perfectly predicted. Although the R-squared gives an indication of how well the model fits the data, a high R-squared is not necessary to infer causality.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \epsilon \tag{3.1}$$

- Y: Dependent variable (outcome of interest)
- $X_1, X_2, ..., X_n$: Independent (or predictor) variables
- β_0: Intercept term (constant)
- $\beta_1, \beta_2, ..., \beta_n$: Coefficients representing the effect of each independent variable
- ϵ: Error term, capturing unexplained variation in Y

For causal inference, the goal is to estimate the effect of a primary causal variable of interest, usually X_1. Only the accompanying coefficient β_1 can be interpreted causally, and only when the correct variables are included in the model. To achieve causal interpretation, it is crucial to ensure that the model accounts for all relevant factors that could confound the relationship between the dependent and independent variables. Confounding would occur when a variable that influences both the dependent and independent variables is not included in the model, leading to distorted associations. For this study, the causal variable of interest X_1 is the thermal quality of the dwelling, as defined by the energy index or the energy label. The goal is to identify the causal effect of the thermal quality on the gas consumption (the dependent variable Y), i.e., estimating β_1.

3.1.1 Approach

Using linear regression models, this study aims to evaluate the relationship between energy renovations and gas consumption, providing insights into the potential for energy efficiency improvements to reduce residential energy use. The main research question is to determine how energy renovations influence the energy consumption in Dutch residential buildings. Therefore, the goal is more specifically to identify the causal effect of energy renovations on energy consumption. This goal aligns with the goal to identify the causal effect of the thermal quality on gas consumption, when a suited sample is selected.

As will be explained in Section 4.1, the data that is used originates from a national housing survey representing the whole Dutch housing stock. The observations that are used to create the regression model are called the sample data. Not all data points present within the survey should be used in the sample. By using two selection criteria on all available observations an appropriate sample can be constructed:

1. **Setting a maximum cut-off construction year to make the energy index representative of renovations:**

   By selecting only dwellings constructed before the cut-off year, only older dwellings will be present within the sample. Modern homes typically have higher construction quality and adhere to stricter energy standards. Consequently, when modern homes have a good energy index it is likely due to their original construction rather than subsequent renovations. In contrast, for older homes, a good energy index most likely reflects energy renovations, as these dwellings were originally built with poor thermal quality. Therefore, within the context of this study, the energy index indirectly represents the extent of energy renovations (acting as a proxy), as favorable energy indices can only be attributed to renovations in older dwellings. The cut-off year of 1980 is decided based on the data, and will therefore be explained in Section 4.2.1 of the Data chapter.

2. **Selecting only gas-heated dwellings:**

   The energy consumption for heating of dwellings that have undergone substantial renovations need to be compared with those that have not. In the Netherlands, dwellings are primarily heated using natural gas, although other systems using wood or electricity, and district heating also occur. Gas consumption is easier to estimate for heating consumption than electricity consumption, as it has less other households uses. Electricity is integrated with many household uses, making it impossible to separate the heating consumption from that of appliances unrelated to heating. Gas also has multiple household uses, such as providing domestic hot water and cooking. The regression model can take this into account by including variables related to these uses, this will be further explained in Section 3.3.3. Furthermore, it would not be feasible to compare both gas and electricity consumption for heating, and there might not be any observations of old, electrically heated dwellings. Therefore, the analysis is limited to gas-heated homes to facilitate comparing heating energy consumption. The implementation of this restriction is discussed in Section 4.2.2.

Interpretation

By using ordinary least squares regression models, hypotheses can be tested. When the coefficient of a variable is statistically significant, that means the probability of observing the data is very small if the variable would in reality not have an effect. The reported significance levels denote whether the probability is smaller than 10%, 5%, or 1% ($p \leq 0.1$, 0.05, or 0.01). The regression results provide insight into whether a variable has a significant effect on the dependent variable, and presents an estimated magnitude of the effect.

Linear regression is chosen due to its simplicity and ability to estimate causal relationships in observational data, provided that model assumptions are met. To ensure valid statistical inference despite potential heteroskedasticity, when the variance of the error term is not constant across observations, heteroskedasticity-robust standard errors are used. The main hypothesis that will be tested is that gas consumption varies (continuously) with changes in energy efficiency as captured by the energy index.

A key challenge to causal interpretation in regression analysis is endogeneity, which arises when an independent variable is correlated with the error term. One potential source of endogeneity is omitted variable bias, where unobserved factors (variables not included in the model) influence both the thermal quality of the dwelling and gas consumption, i.e., omitting a confounding variable from the model as will be explained in Section 3.3.3. For example, environmentally conscious households may be more likely to renovate their homes and also tend to use less gas, creating a spurious correlation. To mitigate omitted variable bias, control variables are carefully selected based on the causal graph, as explained in Section 3.3. Additionally, restricting the sample to homes built before 1980 helps control for changes in construction standards that could otherwise confound the relationship.

3.2 Directed Acyclic Graph

Directed Acyclic Graphs (DAGs) are a valuable tool in statistical research, particularly for causal inference. They illustrate the assumed causal relationships among variables in the model. A DAG represents beliefs about how the variables are related, based on common sense and insights from the literature. A DAG consists of nodes (representing variables) and directed edges (representing causal links), arranged so there are no feedback loops. This structure allows the mapping of theoretical relationships between variables, making explicit assumptions about causality that might otherwise remain implicit.

By visualizing the relationships, the DAG helps identify which variables need to be included as controls in the regression model to mitigate confounding and clarify other sources of bias (Rohrer, 2018). For instance, controlling for confounding variables is crucial to isolate the causal effect of the energy index on gas consumption. Failure to account for confounders that influence both the independent and dependent variables can lead to biased estimates.

In this study, the DAG is an integral part of the modeling strategy. It serves as a guide to select appropriate control variables and ensures that the regression model captures the true causal pathway. For example, variables such as household size and income, which may affect both energy efficiency and gas consumption, must be controlled for to ensure that the effect of the energy index is estimated accurately. Furthermore, the DAG emphasizes the importance of avoiding over-controlling. This balance is key to maintaining the validity of the model while improving its interpretability. By systematically structuring and evaluating the relationships between variables, the DAG enhances both the transparency and robustness of the causal analysis. The DAG is shown in Figure 3.1. The assumed causal relationships are explained below:

1. Dwelling characteristics, such as dwelling type and construction period, influence the thermal quality. For example, older dwellings are more likely to be built with bad isolating materials and construction techniques, leading to a lower thermal quality. The specific dwelling characteristics considered are described in Section 3.5.1.

2. Provincial differences can influence dwelling characteristics due to varying historical construction practices, regional regulations, or climate considerations across the Netherlands.

3. Household characteristics influence the thermal quality of the dwelling. Especially for owner-occupied dwellings, the residents have decided over renovations in the past, determining the current thermal quality. There may also be a relation for rental properties, as households may prefer to rent better insulated dwellings based on their behavior or environmental attitudes. Household characteristics will be specified in Section 3.5.2.

4. Household characteristics influence dwelling characteristics. Households select dwellings based on their preferences and needs. Although some preferences may be personal and have no systematic effect, some preferences are likely to be structural. For example, the number of residents influencing the area of the dwelling.

5. The thermal quality is a direct predictor of gas consumption among the selected sample of gas-heated dwellings. Higher thermal quality, reflected in a lower energy index, leads to lower gas consumption.

6. Some dwelling characteristics directly influence the gas consumption, independently of the overall thermal quality. For example, the presence of a bath may increase hot water use and, therefore, gas consumption, even if the thermal quality is otherwise favorable.

7. The province represent the geographical location. In the Netherlands there are significant climate and temperature differences between provinces. Colder provinces typically experience higher heating demands, resulting in higher household gas consumption.

8. Household characteristics such as the income, energy-related behavior and attitudes, age composition, and number of residents directly influence gas consumption of a dwelling. For example, larger households generally consume more gas, and higher-income households may be less sensitive to heating costs, resulting in higher gas use regardless of the dwelling's energy efficiency.

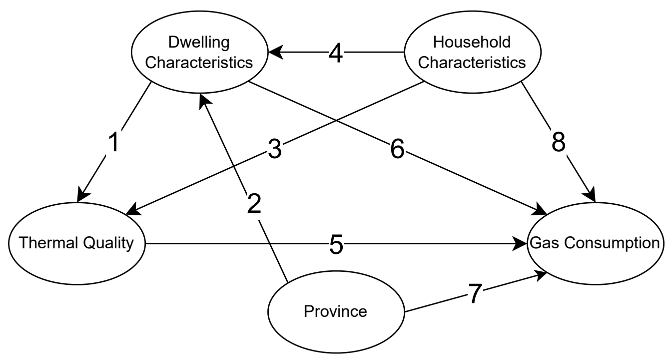

Figure 3.1: Directed Acyclic Graph

Diagram of the causal relations determining the gas consumption of a dwelling. The arrows indicate causal relationships.

3.3 Selected Variables

3.3.1 Dependent Variable: Gas Consumption

The dependent variable in this study is gas consumption, which is a direct indicator of household energy usage for heating purposes. To make estimates less prone to outlier influence and allow for easier interpretation of the regression coefficients, the natural logarithm of gas consumption is used as the dependent variable in the regression models. Using a log-transformed dependent variable allows the regression coefficients to be interpreted as percentage changes in gas consumption, which is more intuitive when examining factors like renovations and household characteristics.

3.3.2 Causal Variable of Interest: Thermal Quality

The primary independent variable, or the causal variable of interest, is the thermal quality (TQ). The thermal quality is based on the measured energy index of the dwelling. The energy index serves as a measure of the dwelling's thermal efficiency, reflecting how well the house retains heat. A lower energy index indicates a more energy-efficient home. Given that the sample consists of older homes (built before 1980), the energy index serves as a proxy for the extent of energy renovations, as older homes with lower energy indices are those that have undergone significant improvements.

To enhance interpretability, the energy index is transformed into a thermal quality measure according to Equation 3.2. The estimated coefficients are interpreted as the percentage change in gas consumption given a one-unit increase in the accompanying variable. For the energy index, a one-unit increase is illogical, as this would represent a decrease in thermal quality. Using the thermal quality ensures that higher values correspond to better thermal performance, which aligns with the expected direction of energy efficiency improvement. Specifically, the scale is reversed such that the highest (i.e., worst) energy indices present in the sample data correspond to the lowest thermal qualities. The estimated coefficient for thermal quality thus indicates the percentage change in gas consumption resulting from an improvement in thermal efficiency, making interpretation more intuitive and aligned with the study's objectives.

$$\text{Thermal Quality} = 5 - \text{Energy Index} \tag{3.2}$$

The continuous thermal quality (or energy index) can be converted to the categorical energy label (A to G), which is more commonly known. For this study, the thermal quality is chosen as the main causal variable of interest for the main models. When using the thermal quality, there is no information loss coming from discretization, which happens when a continuous variable is collapsed into categories. However, using the thermal quality, the functional form, the mathematical relationships describing the model, has to be prescribed. In contrast, when using a categorical independent variable the effects between adjacent labels do not necessarily need to follow a polynomial equation (or other prescribed function). It should be noted that the conversion between thermal quality and energy label is not strictly linear, as can be seen in Table 3.1, and some energy labels cover a broader range than others. In alternative models, this categorical version of the thermal quality, the energy label, is used as the independent variable.

3.3.3 Control Variables

The focal relationship of the research is the causal effect of the thermal quality X on the gas consumption Y. Confounding variables influence both the causal variable of interest X and the dependent variable Y. When omitting confounders from the model, spurious relationships can be found, showing an association between X and Y that is in reality due to the confounding variable.

For example, household characteristics such as the income influence both X and Y. As-

Table 3.1: Conversion between Energy Label, Energy Index, and Thermal Quality

Energy Label	Energy Index	Thermal Quality	Range Size
A++	≤ 0.60	≥ 4.40	
A+	0.61 - 0.80	4.20 - 4.39	0.2
A	0.81 - 1.20	3.80 - 4.19	0.4
B	1.21 - 1.40	3.60 - 3.79	0.2
C	1.41 - 1.80	3.20 - 3.59	0.4
D	1.81 - 2.10	2.90 - 3.19	0.3
E	2.11 - 2.40	2.60 - 2.89	0.3
F	2.41 - 2.70	2.30 - 2.59	0.3
G	>2.70	<2.3	

suming income positively influences the thermal quality (more resources available for renovations) and positively influences gas consumption (more resources means less sensitive to energy costs), this will create a positive association between X and Y that is due to income, leading to a biased estimate. Therefore, controlling for the income is important to estimate the causal effect of the thermal quality. Including the confounding variable income reduces the bias of the estimate.

To allow for unbiased estimation of the causal effect, all confounders need to be controlled for (i.e., included in the model). Looking at Figure 3.1, at least all dwelling and household characteristics influencing both the thermal quality and gas consumption should be included in the model to minimize the bias of the estimate.

In addition to controlling for confounders, competing exposures are also controlled for. Competing exposures are variables influencing the dependent variable Y that are not related to the causal variable of interest X. Including competing exposures does increase the precision of the causal inferences.

For example, the presence of a bath directly increases the gas consumption due to a higher domestic hot water usage, assuming the water is gas-heated. Including the presence of a bath does not affect the bias, as it is not associated with the energy index. However, it does increase precision of the estimated causal effect of thermal quality because the variation of gas consumption that is due to the bath is now accounted for. Hence, including competing exposures in the model reduces the variability in the outcome (gas consumption) that is not related to the causal variable of interest (thermal quality), leading to more precise and consistent causal estimates.

Therefore, control variables covering both household characteristics and building-specific features are included. By including variables that might confound the relationship between energy renovations and gas consumption, bias of the estimated effect is minimized. Controlling for other factors that influence gas consumption, besides the thermal quality, will improve precision of the estimate. Precise definitions of these variables will be given in section 4.4, after the used dataset is introduced.

3.4 Simple Regression Model

An initial simple linear regression will be performed to estimate the relationship between the thermal quality and gas consumption without accounting for other factors. Although many factors other than just the thermal quality determine gas consumption, this model serves as a baseline and offers insights into the raw association between renovations and energy use. The model is defined as in Equation 3.3.

$$\log(\text{gas})_i = \beta_0 + \beta_1 \cdot TQ_i + \epsilon_i \tag{3.3}$$

The variables labeled with an underscored i represent the value of that variable for household i. The logarithm of the gas consumption is modeled as a linear function of the thermal quality. Therefore, $\log(\text{gas})_i$ is the natural logarithm of gas consumption for household i and TQ_i is the thermal quality of the dwelling where household i lives. Because the model cannot perfectly describe the relation, an error term ϵ_i is added to represent the unexplained part of the dependent variable. The linear regression estimation method will determine the coefficients β_n to minimize the sum of the squared error terms over all households i.

The model from equation 3.3 assumes a linear relationship between the thermal quality and gas consumption. To explore potential non-linearities in the relationship, a quadratic term for the thermal quality will be added, shown in Equation 3.4. If the coefficient for the quadratic term (β_2) is statistically significant, it indicates that a nonlinear model may provide a better fit, and this functional form might be preferred over the linear model. However, even if the quadratic term is significant, if the improvement with respect to the strictly linear model is marginal, the linear model may still be preferred due to its simplicity and easier interpretation.

$$\log(\text{gas})_i = \beta_0 + \beta_1 \cdot TQ_i + \beta_2 \cdot {TQ_i}^2 + \epsilon_i \tag{3.4}$$

3.5 Multiple Regression Model

To control for the influence of confounding variables, a multiple regression model is employed. This model adjusts for household and dwelling characteristics that act as either confounders or competing exposures. The OLS model is specified in Equation 3.5.

$$\log(\text{gas})_i = \beta_0 + \beta_1 \cdot TQ_i + \vec{\gamma} \cdot \vec{B}_i + \vec{\delta} \cdot \vec{H}_i + \vec{\zeta} \cdot \vec{A}_i + \epsilon_i \tag{3.5}$$

The $\vec{B}_i$, $\vec{H}_i$, and $\vec{A}_i$ vectors represent the control variables, respectively the building, households and attitude characteristics of household i. The scalar product of these controls with their respective coefficient vectors $\vec{\gamma}$, $\vec{\delta}$, and $\vec{\zeta}$ is taken. The control variables, including an explanation of why they were included are presented below. The complete variable list including the exact definitions will be discussed in Section 4.4 of the Data chapter.

The results will be presented in a table with multiple columns, including an additional type of control variables at a time. The final column will have the regression results for the full model. Furthermore, robustness checks will be performed for the final model. By analyzing the estimates under different specifications of the model, the sensitivity to model choices can be determined. The checks will show whether the found results are consistent under relatively small changes of the model.

3.5.1 Building Characteristics ($\vec{B}$)

Several building characteristics are included:

- The total floor *area of the home* is a key determinant of gas consumption. Larger homes generally require more energy for heating, regardless of their thermal quality, due to their greater volume and surface area.
- The presence of a *bath* is included as a proxy for higher hot water usage. Households with a bath are expected to use more gas, independent of heating efficiency.
- The *construction period* of the dwelling is included to control for unmeasured changes in construction standards. Although the sample is already restricted to homes built before 1980, controlling for construction year allows accounting for incremental improvements in building standards and thermal efficiency over time. This is in line with the paper from Brounen et al. (2012), that attributes the identified relationship between building vintage and gas consumption to secular improvements in construction technology.
- The *dwelling type* is included because it influences the heat loss area of the dwelling. A detached house will on average have a much greater (fraction of the) surface area exposed to the outside environment than a terraced home or an apartment. Therefore (semi-)detached will lose more heat and thus consume more energy to keep a steady temperature.
- The presence of a *gas stove* indicates additional gas consumption for cooking. By including this variable, part of the gas consumption due to cooking can be isolated from the heating-related gas consumption.
- The geographic location, represented by the *province*, controls for regional temperature and climate differences. Coastal temperatures are often higher in winter than inland temperatures, so dwellings located in provinces along the coast will likely consume less

energy for heating than the other provinces. Furthermore, including the province can control for possible unmeasured geographical systematic differences between provinces, such as construction standards.

- Lastly, the presence of *solar panels* is included as a control variable. Although solar panels do not directly influence gas consumption, they are incorporated into the energy index (and thus also the thermal quality variable).[1] To ensure that the energy index accurately reflects the actual thermal quality of the dwelling (e.g., insulation and heat retention), it is essential to control for the presence of solar panels. By doing so, the analysis can more precisely isolate the impact of insulation and other thermal efficiency measures on gas consumption, without being affected by presence of solar panels, which primarily affect electricity generation.

3.5.2 Household Characteristics ($\vec{H}$)

Several household characteristics are included:

- *Age* of the residents may affect both energy use habits and sensitivity to indoor temperatures. For example, older individuals might prefer warmer indoor environments, leading to higher gas consumption.
- Household *income* influences the ability to afford energy-efficient renovations or dwellings. It also affects energy use behavior, higher-income households may use more gas due to less financial sensitivity to heating costs. This effect is not likely to continue linearly, as indoor temperature is not expected to rise indefinitely for increasing incomes. To allow for diminishing effects for higher incomes, the income variable is also included squared in the model.
- The *education* level of the residents captures sociodemographic differences that may correlate with energy behavior. Education level can act as a proxy for awareness of environmental issues and energy-saving behaviors. It may also be associated with the likelihood of living in more efficient homes.
- The *number of residents* is included to account for the general increase in gas consumption due to more people living in the dwelling, leading to more rooms being heated and higher overall occupancy.

[1] The NEN 7120, which was the method of determination for the energy index in 2018 is not accessible, as it is locked behind a paywall. Public websites currently published only discuss the new method (NTA 8800) and do not give information on the old method. To determine whether solar panels were included in the NEN 7120, the Wayback Machine was used. This is an archive that includes old versions of websites. On a page from 2018, it was found that solar panels were included in the NEN 7120 (Milieu Centraal, 2018).

- Additionally, the number of *children* is included to capture the specific and additional effects children may have on gas consumption, such as higher indoor temperature settings for comfort and increased daytime occupancy.
- *Ownership type* may influence renovation likelihood and energy behavior. For example, owner-occupied homes may be more likely to undergo energy-efficient renovations, and rental homes with a fixed rental price including utilities may use more gas.
- Finally, the presence of a *partner* in the household may affect gas consumption due to shared living arrangements and combined heating preferences. Partners may go out together more often than two singles, leading to less home presence. Therefore, households with a partner might use common spaces more efficiently.

3.5.3 Attitude and Behavior Characteristics ($\vec{A}$)

Multiple variables represent the energy behavior and attitudes of the household:

- The respondents' perception of their own *frugality* with respect to energy used for heating their dwelling might be a good proxy for their actual behavior. This self-assessed measure may capture behavioral variation that is not captured by the other control variables.
- The value the respondent attaches to the *importance of energy efficient behavior*, may be an indicator of heating behavior. Those who consider it important may be more likely to adopt energy-saving habits.
- Respondents were also asked whether they *actively tried to lower their gas consumption*. When people report they have actively tried, it may indicate behavioral differences leading to lower gas consumption, keeping all other factors equal.
- Finally, the *occupancy during daytime* may be a strong predictor for the gas consumption. Daytime occupancy is chosen as a control, as it is assumed most people are home in the early morning, in the evening, and at night. Most variability in occupancy is expected in the late morning and afternoon.

3.6 Non-Linear Effect

To examine whether the relationship between thermal quality and gas consumption is non-linear, the main regression model will also be estimated with the squared term of the thermal quality, as specified in Equation 3.6. This allows for the possibility that the effect of thermal quality on gas consumption diminishes or increases at different levels of energy efficiency. By including the squared term, the model accounts for potential non-linearities, providing a potentially more accurate representation of how energy renovations influence gas consumption in older Dutch dwellings.

Furthermore, the model is also fitted using the categorical energy label instead of the continuous thermal quality, following Equation 3.7. As explained in Section 3.3.2, when using a categorical independent variable the effect sizes between different energy labels are not forced to follow a prescribed function. Therefore, such a specification allows the effect to be non-linear.

$$\log(\text{gas})_i = \beta_0 + \beta_1 \cdot TQ_i + \beta_2 \cdot {TQ_i}^2 + \vec{\gamma} \cdot \vec{B}_i + \vec{\delta} \cdot \vec{H}_i + \vec{\zeta} \cdot \vec{A}_i + \epsilon_i \tag{3.6}$$

$$\log(\text{gas})_i = \beta_0 + \sum_j \beta_j \cdot \text{Energy Label}_{ji} + \vec{\gamma} \cdot \vec{B}_i + \vec{\delta} \cdot \vec{H}_i + \vec{\zeta} \cdot \vec{A}_i + \epsilon_i \tag{3.7}$$

The squared term is relevant because improvements in thermal quality may not have a uniform effect across the entire range of the thermal quality. For example, energy efficiency measures may yield the largest reductions in gas consumption in poorly insulated dwellings, while further improvements in already well-insulated dwellings may lead to smaller marginal savings.

Chapter 4

Data

To create a linear regression model, data is needed to fit the model. For this research, a national housing survey from a reputable source is used. It concerns observational and cross-sectional data. Observational means that the data is naturally occurring and passively collected, it does not originate from an experimental setting or intervention. Cross-sectional means that the data is collected at a single point in time, so there is no temporal aspect to the data. This type of data provides a snapshot of the population and is suited for fitting a linear regression model and inferring causal relationships.

4.1 WoON Survey

This research uses data from the 2018 WoON national housing survey, a large-scale study that collects information about Dutch households and their living conditions (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (BZK) & Centraal Bureau voor de Statistiek (CBS), 2019a).[1] The WoON survey is administered by Statistics Netherlands (in Dutch: Centraal Bureau voor de Statistiek) and the Ministry of the Interior and Kingdom Relations and is conducted every three years to provide insights into the housing situations of residents and the Dutch housing market.[2]

The survey is based on a stratified sample designed to ensure representation across different regions, housing types, and socioeconomic groups. The survey data is enriched by linking registry data, such as data from the tax administration (in Dutch: Belastingdienst) and the personal records database (in Dutch: Basisregistratie Personen). The target population of the WoON consists of persons aged 18 years or older and living in the Netherlands. The cross-sectional dataset contains information from more than 50,000 households, providing a rich source of data for analyzing the effects of energy renovations on gas consumption in Dutch residential buildings.

[1] WoON is an acronym of the Dutch name of the survey research: “Woon Onderzoek Nederland”, which translates to: “Housing Research Netherlands”.

[2] The data is restricted and not freely available on the internet. Users may request access to files by providing personal information and a research purpose and motivation for the request, which is what was done for this research.

4.1.1 Energy Module

The 2018 WoON survey includes an energy module that gathered detailed information on household energy consumption and included a technical inspection of the dwelling by certified inspectors (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (BZK) & Centraal Bureau voor de Statistiek (CBS), 2019b). This inspection significantly enhances the reliability of the data, as it allows for an accurate assessment of key factors affecting energy use, such as insulation, heating systems, and other thermal characteristics of the dwelling. Unlike the main WoON survey, which is conducted every three years, the energy module is only administered every six years. As a result, the more recent WoON survey from 2021 does not contain this critical component.[3]

While the dataset is six years old, it remains highly relevant for studying energy consumption in Dutch dwellings. The housing stock in the Netherlands, particularly older buildings, is relatively static in terms of structural characteristics, and large-scale renovations that would significantly alter the energy performance of most homes occur gradually over longer time periods. Additionally, the energy module from 2018 offers valuable insights into both the physical properties of homes and the behavior of their residents, factors that are unlikely to have changed drastically since then. As a result, the data still provides a reliable basis for analyzing the impact of energy renovations on gas consumption, making it suitable for the goals of this study.

The energy module is a study of the energetic quality of the Dutch housing stock, and the energy consumption and behavior of residents. Participants were randomly selected from WoON 2018 respondents that indicated they would be open to participating in a follow-up survey. The energy module consists of two parts:

1. *Resident Survey:* Data is collected on respondents' behavior affecting energy consumption, using a follow-up survey. The questions are for example about how they heat and ventilate the dwelling, how they use water, and whether energy-saving measures have been installed or are planned.

2. *Technical Inspection of the Dwelling:* After finishing the survey, all respondents are subjected to a home inspection by certified professionals. This is a comprehensive home inspection, similar to an energy label assessment. Detailed information on dwelling characteristics is collected, such as floor area, type of glass, heating systems, and insulation.

The 2018 WoON survey had a large sample size of over 67,000 households, with 4,506 of these also participating in the energy module. This provides a sufficient sample for robust statistical analysis, including the application of regression models.

[3] The WoON survey from 2024 will include the Energy Module, but has not been published yet. Therefore, the 2018 version is used.

The final energy module dataset contains multiple variable origins. Besides containing the survey answers and the measurements by the inspector during the house recording, the dataset also contains derivations. Some are based on other variables from the energy module, such as area percentages of glazing types, total area of different types of building properties, and the energy index. Furthermore, the weights, inconsistencies with the WoON survey, and respondent numbers are included.

4.2 Sample Selection

As explained in Section 3.1.1, two selection criteria should be applied to the observations from the WoON survey. Firstly, only old dwellings must be included in the analysis, and a cut-off year needs to be selected. Secondly, only gas-heated dwellings must be included, to ensure the energy consumption used for heating corresponds to the gas consumption.

Finally, because the thermal quality (the rescaled energy index) is the main variable of interest, the sample is restricted to the observations within the energy module. The energy indices in the WoON survey originate from registry data, and the time and method of measurement are unknown. As the energy index/label stays valid for many years, the value could not be representative of the actual state of the dwelling, as renovations could have taken place since the registration. Furthermore, the quality of the measurement is unknown, making the data unreliable. For the energy module, the validity of the measurement of the index is verified, as will be explained in Section 4.4.2.

The energy module consists of 4,506 observations. The final sample, limited to exclusively gas-heated dwellings built before 1980, and with removed inconsistencies consists of 2,062 observations. These 2,062 data points will be used to estimate the coefficients using the regression models.

4.2.1 Selecting the Cut-Off Construction Year

To ensure favorable thermal quality values from the remaining observations can be attributed to renovations, the cut-off construction year should be selected such that the dwellings remaining in the sample data are constructed in a period with poor construction standards. This is determined by analyzing the data to determine from which point in time buildings are always built without poor thermal quality.

To determine this point in time, the thermal quality is plotted as a function of the construction year in Figure 4.1. Some dwellings are listed as having been constructed in the year 1000, which renders the scatterplot with all observations difficult to interpret. Therefore, only dwellings built after after 1900 are shown, excluding 119 observations. For a version of the figure that includes all observations, see Appendix A.

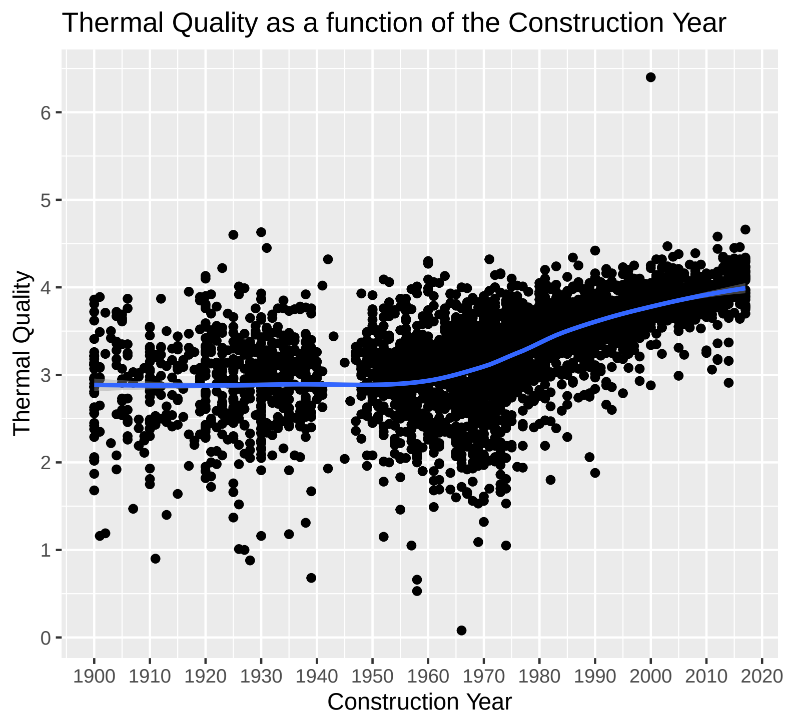

Figure 4.1: The Thermal Quality as a Function of the Construction Year
The thermal quality values of all dwellings included in the energy module are plotted against their construction year. The blue line is a LOESS regression line, a local regression/estimation similar to a moving average. This line stays constant until approximately 1960, from where it starts to increase.

As can be seen, the thermal quality improves for all buildings constructed in the last decades. As expected, the baseline thermal quality really improves for dwellings more recently constructed due to improved construction standards. The thermal quality seems to start increasing for dwellings built after 1960, but there are still many dwellings with label G (corresponding to thermal quality below 2.3) until approximately 1975.

Although the scatterplot gives a clear indication that thermal quality increases significantly for more recently constructed buildings, the density of observations makes it hard to evaluate what the exact cut-off year should be. Therefore, the energy labels (the discretized thermal quality) are also plotted as a histogram, shown in Figure 4.2.

The figure shows the distribution of energy labels for different construction periods. The histograms show that while there seems to be a small improvement between 1960 and 1970, the distribution of energy labels for dwellings constructed in that period stays approximately similar to those built before 1960. Dwellings constructed between 1970 and 1980 seem to have significantly improved energy labels compared to older buildings. However, there still remain approximately equal amount 'bad' labels (E/F/G) as 'good' labels (A/B).

After 1980, there are barely dwellings present in the data with energy labels worse than C, indicating that all dwellings from this period are constructed with good thermal quality due to improved construction standards. Due to the absence of poor energy labels constructed after 1980, this year is chosen as the cut-off year.

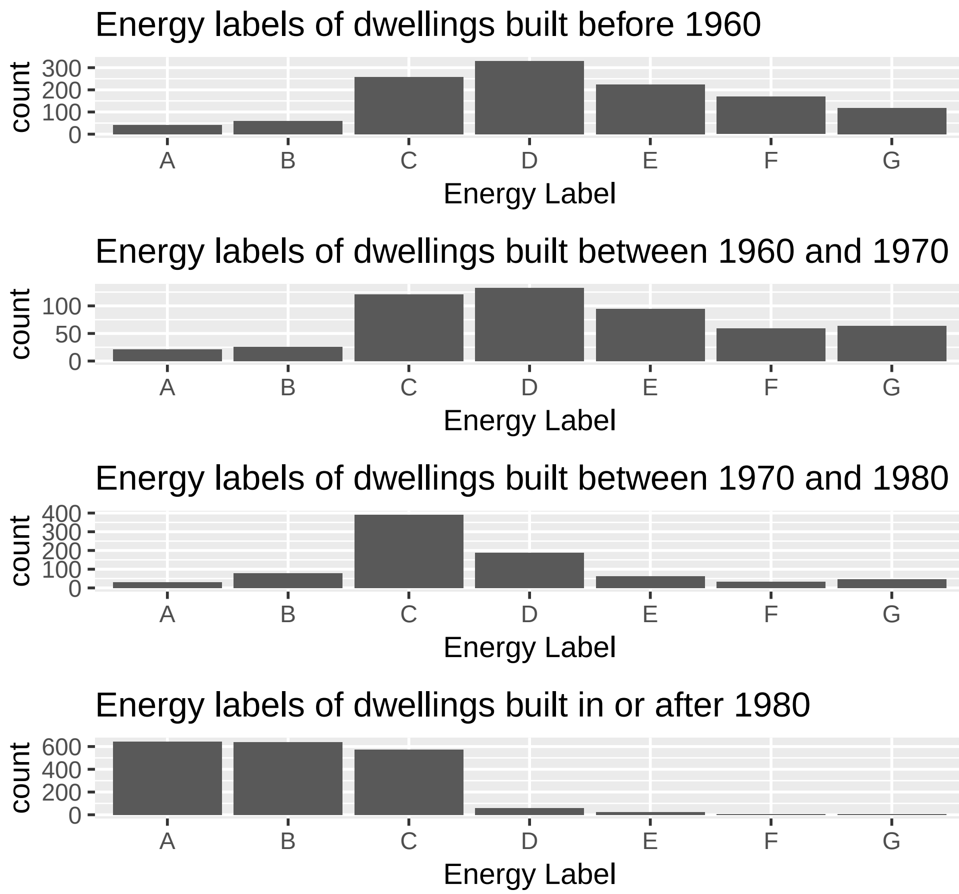

Figure 4.2: The Distribution of Energy Labels for Dwellings Built in Different Construction Periods

The frequencies of energy labels for dwellings from different construction periods are shown. For dwellings built before 1980, all energy labels occur, with the majority having a C or D labels, and only few dwellings with A or B. For dwellings built after 1980, almost none have an energy label of D or worse. Therefore, it can be inferred that construction standards have significantly improved, leading to more favorable energy indices for all constructed buildings.

4.2.2 Selecting Gas-Heated Dwellings

To ensure that the energy consumption for heating is represented by the reported gas consumption, it is necessary to only include gas-heated dwellings. There are multiple dummy (or binary) variables present in the dataset indicating whether a certain type of heating is present within the dwelling. These include a central heating boiler, wood-fired heating appliance, pellet burner, gas heater, heat pump, block or district heating, and a category for other types of home heating. Only the dwellings where a central heating boiler or gas heater are present are included in the sample, the other heating sources do not consume gas. Dwellings that include both gas and non-gas heating systems are excluded. An overview of the main differences between central heating systems and gas heaters is shown in Table 4.1.

Central heating boilers are part of a central heating system, where one boiler heats water and then distributes this hot water or steam through a system of pipes to radiators throughout the entire home. Gas is consumed by the boiler to heat the water, and the water is circulated, emitting heat throughout the dwelling. Central heating boilers are available with different efficiencies, such as VR (improved yield) and HR (high yield). They can also be integrated with the domestic hot water supply (combination boiler).

Gas heaters, on the other hand, are usually standalone units that heat a single room or space directly by burning natural gas. It produces hot air or radiant heat locally and does not require a network of pipes or radiators. Gas heaters are combined with a separate boiler or geyser to provide hot water.

Gas heaters are less efficient than central heating boilers, especially when used to heat multiple rooms. The type of gas-heating is thus likely to influence the gas consumption. Although above-mentioned variables specifying the type of heating are used to select the sample, they are not included in the regression model.

Energy renovations of dwellings do not only entail improving insulation, but also replacing inefficient heating systems with better ones (i.e., replacing gas heaters by central heating). The (primary) heating system is used to determine the energy index. Therefore, the thermal quality already includes the effect of more efficient heating systems, and it should not be included separately in the regression model.

Table 4.1: Main Differences between Central Heating Systems and Gas Heaters

Feature	**Central Heating Boiler**	**Gas Heater**
Heating Coverage	Whole house, via a network of pipes throughout the dwelling	Single room or area only
Hot Water Supply	Yes, often for taps and showers	No
Heat Distribution	Via radiators or underfloor heating	Direct air or radiant heat in the room
Location	Installed in utility room, kitchen, attic, or basement	Installed in the room to be heated
Control System	Central thermostat, possibly with zoning	Local control
Installation Complexity	High, requires pipework, radiators, and system setup	Low, often wall-mounted or free-standing unit

4.3 Survey Weights

The WoON survey design includes oversampling, a method to study small groups. This is done by selecting respondents in such a way that ensures certain smaller groups have sufficient responses, such as small regions. Doing this can skew the results, as these oversampled subpopulations now make up a larger share of the sample than they do in the total population.

Besides the sampling bias introduced by the design, surveys also often suffer from a non-response bias. Some target groups may be more likely to fill in the survey. Especially for the energy module, which includes a house visit, specific groups may drop out of the research. If these groups are systematically different from the groups that do not drop out, this can also skew the results.

The results can be made representative of the population by applying survey weights. By weighting the responses, it is possible to make statements about the entire Dutch housing stock. The weights corrects for selectivity in response, and for over- and under-representation in the sampling design, ensuring that oversampled groups do not disproportionately influence the results. The WoON data includes weights, as well as documentation explaining how they were determined.[4]

4.3.1 Implementation

When making statements about population quantities, not using survey weights means the estimates may not reflect the real distribution of housing types and demographics. By weighting the variables, results are generalizable to the total population of interest. Using weights when making population-level inferences ensures that estimates of total energy consumption and gas reductions reflect the true distribution of housing and household characteristics.

Omitting survey weights may not be problematic for estimating the causal effect of thermal quality on gas consumption. The oversampling might be correlated with gas consumption and thermal quality, e.g., by oversampling low-income households who tend to live in less energy-efficient housing. Survey weights would then correct for selection bias by adjusting for differences in observed characteristics between the sample and the target population.

The regression already controls for many of these characteristics, such as age, province, income, and number of residents. Because the model is directly adjusting for differences in many relevant variables used in the weighting model, using the weights is not necessary, because the controls serve a similar purpose. However, not all variables used in the weighting model are

[4]Originally, the respondents belonging to the oversampling design from the WoON would not be included in the Energy Module. But, due to a higher and more selective dropout than previously assumed, they were also approached. Because of this change in design, the original weighting model was not adequate anymore and had to be adjusted. Since only the Energy Module subsample of the WoON survey is used, these adjusted household weights are used.

included as controls, and the weights might still have added value. Therefore, the model is ran both ways, with and without weights, and the results are compared as a robustness check.

After estimating the causal effect (without using weights), the estimated coefficient(s) will be used to estimate the energy savings from projected renovations across the population of interest. To achieve a projection that is representative of the actual Dutch housing stock, weights will be used here.

4.4 Constructed Variables

In this section, all variables used in the regression analysis will be defined. For a complete overview of all used variables from the WoON survey, including their original description and variable name (in Dutch), see Appendix B.

4.4.1 Dependent Variable: Gas Consumption

The dependent variable is annual gas consumption. In the WoON dataset, the energy data was determined based on data from grid companies. If the consumption could not be linked, missing values were imputed. The continuous variable that represent gas consumption is given in cubic meters per year ($m^3\text{year}^{-1}$). Gas consumption includes all natural gas usage within the dwelling, not just gas used for heating but also for, e.g., hot water and cooking. As robustness checks, different specifications of the dependent variable will be used across all models. All specifications are shown in Table 4.2.

Table 4.2: Dependent Variable: Gas Consumption

Variable	**Clarification**	**Unit**
gasUsage	Gas consumption (Source: grid companies)	$m^3\text{year}^{-1}$
gasPerArea	Gas consumption from registry data divided by area of the dwelling	$m^3 m^{-2}\text{year}^{-1}$
log(gasUsage)	Natural logarithm of the gas consumption	-
log(gasPerArea)	Natural logarithm of the gas consumption per area	-

4.4.2 Causal Variable of Interest: Thermal Quality

The thermal quality is the main independent variable of interest, providing a comprehensive measure of a dwelling's thermal efficiency, as explained in Section 2.2.1. The thermal quality is a rescaling of the energy index, which is calculated based on various factors such as the insulation of walls, roofs, and floors, the type of heating system, and the presence of energy-saving technologies, such as double glazing or solar panels.

To ensure the validity of the energy indices in the original data, the researchers designing the WoON survey included double inspections for approximately 10% of all dwellings. This way, the results could be compared to determine whether chance or systematic differences between the different inspectors exist, and whether their ratings are sufficiently similar. The most important analyzed variables on inter-rater agreement are energy index, and the derived energy label. All statistical tests on the results easily meet the lower limits set by the survey design. Across the sample, the inter-rater agreement for the energy index variable is very high and no significant systematic differences occur.

The distribution of the thermal quality across observations in the estimation sample is shown in Figure 4.3. The thermal quality is approximately normally distributed, with a peak around value 3, corresponding the energy label D. There are very few occurrences of extreme values at both ends of the distribution, indicating minimal outliers.

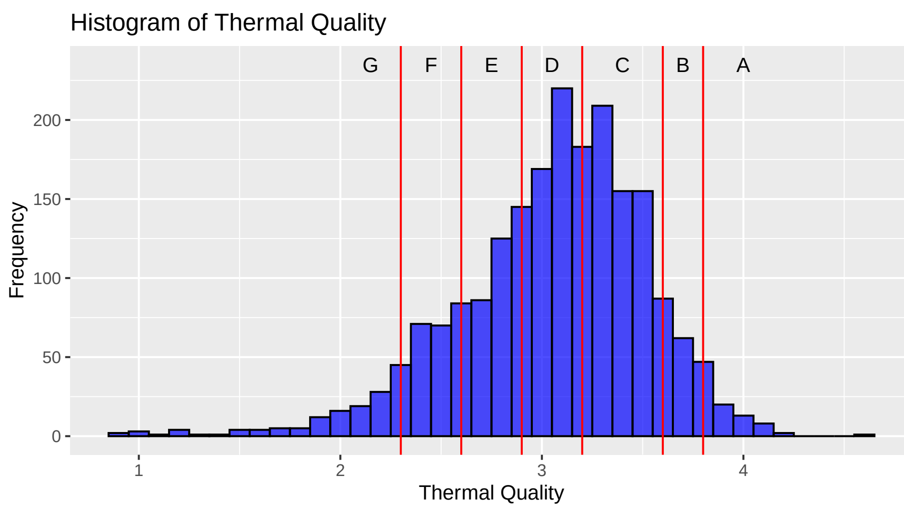

Figure 4.3: Histogram of Thermal Quality

Histogram of the thermal quality for all observations included in the estimation sample. The corresponding energy labels are also shown.

For the causal variable of interest there are two specifications which are used throughout the models: the thermal quality (the transformed energy index) and the derived energy label. The best energy label reported in the WoON survey is A+. However, after using the selection criteria to create the estimation sample, only two dwellings with this label remained. As a category of two observations is not preferred, the A+ and A labels are combined into the energy label A. The continuous and categorical specifications are summarized in Table 4.3.

Table 4.3: Causal Variable of Interest: Thermal Quality

Variable	**Clarification**	**Unit**
energyIndex	Energy index calculated on the basis of the results from the home inspection	-
thermalQuality	Rescaling of the energy index according to Equation 3.2 ($TQ = 5 - EI$)	-
energyLabel	The energy label based on the calculated energy index (A to G)	cat(7)

4.4.3 Control Variables

Control variables account for other factors than the causal variable of interest that influence gas consumption. These variables are drawn from the WoON dataset and its Energy Module, and include both household characteristics and dwelling-specific factors, as discussed in Section 3.5. Tables 4.4, 4.5, and 4.6 summarize the variables of respectively the dwelling, the household, and the energy attitudes and behavior of the residents.

The variables representing the **heating system** are included as these are used to construct the sample. As explained in Section 4.2.2, only dwellings using natural gas for heating are included in the research. The two shown variables (central heating boiler and gas heater) represent the heating systems using natural gas. Other excluded heating types are wood-fired, pellet stove, heat pump, block or district heating, and other types (unspecified).

Table 4.4: Dwelling Characteristics

Variable	**Clarification**	**Unit**
areaHome	Total floor area of the dwelling from registry data	m^2
bath	Binary variable indicating whether the dwelling has at least one bath	T/F
constructionYear	Construction year of the dwelling from registry data	-
constrYear	Categorical variable representing the construction period (<1945, 1945–1969, 1970–1979)	cat(3)
dwellingType	Structural type of dwelling (corner, detached, semi-detached, terraced, or apartment)	cat (5)
centralHeatingBoiler	Binary variable indicating whether the dwelling is heated by a central heating boiler	T/F
gasHeater	Binary variable indicating whether the dwelling is heated by gas heater	T/F
gasStove	Binary variable indicating whether there is a gas stove	T/F
province	Geographic location of the dwelling	cat (12)
solarPanel	Binary variable indicating whether the dwelling contains at least one solar panel	T/F

Table 4.5: Household Characteristics

Variable	Clarification	Unit
age	Age class of the respondent (17—34, 35—64, 65+)	cat (3)
disposableIncome	Combined disposable income of the household	€1000
educ	Binary variable representing whether the highest education level achieved by either the respondent or their partner was in higher education	T/F
nrChild	Categorical variable representing the number of children in the household (0, 1, 2, 3+)	cat(4)
nrResidents	Number of residents in the dwelling	-
ownership	Ownership type (social rent, private rent, or owner-occupied)	cat (3)
partner	Binary variable representing whether the respondent lives together with their partner	T/F

Table 4.6: Energy Attitudes and Behavior Characteristics

Variable	Clarification	Unit
frugal	Binary variable: Do they think they are frugal or very frugal with respect to their energy used for heating?	T/F
important	Binary variable: Do they think energy-efficient behavior is very important?	T/F
loweredGas	Binary variable: Did they actively try to use less gas?	T/F
occup	Representing the occupancy of the dwelling during the day, from 09:00 until 18:00 (almost always, depends, almost never)	cat(3)

4.5 Data Preparation

First, the datasets from the WoON survey (67523 x 922) and its energy module (4506 x 1313) are merged. This is done by using the respondent number, only observations also present in the energy module are kept, resulting in a dataframe consisting of 4,506 observations and 2,234 variables. Then, all relevant variables are selected and the variables and their categories are renamed in English.

Only observations representing gas-heated dwellings built before 1980 are kept (the cut-off year as determined in Section 4.2.1). The only two dwellings in the sample with energy label A+ are grouped together with the A label under the 'A' category.

The original values or categories of some variables are already suited for the regression analysis, but some need editing. Fewer categories are generally preferred for regression analysis to simplify interpretation and avoid potential overfitting. When possible, binary variables (i.e., two categories) are preferred, as they are easier to interpret compared to a categorical variable with more levels. While fewer categories are preferred for easier interpretation, they typically also ensure there are no categories with very few observations. When categories are sparse, regression models may produce unreliable estimates due to limited observations within certain groups. Therefore, variables are converted to binary variables if only two categories are sufficient. For other variables, the amount of categories is reduced or maintained.

The construction year is changed from a continuous variables to a categorical one. The relationship between construction year and energy efficiency is not linear. A categorical approach allows for capturing differences between eras rather than assuming a continuous relationship. As explained in Section 3.5.1, the construction year is included to capture potential structural differences in dwellings built during different historical periods.

Pre-war buildings are a category, as it is expected that these differ in terms of construction techniques from those built after the war. Dwellings built after the war are divided into two categories, with 1970 being the threshold. As can be seen in Figure 4.2, around 1970 the thermal quality starts to structurally increase, indicating increasing construction standards. Three periods are thus chosen as categories: before 1945, from 1946 to 1969, and from 1970 to 1979.

The two attitude variables were asked on a 5-point scale, the self-reported frugality and the attached importance to energy efficient behavior, and transformed to a binary variable. For the importance, only the respondents answering they think energy-efficient behavior is very important were included. For the frugality, both the answer frugal and very frugal are included.

The occupancy is based on whether the respondents are almost always, sometimes, or almost never at home during 09:00 until 18:00. They answered this question for three separate time intervals ($9-12, 12-15, 15-18$). If they answered with almost always or almost never at least two out of three times, their occupancy is set to respectively always or never.

Besides the observations that were dropped because they did not meet the criteria of being built before 1980 and being gas-heated, other observations were also dropped. For example, some households reported more children living in the dwelling than the total amount of residents. Furthermore, observations that reported a disposable income below zero are dropped.[5] The final estimation sample consists of 2,062 observations.

[5]A negative disposable income does not necessarily seem to be incorrect, as Statistics Netherlands also publishes data with negative disposable incomes themselves (Centraal Bureau voor de Statistiek, 2022). However, these observations still need to be dropped because the regression model includes the income in a logarithm, which is not defined for values below zero.

4.6 Descriptive Statistics

Before running the regression analysis, descriptive statistics are produced. These descriptive statistics provide an initial understanding of the data. The descriptive statistics of the sample data are shown in Appendix C. The tables include descriptive statistics for the full estimation sample, as well as stratified by energy label. The descriptive statistics are also shown for the full energy module in Appendix D.

The average annual gas consumption is approximately 1,550 m^3, with a substantial range from 44 to 8,583 m^3, indicating significant variation in household energy needs. The key explanatory variable, thermal quality, has a mean of 3.1, corresponding to energy label D. Other dwelling characteristics, such as dwelling area and presence of technologies like solar panels or gas stoves, show expected variation. Respondents tend to value energy efficiency, with over 90% selecting ‘important’ or ‘very important’ in their stated attitudes. Reported energy-saving behavior (e.g., frugality) also indicates a general tendency toward energy-conscious living, though a small minority identifies as explicitly non-frugal.

Systematic differences between households living in more energy-efficient dwellings (labels A–C) and those in less efficient ones (labels D–G) are present. Dwellings with poorer energy labels tend to consume substantially more gas, both in absolute terms and per square meter.

In terms of dwelling characteristics, households in energy-efficient homes are more likely to have solar panels and central heating boilers, and are less likely to rely on gas heaters. Renovated dwellings are also less likely to use a gas stove for cooking. Moreover, the average dwelling size tends to increase with worse labels, though variation is considerable.

Behavioral and demographic variables show more mixed patterns. For instance, higher levels of frugality are observed in higher-rated dwellings. Residents living in renovated dwellings also think energy-efficient behavior is more important than those living in non-renovated dwellings. This might indicate a self-selection effect, where people choose to live in dwelling based on their pre-existing opinions about energy consumption. Education levels and disposable income are relatively stable across labels, with no strong monotonic trend. Furthermore, indoor temperature is relatively steady for most energy labels, around 18.5 degrees Celsius. However, for energy labels A and G the average temperature is below 18 degrees Celsius.

Chapter 5

Results

In this chapter, the relationship between thermal quality and gas consumption is investigated. After the descriptive overview, the simple linear regression model is presented. Then, the main model, containing all selected control variables is discussed. This model is ran again while allowing non-linear effects. Using the estimates from the regression models, the national gas savings given current policy goals is projected. Finally, the model is subject to a robustness analysis.

5.1 Descriptive Overview of Gas Consumption

Understanding the relationship between energy efficiency and gas consumption is crucial for evaluating the impact of energy renovation efforts. To provide an initial overview, a scatterplot of the thermal quality versus total gas consumption is shown in Figure 5.1. Linear regression lines are overlaid, clearly indicating a negative relationship: as the thermal quality increases, gas consumption decreases. However, the scatterplot itself reveals limited visual insight due to the high density of data points, which obscures detailed patterns and variability within the dataset.

To better illustrate the pattern within the data, a histogram is made where the energy efficiency is represented by the energy label instead of the thermal quality. Figure 5.2 shows the average gas consumption per energy label for two datasets. First, the average consumption is shown for the full energy module dataset. Second, it is shown for all observations within the estimation sample, including only gas-heated dwellings constructed before 1980.

The histogram clearly shows that homes with poorer energy labels have a substantially higher average gas consumption compared to those with better labels, as expected. This pattern is consistent for both the estimation sample and the full dataset, although there are some deviations when all observations within the energy module are included.

For the full energy module dataset, the average gas consumption for dwellings with energy label A seems unexpectedly high, while for label G it is unexpectedly lower than for label F. Because these deviations are not present within the estimation sample, it is possible that this is due to some of these dwellings being heated by heating sources not using gas. When this is the case, the energy efficiency of the home becomes a worse predictor of the total gas consumption. It could also be due to the energy labels being unreliable, as they are not verified

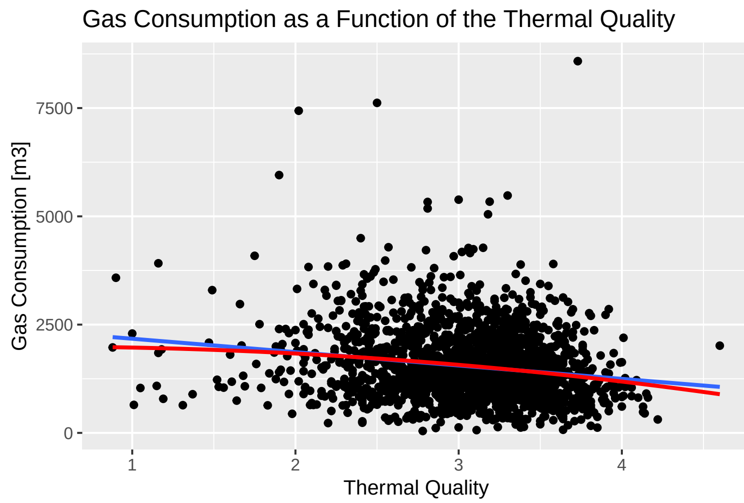

Figure 5.1: Gas Consumption as a function of the Energy Index

Scatterplot showing the gas consumption of observations in the estimation sample as a function of the thermal quality of the dwelling. Linear regression lines are shown for a linear (blue) and quadratic (red) relationship.

during the survey, or due to confounding factors influencing both the energy efficiency and the gas consumption.

Furthermore, when comparing both sets of included observations, it can be seen that dwellings in the estimation sample use more gas on average for a given energy label. This is expected as these dwellings are selected on the condition of being gas-heated, leading to a higher gas consumption. Their construction period (built before 1980) may further influence this, as they are built with worse construction standards than newer buildings and are thus more likely to have cracks or other imperfections which are not detected when collecting data about the thermal quality.

5.2 Simple Linear Regression

A series of Ordinary Least Squares (OLS) regressions was conducted to examine the relationship between the thermal quality and residential gas consumption. The dependent variables analyzed were the logarithm of total gas consumption (log(gas)) and the logarithm of gas consumption per area (log(gasPerArea)). The primary explanatory variable, the thermal quality, reflects the energy performance of a dwelling. To capture both linear and nonlinear effects, two model specifications were employed for each dependent variable: a linear model (Models 1 and 3) and a second-order polynomial model (Models 2 and 4). Standard errors are robust, ensuring unbiased estimation under heteroskedasticity, while the F-statistic is valid only under homoskedasticity.

The regression results are presented in Table 5.1. In the linear models (**Models 1 and 3**),

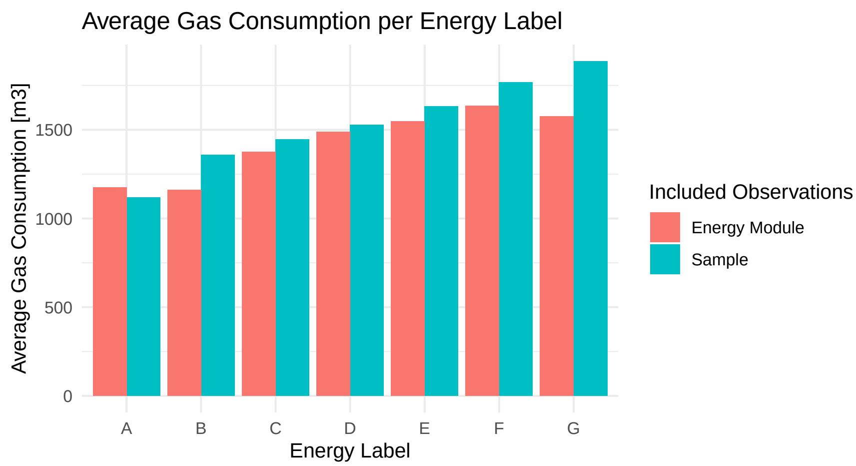

Figure 5.2: Average Gas Consumption per Energy Label

The average gas consumption in m^3 per year is shown for different energy labels.

the coefficients for the thermal quality are both negative and statistically significant at the 1% level. Specifically, a one-unit increase in the thermal quality, corresponding to an increase of approximately 3 energy label levels (Table 2.1), is associated with a 19.3% decrease in total gas consumption and a 18.9% decrease in gas consumption per unit area. These findings are consistent with expectations, as higher energy efficiency leads to lower gas consumption.

Table 5.1: Simple Linear Regression

	Dependent variable:			
	log(gasUsage)		log(gasPerArea)	
	(1)	(2)	(3)	(4)
thermalQuality	-0.193^{***} (0.027)	0.243 (0.199)	-0.189^{***} (0.025)	0.356^{*} (0.198)
thermalQualSq		-0.076^{**} (0.034)		-0.095^{***} (0.034)
Constant	7.794^{***} (0.083)	7.185^{***} (0.287)	3.080^{***} (0.076)	2.320^{***} (0.286)
Observations	2,062	2,062	2,062	2,062
R^2	0.027	0.030	0.034	0.039
Adjusted R^2	0.027	0.029	0.033	0.038
Residual Std. Error	0.542 (df = 2060)	0.541 (df = 2059)	0.474 (df = 2060)	0.473 (df = 2059)
F Statistic	57.305^{***} (df = 1; 2060)	31.481^{***} (df = 2; 2059)	71.903^{***} (df = 1; 2060)	41.785^{***} (df = 2; 2059)
Note:				*p<0.1; **p<0.05; ***p<0.01

Models 2 and 4 incorporate a second-order polynomial term to explore potential nonlinear effects of thermal quality on gas consumption. The F-statistic tests whether the thermal quality variables jointly have a significant effect on gas consumption. Robust F-tests confirm that the thermal quality variables are highly jointly significant.[1] The positive linear term indicates an initial increase in gas consumption for higher thermal quality values. The negative quadratic term suggests that from a thermal quality of 1.6 (corresponding to energy label G), increasing

[1]The robust F-statistics are $F_2 = 28.9^{***}$ and $F_4 = 33.8^{***}$.

thermal quality leads to a decrease in gas usage. Furthermore, the marginal effect becomes increasingly negative, meaning that the reduction in gas consumption accelerates as thermal quality improves.

The regression lines from Model 1 and Model 2 are shown in Figure 5.3. For the linear model, the goodness-of-fit measure R^2 is 0.027, for the quadratic model R-squared is 0.030, which is only 0.003 higher. The R-squared of Model 1, $R^2 = 0.027$, means that 2.7% of the variation of gas consumption is explained by the thermal quality. Model 2 thus explains 0.3% more of the variation, indicating the quadratic model might be slightly better than the linear model.

Although the explanatory power is relatively low, this is expected due to the multifaceted nature of residential gas consumption, which is influenced by many factors besides energy efficiency. Nevertheless, the F-statistics for all models are highly significant at the 1% level, indicating that the thermal quality explains a statistically significant portion of the variance in gas consumption.

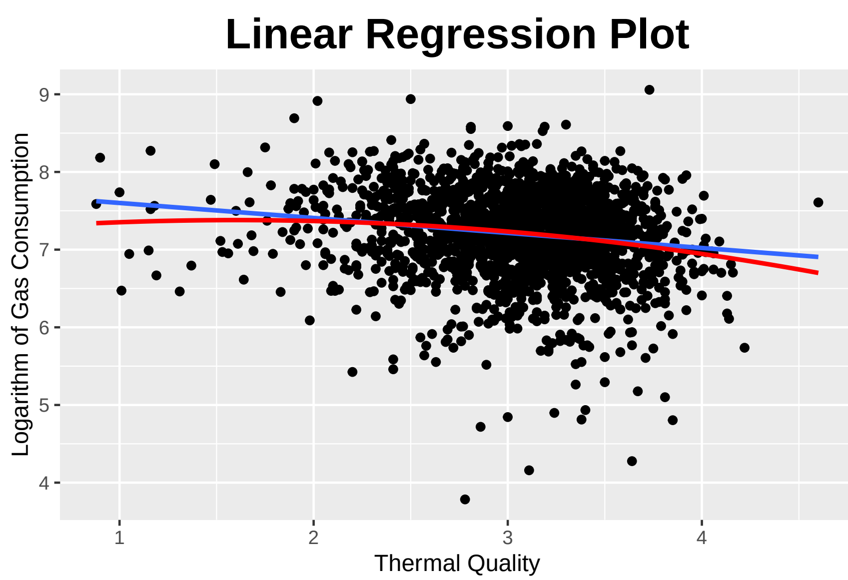

Figure 5.3: Simple Linear Regression Lines

The regression lines for the linear (blue, Model 1) and quadratic (red, Model 2) equations plotted against the sample data.

The results underscore the strong association between energy efficiency, as measured by the thermal quality, and household gas consumption. The negative and significant coefficients in the linear models suggest that improving the energy efficiency of dwellings could lead to substantial reductions in gas usage. While the simple linear and polynomial regressions provide valuable insights into the relationship between thermal quality and gas consumption, further analysis using multiple linear regression could refine these findings. By including additional control variables such as dwelling features (e.g., floor area, demographics) and household characteristics (e.g., occupant behavior, income), it is possible to account for other determinants of gas consumption. This approach could reveal more nuanced relationships and provide a clearer picture of the isolated effect of the thermal quality on gas usage.

5.3 Multiple Linear Regression

Table 5.2 presents the regression estimates for four model specifications. The first column includes thermal quality and dwelling characteristics, the second model adds households characteristics, the third model adds occupancy data, and the final model adds behavioral characteristics. In all models, the dependent variable is the natural logarithm of annual gas consumption. Geographic variation is controlled for using province fixed effects, though these are omitted from the table. Standard errors are robust, ensuring unbiased estimation under heteroskedasticity, while the F-statistic is valid only under homoskedasticity.

Table 5.2: Multiple Linear Regression

	Dependent variable:			
	log(gasUsage)			
	(1)	(2)	(3)	(4)
thermalQuality	−0.196*** (0.025)	−0.178*** (0.025)	−0.175*** (0.025)	−0.164*** (0.025)
log(areaHome)	0.387*** (0.040)	0.303*** (0.040)	0.302*** (0.040)	0.295*** (0.040)
constrYear1945-1969	−0.040 (0.026)	−0.024 (0.025)	−0.025 (0.025)	−0.024 (0.025)
constrYearafter_1969	0.005 (0.027)	0.005 (0.027)	0.003 (0.027)	0.002 (0.027)
dwellingTypecorner	0.331*** (0.035)	0.312*** (0.035)	0.309*** (0.035)	0.293*** (0.035)
dwellingTypedetached	0.492*** (0.042)	0.469*** (0.042)	0.466*** (0.042)	0.449*** (0.042)
dwellingTypesemiDetached	0.418*** (0.038)	0.396*** (0.038)	0.393*** (0.038)	0.369*** (0.037)
dwellingTypeterraced	0.143*** (0.031)	0.125*** (0.032)	0.124*** (0.032)	0.116*** (0.032)
bath	0.088*** (0.023)	0.054** (0.023)	0.053** (0.023)	0.050** (0.022)
gasStove	−0.040* (0.023)	−0.028 (0.022)	−0.027 (0.022)	−0.015 (0.022)
solarPanel	0.008 (0.026)	−0.015 (0.026)	−0.016 (0.027)	0.001 (0.026)
ownershipprivateRent		0.083** (0.038)	0.084** (0.038)	0.088** (0.038)
ownershipsocialRent		−0.037 (0.028)	−0.040 (0.029)	−0.036 (0.028)
nrResidents		0.042 (0.028)	0.037 (0.028)	0.031 (0.027)
logIncome		−0.039 (0.037)	−0.036 (0.037)	−0.035 (0.032)
logIncomeSq		0.013** (0.006)	0.014** (0.006)	0.013** (0.005)
nrChildren1		0.084** (0.041)	0.084** (0.041)	0.070* (0.040)
nrChildren2		0.026 (0.063)	0.036 (0.063)	0.035 (0.061)
nrChildren3+		−0.010 (0.094)	0.003 (0.094)	−0.004 (0.091)
partner		0.027 (0.033)	0.016 (0.034)	0.017 (0.033)
educhigherEduc		0.029 (0.021)	0.031 (0.021)	0.032 (0.021)
age35-64		0.070* (0.038)	0.059 (0.039)	0.059 (0.038)
age65+		0.184*** (0.041)	0.160*** (0.042)	0.159*** (0.041)
occupdepends			−0.035* (0.021)	−0.037* (0.021)
occupnever			−0.062* (0.033)	−0.056* (0.033)
frugal				−0.162*** (0.020)
important				−0.004 (0.022)
loweredGas				−0.008 (0.020)
Constant	5.980*** (0.198)	6.094*** (0.209)	6.119*** (0.208)	6.222*** (0.206)
Observations	2,062	2,062	2,062	2,062
R^2	0.403	0.427	0.428	0.449
Adjusted R^2	0.396	0.418	0.418	0.439
Residual Std. Error	0.427 (df = 2039)	0.419 (df = 2027)	0.419 (df = 2025)	0.412 (df = 2022)
F Statistic	62.439*** (df = 22; 2039)	44.448*** (df = 34; 2027)	42.166*** (df = 36; 2025)	42.302*** (df = 39; 2022)

Note: *p<0.1; **p<0.05; ***p<0.01

Additional Note: Province is included in the model, but omitted from the table.

Model 1 includes only dwelling characteristics, explaining 40.3% of the variation in gas consumption. For this model, a one-unit increase in thermal quality is associated with a 19.6% decrease of gas consumption. The coefficient is precisely estimated and highly statistically significant. The estimated effect is slightly larger than the 19.3% reduction estimated in the simple regression model (Table 5.1).

The area of the dwelling significantly influences gas consumption, with an elasticity of 0.387. This suggests that a 1% increase in area leads to a 0.387% increase in gas consumption. It is expected that the elasticity is positive and smaller than one, as smaller homes heat a higher proportion of their total space, whereas larger homes likely have unheated areas.

Dwelling type also plays a significant role. Compared to apartments (the reference category), terraced houses use about 14% more gas, corner and semi-detached houses consume between 33% and 42% more, and detached houses use approximately 49% more.[2] These differences align with the increasing proportion of exposed surface area across dwelling types.

Other significant dwelling characteristics include the presence of a bath, which increases gas consumption by approximately 9%. The positive sign and relatively small effect are as expected. Construction period, the presence of a gas stove, and the presence of solar panels, however, do not have significant effects.

For the construction period, there is no statistically significant difference between dwellings built before 1945, and the other two defined periods. Controlling for other factors such as the thermal quality and the province could be enough to limit the effect of unmeasured construction quality and standards. The coefficient for the gas stove variable is negative, although not statistically significant. This might indicate the limited share of cooking in total gas use, compared to heating and providing hot water. The presence of solar panels has an estimate small in both magnitude and statistical significance.

Although not all coefficients are statistically different from zero, their inclusion still controls for differences between households, limiting confounding and explaining some of the variation in gas consumption, improving the coefficient estimate of thermal quality.

Adding household characteristics in **Model 2** increases the explained variation by 2.4 percentage points. The model now explains 42.7% of variation in gas consumption.[3] The effect of thermal quality remains strong and statistically significant, though slightly reduced in magnitude (to 17.8% reduction of gas used per unit of thermal quality).

[2] For categorical variables, coefficients and significance levels are interpreted relative to the reference category. While the choice of reference category affects the estimates and interpretation of coefficients, it does not influence the identification of the causal effect of thermal quality.

[3] The R-squared only increases by 0.024, meaning that only 2.4% more variation is explained than in the model only including dwelling characteristics. It might seem that household characteristics do not explain much of the variation in gas. However, this is due to the order in which variables are added. For a model including only the household characteristics, $R^2 = 0.257$ indicating that they indeed explain a significant portion, but are likely explaining much of the same variation that is also captured by the dwelling characteristics.

The home's area coefficient decreases, likely due to the inclusion of the number of residents. Each additional resident increases gas consumption by 4.2%, likely reflecting greater use of heated space and hot water. Whether the respondent has a partner does not influence the gas consumption significantly. Compared to households with no children, having one child increases the gas consumption by 8.4%, keeping other factors such as the number of residents constant. This suggests that households with children consume gas differently than same-size households with only adults. An explanation could also be related to the number of heated rooms, as two adults living together are often partners, sharing a bedroom, and children usually have a separate room. This means that a one-adult, one-child household likely heats one more (bed)room than a two-adult household, which could explain the higher gas consumption.

Privately rented dwellings consume 8.3% more gas than owner-occupied homes, while social housing shows no significant difference. This could indicate differences in maintenance quality or insulation practices. It could also indicate differences in the typical households that live there, that are not represented by the included variables. For example, privately rented dwellings may be more frequently occupied by expats or temporary residents who are less accustomed to the (relatively) cold Dutch winters. Limited familiarity with local heating systems or a preference for warmer indoor temperatures could lead to higher gas usage, independent of the dwelling's energy efficiency.

Higher disposable income levels are associated with increased gas consumption. Contrary to expectations, the model shows increasing effects for higher incomes. The elasticity increases for higher incomes. For an income of 35 thousand euros per year, the elasticity is 0.053, indicating that when income increases by 1%, gas consumption rises by 0.053%.[4] Higher income levels are associated with increased gas consumption, with a relatively small elasticity (smaller than 0.1 for incomes up to 210 thousand euros per year).

This suggests that gas consumption is relatively inelastic with respect to income changes, possibly due to heating being largely a necessity rather than a luxury. Gas being used for heating or hot water follows relatively fixed requirements when dwelling and household characteristics are known. The smaller elasticity for lower income households might be an indication that these household prioritize other expenditures above heating. After controlling for income, the education level does not have a statistically significant effect on the gas consumption.

The age of the primary resident also explains some of the gas consumption in a dwelling, with residents aged 65 or older consuming approximately 18% more gas than those aged between 17 and 34. This aligns with expectations that older people often prefer higher indoor temperatures and spend more time at home.

Information about the occupancy is added to **Model 3**, increasing the explained variation by only 0.1 percentage point compared to Model 2. The coefficient for thermal quality remains

[4]The elasticity is equal to $\beta_{logIncome} + 2 \cdot \beta_{logIncomeSq} \cdot log(income) = -0.039 + 0.026 \cdot log(35) = 0.053$.

strong and statistically significant, with a modest reduction in magnitude to a 17.5% decrease in gas consumption per unit increase in thermal quality.

The occupancy variable captures how often the dwelling is occupied during the day. Compared to the reference category ‘almost always’, dwellings where occupancy ‘depends’ use 3.5% less gas, while those ‘almost never’ occupied during the day consume 6.2% less. Both effects are only marginally significant ($p < 0.1$), and not statistically significant at the more commonly used 5% level. The effect sizes are in line with the expectation that homes that are unoccupied or less frequently occupied during daytime hours are likely to lower their heating levels when no one is present, thereby reducing overall gas consumption.

The inclusion of occupancy slightly attenuates the effect of other variables such as the number of residents and age categories, suggesting that daytime presence partially overlaps with other household-level characteristics. Nevertheless, the direction and statistical significance of most coefficients remain similar to Model 2, indicating that occupancy contributes only marginally to the explanatory power of the model beyond what is already captured by dwelling and household characteristics.

The final model, **Model 4**, incorporates attitude and behavior variables, providing the most comprehensive estimation of the causal effect of thermal quality on gas consumption. The estimated effect indicates a 16.4% reduction in gas consumption per unit increase in thermal quality. This model explains 44.9% of the total variation in gas consumption. As outlined in Section 3.3.3, this final model minimizes bias in estimating the causal effect of thermal quality on gas consumption by accounting for relevant control variables.

Self-reported frugal households consume approximately 16% less gas than those that do not consider themselves frugal, highlighting the substantial role of behavioral factors. The importance attached to energy efficient behavior, and whether they actively tried to lower their gas consumption do not have statistically significant effects. The gas consumption of people that are almost never at home during the day is still 6% lower than for those that are almost always at home.[5]

Beyond its high statistical significance, the reduction in gas consumption attributed to frugal behavior is meaningful in magnitude. The estimated effect size is comparable to improving the thermal quality by one unit, equivalent to an improvement of approximately three energy labels. This finding underscores the considerable impact that frugal behavior can have on reducing gas consumption. To further investigate the frugality variables, the regression model is re-estimated using different categorizations in Appendix E.

Among the control variables, most cannot be easily modified. Household composition (e.g.,

[5] Excluding the frugal variable from the model causes the other behavioral variables to gain statistical significance. This suggests that self-reported frugality explains much of the same variation that these other behavioral variables capture. In other words, frugality appears to dominate the behavioral explanation of gas consumption.

number of residents, their ages, income) may change, leading to a different gas consumption, but this change typically involves (parts of) the household relocating to a different dwelling rather than altering the same dwelling's gas consumption. For a given household remaining in the same dwelling, the most feasible modifications involve improving thermal quality or altering behavioral practices. The large and significant effect of behavioral variables, particularly frugality, suggests substantial potential for reducing gas consumption through behavioral change.

5.4 Non-Linear Renovation Effect

To investigate the non-linearity of the effect of thermal quality on gas consumption, regression models are fitted using model specifications that allow for non-linearities, as explained in Section 3.6. The results are shown in Table 5.3. When adding a quadratic term for the thermal quality in **Model 1**, the coefficients are fitted corresponding to Equation 5.1.

$$\log(\text{gas}) = \beta_0 + 0.393 \cdot TQ - 0.097 \cdot TQ^2 + ... + \epsilon \tag{5.1}$$

$$\frac{\partial log(gas)}{\partial TQ} = 0.393 - 0.194 \cdot TQ \tag{5.2}$$

The coefficient for the linear term (+0.393) is positive, while the coefficient for the quadratic term (−0.097) is negative. Both coefficients are statistically significant, and R-squared increases from $R_{linear} = 0.449$ to $R_{quadr} = 0.453$, meaning slightly more variation in gas consumption is explained when including the quadratic term in the regression model.

The partial derivative with respect to the thermal quality is shown in Equation 5.2 and plotted in Figure 5.4. The derivative is larger than zero for thermal quality values below 2. This implies that improving the thermal quality for these values leads to an increase in gas consumption. This is an unexpected result and counter-intuitive. This trend is likely due to data sparsity in the range. All thermal quality values below 2 correspond to the worst energy label G, and the density of observations is not very high for this region. The thermal quality distribution is bell-shaped with the mean around 3, and only 2.2% of the sample data (46 out of 2062 observations) have a thermal quality below 2. Because of the low amount of observations within this range, the positive renovation effect for thermal qualities below 2 is considered an artifact.

The mean of thermal quality in the sample data is 3.06, corresponding to energy label D. At this mean thermal quality the partial effect is equal to −0.201. A one-unit increase in thermal quality, e.g., from 3.07 to 4.07 would lead to an energy label well above the label A threshold (3.8), and a 20.1% decrease in gas consumption.

Table 5.3: Non-Linear Multiple Linear Regression Models

	Dependent variable:			
	log(gasUsage)	log(gasPerArea)	log(gasUsage)	
	(1)	(2)	(3)	(4)
thermalQuality	0.393^{**} (0.156)	0.372^{**} (0.157)		
thermalQualSq	-0.097^{***} (0.027)	-0.092^{***} (0.028)		
energyLabelA				-0.395^{***} (0.073)
energyLabelB			0.101 (0.069)	-0.295^{***} (0.062)
energyLabelC			0.219^{***} (0.060)	-0.176^{***} (0.048)
energyLabelD			0.308^{***} (0.060)	-0.087^{*} (0.046)
energyLabelE			0.335^{***} (0.064)	−0.060 (0.049)
energyLabelF			0.356^{***} (0.067)	−0.039 (0.050)
energyLabelG			0.395^{***} (0.073)	
Observations	2,062	2,062	2,062	2,062
R^2	0.453	0.266	0.455	0.455
Adjusted R^2	0.442	0.251	0.443	0.443
Residual Std. Error	0.410 (df = 2021)	0.417 (df = 2021)	0.410 (df = 2017)	0.410 (df = 2017)
F Statistic	41.876^{***} (df = 40; 2021)	18.304^{***} (df = 40; 2021)	38.213^{***} (df = 44; 2017)	38.213^{***} (df = 44; 2017)
Note:				*p<0.1; **p<0.05; ***p<0.01
Additional Note:				All other control variables are included in the model, but omitted from the table.

For thermal qualities above 2, the derivative is negative and increasing in magnitude. This means that changes at higher thermal quality values are more influential than those on the lower end, when increasing thermal quality by the same amount of units. The results imply that improvements from energy label G to F or E may not have a large effect on gas consumption. The results from **Model 2**, where the dependent variable is defined as gas per area, lead to approximately the same estimated coefficients, also indicating that renovations for dwellings with higher initial thermal quality have a larger effect on the gas consumption per unit area.

Models 3 and 4 use the energy label instead of the thermal quality. For Model 3, the reference category is label A, and for Model 4, the reference category is label G. In the absence of a prescription on the relation between the causal variable of interest and the gas consumption, the estimates indicate a clear non-linear effect.

The differences between coefficients of two energy labels indicate the relative effect of improving the first to the second energy label. For example, improving a dwelling from label F to label C will lead to approximately 13.7% less gas consumption ($0.219 - 0.356 = -0.137$).

The differences between coefficient magnitudes for consecutive energy labels increase for better energy labels. For example, the difference between label G and F is 0.039, corresponding to a decrease in gas consumption of 3.9%. The differences between all consecutive energy labels are shown in Table 5.4. It can clearly be seen that improving by one energy label has a larger effect when the initial energy label is better.

There are two deviations from this pattern. First, the improvement from B to C is larger than from B to A. Second, the improvement from G to F is larger than from F to E, and from E to D. Both can be explained according to how the energy labels are defined. They are based on the continuous energy index, with some labels occupying a larger range (see Table 3.1).

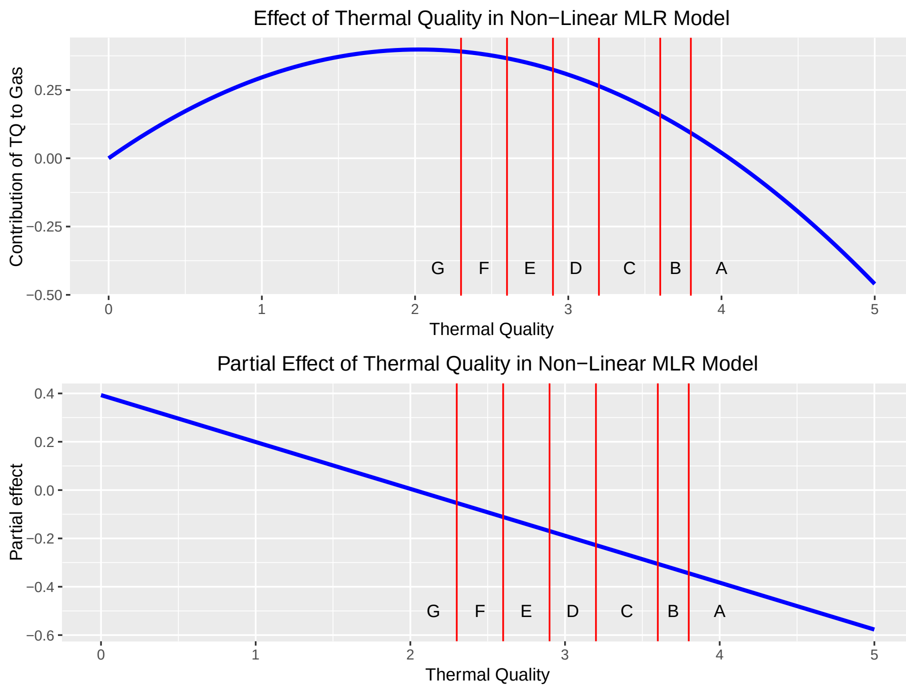

Figure 5.4: Partial effect of Thermal Quality in the Non-Linear Multiple Linear Regression Model

The contribution of thermal quality and thermal quality squared on gas consumption is shown in the top figure, and the partial effect of thermal quality is shown in the bottom figure.

Label B has the smallest (limited) range, while label C has a large range. Therefore, the jump from B to C represents a larger increase in the thermal quality than from A to B, which could explain the larger estimated effect. Additionally, the smaller estimated effect of moving from B to A may reflect diminishing returns (or stagnating increasing returns) at the upper end of the energy label scale. This interpretation is supported by the lack of a statistically significant difference in gas consumption between labels A and B, suggesting that energy savings plateau at higher thermal quality levels.

Regarding the coefficient of improving from label G to F, the range is also relevant. Since label G covers the largest range of thermal quality in the estimation sample, the difference between the mean thermal quality of label G and F is largest. Due to this larger than average jump in thermal quality from G to F, the expected gas savings are also larger.

For Model 4, with label G as the reference, there is no (highly) statistically significant difference between label G and F, E, and D. This corroborates the interpretation that renovations improving 'bad' energy labels by a small amount might not lead to significant reduction in gas consumption. The small effect size also indirectly leads to statistically insignificant differences, as this is determined by comparing the effect size with the standard error.

Overall, all models from Table 5.3 seem to support the conclusion that the renovation effect

Table 5.4: Gas Usage Reductions when Upgrading Energy Labels by One Category

Energy Labels	Difference in coefficients	Difference between mean TQ
B to A	−0.101	0.25
C to B	−0.118	0.32
D to C	−0.089	0.32
E to D	−0.027	0.29
F to E	−0.021	0.30
G to F	−0.039	0.51

is non-linear, and increasing for dwellings with higher thermal quality. This is in contrast to the expectations before running the analysis, as it was expected that energy efficiency improvements in poorly insulated dwellings might yield the highest reductions in gas consumption.

Although it is unexpected, it is plausible that when there are two (or more) primary sources of heat loss in a dwelling (e.g., windows and walls), modifying one will have a limited effect. When upgrading the windows, there may be a negligible heat loss through the windows, but this does nothing to prevent heat loss through the walls. There would still be a considerable amount of heat lost through the aspects of the dwelling that are poorly insulated. While the exact methodology behind energy labels is extensive and detailed, it is likely that these kind of renovations (only addressing part of the thermal envelope) can lead to these gradual improvements of the energy index/labels.

5.5 Projected Energy Savings

To estimate the potential reduction in residential gas consumption resulting from energy renovations, the effect of upgrading all dwellings in the sample data to a minimum thermal quality is calculated. In line with Dutch policy goals for rental dwellings in 2030, the effect of upgrading all dwellings to energy label D will be estimated, corresponding to a thermal quality of at least 2.9 as shown in Table 3.1. Note that the simulated scenario also includes owner-occupied dwellings, while the policy goal does not.

The projected gas savings if the dwelling was label D will be estimated for all labels currently below that (labels E, F, and G). The estimations are ceteris paribus, i.e., it is assumed that all other factors are constant. All calculations incorporate the survey weights provided in the dataset to ensure valid population-level inferences. Using the weights, the gas consumption reduction calculated should reflect the actual gas consumption in cubic meters in the Netherlands. Survey weights are discussed in more detail in Section 4.3.

The analysis consists of three estimation strategies, each based on regression models described earlier in this chapter. The projected gas consumption will be estimated using the model linear in thermal quality from Equation 3.5, using the model quadratic in thermal quality from Equation 3.6, and using the categorical regression model from Equation 3.7.

The calculated gas savings are limited to observations from the estimation sample, excluding dwellings that are not strictly gas-heated or were built after 1980. As a result, around 30% of dwellings with energy label E, F, or G are not included in the projection. In a scenario where all dwellings are upgraded to at least label D, these excluded dwellings would also be renovated, leading to greater overall energy savings than estimated here. Nevertheless, the estimation sample covers over 70% of dwellings with label E, F, or G.

5.5.1 Projected Percentage Reductions

The proportional change in gas consumption for each household (r_i) is estimated using multiple approaches. Equations 5.3, 5.4, and 5.5 define three alternative specifications for estimating percentage reductions. Since the models are estimated with log(gas) as the dependent variable, interpretation of the coefficients is naturally related to the percentage decrease in gas consumption.

Linear estimate

In the linear specification, the projected reduction is proportional to the gap between the target thermal quality and the observed value:

$$r_{i,lin} = -0.164 \cdot (2.9 - \mathrm{TQ}_i) \tag{5.3}$$

Here, TQ_i is the thermal quality of household i and -0.164 is the linear regression coefficient estimated by the model presented in Table 5.2.

Quadratic Estimate

In the quadratic specification, the projected reduction includes both linear and non-linear terms in thermal quality:

$$r_{i,quadr} = 0.393 \cdot (2.9 - \mathrm{TQ}_i) - 0.097 \cdot (2.9^2 - \mathrm{TQ}_i^2) \tag{5.4}$$

Here, 0.393 and -0.097 are the coefficients for the linear and quadratic terms respectively, as shown in Table 5.3.

Categorical Estimate

Based on the model using categorical energy labels, fixed percentage reductions are assigned to households with labels below D:

$$r_{i,cat} = \begin{cases} -0.087 & : \text{ if Label}_i = \text{G} \\ -0.048 & : \text{ if Label}_i = \text{F} \\ -0.027 & : \text{ if Label}_i = \text{E} \end{cases} \tag{5.5}$$

Here, −0.087, −0.048, and −0.027 are the estimated coefficients based on the difference in estimated coefficient of different labels as shown in Table 5.4.

5.5.2 Projected Gas Savings

To calculate the projected gas savings per household, the percentage reduction is multiplied by their current gas consumption, as shown in Equation 5.6.

$$\text{gas}_{i,\text{saved}} = \text{gas}_{i,\text{current}} \cdot r_i \tag{5.6}$$

To interpret the projected gas consumption and savings, the weighted gas consumption is used. The current gas consumption and projected savings are calculated using Equations 5.7 and 5.8. w_i is the survey weight corresponding to the household.

$$G_{\text{current}} = \sum_i \text{gas}_{i,\text{current}} \cdot w_i \tag{5.7}$$

$$G_{\text{saved}} = \sum_i \text{gas}_{i,\text{saved}} \cdot w_i \tag{5.8}$$

The total gas reduction due to renovations is calculated for the three different models: linear, quadratic, and categorical. The savings are presented in Table 5.5 as percentage reductions compared to the weighted gas consumption of the full energy module, the estimation sample, and a subset of the estimation sample containing only observations with label E, F, or G. The reported percentages are calculated by dividing the same estimated gas savings (G_{saved}) by the three different baseline consumption levels (G_{current}).

Across all three models, energy renovations are associated with a decrease in gas consumption, although the magnitude of savings varies by model and subset. When compared to the gas usage of the full energy module, the estimated reductions are modest, ranging from 0.74% to 1.27%. When renovating all strictly gas-heated dwellings to at least energy label D, the expected gas savings are thus approximately 1% of that of the gas consumption of the full Dutch housing stock. When compared to the estimation sample, the reductions are between 1.42% and 2.43%.

Table 5.5: Projected Percentage Savings Compared to the Weighted Gas Consumption of Different Sets of Observations

Method	Full Energy Module	Estimation Sample	Labels E/F/G from Sample
Linear	−0.0127	−0.0243	−0.0666
Quadratic	−0.00743	−0.0142	−0.0390
Categorical	−0.00861	−0.0165	−0.0452

5.6 Robustness Checks

Robustness analysis is important to investigate how design choices, such as the selection of control variables, influence the magnitude and significance of the estimated causal effect of energy renovations. By using different model specifications, it can be assessed whether the results are consistent, or are sensitive to design choices. Several robustness checks are performed, the results are shown in Table 5.6. The four models represent the same model and data as the main linear estimation model (Model 4 in Table 5.2), but are altered in some way:

1. The dependent variable is the natural logarithm of gas per area, instead of the natural logarithm of gas.

2. The regression is fitted using survey weights.

3. Only dwellings with central heating and no gas heater are included.

4. An additional control variable is included: the average temperature set on the thermostat.

Table 5.6: Robustness Analysis

	Dependent variable:			
	log(gasPerArea)	log(gasUsage)		
	(1)	(2)	(3)	(4)
thermalQuality	-0.153^{***} (0.025)	-0.111^{***} (0.031)	-0.199^{***} (0.028)	-0.237^{***} (0.035)
Observations	2,062	2,062	1,954	1,246
R^2	0.261	0.469	0.449	0.492
Adjusted R^2	0.247	0.459	0.438	0.475
Residual Std. Error	0.418 (df = 2022)	16.535 (df = 2022)	0.409 (df = 1914)	0.386 (df = 1205)
F Statistic	18.353^{***} (df = 39; 2022)	45.827^{***} (df = 39; 2022)	39.992^{***} (df = 39; 1914)	29.143^{***} (df = 40; 1205)

Note: *p<0.1; **p<0.05; ***p<0.01

Additional Note: All other control variables are included in the model, but omitted from the table.

The main model resulted in as estimate for the causal effect of thermal quality equal to −0.164, corresponding to a 16.4% decrease in gas consumption for a one-unit increase in thermal quality. The R-squared was 0.449, which means that 44.9% of the variation in gas was explained by the independent variables.

Model 1 changes the dependent variable to gas consumption per area, changing the estimate to −0.153. The other included control variables are the same, except for the area of the dwelling. In the original model it is included in a logarithm, but due the behavior of logarithms it needs to be included without being log-transformed.[6]

The magnitude of the estimated coefficient for thermal quality is slightly smaller than in the original model. The R-squared is a lot smaller, only 26.1% of the variation in gas per area is explained by the independent variables. The decreased R-squared suggests that dwelling size is a major determinant of total gas consumption, explaining much of its variation. When its direct influence is removed, by using gas consumption per square meter, there remains more unexplained variation. Another explanation could be that the area of the dwellings is not necessarily equal to the heated area of the dwelling. Households may choose to heat only specific rooms, while leaving other areas unheated. This means that gas consumption per total square meter might not reflect actual heating intensity, introducing additional variation that is not captured by the independent variables.

For **Model 2**, the model is fitted using the survey weights as provided in the WoON dataset. As explained in Section 4.3, survey weights are not necessary to estimate the causal effect of thermal quality on gas consumption. However, they are used here to check the influence of using a weighted regression model. The estimated effect changes to −0.111, with 46.9% of the variation in gas consumption explained.

This suggests that applying survey weights changes the estimated effect of thermal quality, making it less negative compared to the unweighted model. The increase in R-squared from 0.449 to 0.469 indicates a modest improvement in model fit, but does not substantially change the overall explanatory power of the model.

Model 3 restricts the sample data to dwellings with only a central heating system, excluding 108 observations that use gas heaters. As explained in Section 4.2.2, gas heaters provide local heating in a single area, while central heating boilers heat the whole house by circulating hot water from the boiler throughout the dwelling. Using these data, the estimate increases in magnitude to −0.199, and the R-squared is exactly the same as in the main model, 0.449. The change suggests that restricting the sample to a single heating system, the relationship between thermal quality and gas consumption becomes somewhat stronger, while the explanatory power of the model remains unchanged.

The larger effect could imply that in the selected heating system, central heating, improvements in thermal quality have a greater impact on gas consumption. This might suggest that

[6]The model $[\log(\text{gas}/\text{area}) = \beta_0 + \beta_1 \cdot \text{Thermal Quality} + \beta_2 \cdot \log(\text{area}) + \dots + \epsilon]$ can be written as $[\log(\text{gas}) = \beta_0 + \beta_1 \cdot \text{Thermal Quality} + (\beta_2 + 1 \cdot) \log(\text{area}) + \dots + \epsilon]$. Therefore, when keeping log(area) as an independent variable, only its estimated coefficient will change (by 1), and all other coefficients will stay the same.

homes with central heating are more sensitive to energy efficiency improvements such as insulation and ventilation measures than dwellings with gas heaters.[7]

It could also mean that improvements of the thermal quality due to updating the heating system have a relatively small effect compared to improvements due to insulation and ventilation (when keeping the heating system constant). Heating system upgrades affect how efficiently gas is used to produce heat, but do not necessarily reduce heat loss. Insulation and ventilation improvements reduce heat loss, requiring less gas to maintain indoor temperatures. This might mean that when the heating system is held constant, improvements in thermal quality due to insulation and ventilation have a relatively greater effect.

Therefore, the stronger effect could be due to either a larger insulation effect for central heating compared to gas heaters, or due to the fact that when the heating system is held constant, thermal quality is primarily a function of insulation and ventilation improvements.

Finally, **Model 4** introduces average thermostat temperature as an additional control variable. Because this variable is only available for a subset of the data, the sample size decreases by 816 observations. Controlling for indoor temperature increases the absolute value of the thermal quality coefficient from -0.164 to -0.237. The model's explanatory power also improves, with the R-squared rising from 0.449 to 0.492, suggesting that thermostat settings account for a meaningful share of the variation in gas consumption.

Including indoor temperature reveals a substantially larger effect of thermal quality on gas use. This implies that part of the initially estimated effect was suppressed by behavioral responses: households in more energy-efficient dwellings tend to heat their homes to higher temperatures, thereby reducing potential gas savings. This pattern is consistent with the rebound effect, where improved thermal quality lowers the effective cost of heating, leading to increased consumption. While the rebound effect partially offsets the energy savings, it also reflects increased comfort, which may have previously been limited by financial constraints.

When estimating the causal effect of renovations for policy evaluation and forecasting, excluding temperature settings from the model is more appropriate. The objective of this thesis is to quantify the actual gas savings achieved in practice, incorporating real behavioral adaptations, rather than the theoretical maximum under fixed behavior. Since these adaptations are empirically observed and form part of the real-world impact of renovations, the main specification appropriately leaves indoor temperature uncontrolled.

[7]The type of heating system is included in the calculation of the thermal quality, so only including one system makes the changes in thermal quality more dependent on other determinants, such as insulation and ventilation.

Chapter 6

Discussion

This chapter interprets the main findings of the study in light of existing literature. It also addresses several limitations related to data quality, measurement issues, and behavioral complexity that may affect the robustness and generalizability of the results. By critically assessing both the strengths and caveats of the analysis, the chapter aims to position the thesis within the wider body of energy renovation research and to provide guidance for policymakers, practitioners, and future academic work. The discussion begins with a comparison to related studies, followed by an examination of potential sources of bias and measurement error. Finally, the reliability of the increasing returns finding will be discussed.

6.1 Comparison with Existing Literature

The estimated linear causal effect found in this study aligns with findings from previous research, which also report statistically significant but modest effects of energy renovations on gas consumption. Given that this analysis relies on the Dutch implementation of the energy performance certificate guideline, specifically the energy index, the results are primarily comparable to studies focused on the Netherlands using similar metrics.

While peer-reviewed academic studies on this topic remain limited, several reports by Dutch institutions, such as the Netherlands Environmental Assessment Agency (PBL), provide useful benchmarks. For example, Van Den Wijngaart and Van Polen (2020) estimate energy savings from upgrading energy labels, finding a 12–23% reduction when improving from label C to B, depending on the methodology. This is comparable to the 11.8% reduction found in this study for a similar improvement.

Their results also suggest a pattern of increasing returns, with lower savings observed for upgrades at the lower end of the efficiency scale. Specifically, upgrading from label E to D is estimated to reduce gas consumption by 8–13%, while upgrading from label C to B yields larger savings. Although the PBL estimates are based on theoretical calculations rather than observed data, the similarity in effect sizes supports the credibility of this thesis's empirical findings.

Interestingly, while the individual renovation effects are comparable, the projected national gas savings differ considerably. Van Den Wijngaart and Van Polen (2020) project a 7–13% reduction if all dwellings were upgraded to at least label D, whereas this thesis estimates a much smaller effect of 0.7–1.3%. This discrepancy may stem from several factors. Firstly, the projections in this thesis are based on renovating all dwellings from the estimation sample, which excludes homes with labels E, F, and G that do not meet the restriction criteria. This excludes approximately 30% of the dwellings with labels E, F, and G. Secondly, the distribution of energy labels in WoON may not reflect the national housing stock. Thirdly, the paper by Van Den Wijngaart and Van Polen (2020) only includes variables related to dwelling type and construction area, which may lead to confounding. These differences could lead to an underestimation of national-level savings in this analysis, or to an overestimation of savings in the study by Van Den Wijngaart and Van Polen (2020).

Further support for the plausibility of the findings is provided by Majcen et al. (2013a), reporting a 16% reduction in national gas consumption in a scenario where all dwellings are improved by two energy labels (up to a maximum of label B). Although this scenario is not directly comparable, some of the higher savings are likely explained by the more stringent renovation assumptions and the older dataset (2010), which reflects a less efficient housing stock with more renovation potential. However, given the relatively low renovation rate, the vintage of the dataset can only partially account for the difference in outcomes. It is unlikely that energy labels in the more recent data have changed enough to fully explain the discrepancy. Notably, the study by Majcen et al. (2013a) observes that dwellings with energy labels E, F, and G consume a similar amount of actual primary energy, and also expresses doubt about the effectiveness of improving label G by one or two labels.

This thesis also explores potential non-linearities in renovation effectiveness. Van Den Brom et al. (2019) show that the impact of renovation depends strongly on the initial thermal quality: insulation and deep renovations are more effective in poorly insulated dwellings, while heating and ventilation upgrades are more beneficial in well-insulated homes. These findings are consistent with this study's conclusion that renovation effects may be non-linear. However, their research highlights that such non-linearities may depend on the specific renovation measures, which are not explicitly captured in the thermal quality index used in this thesis.

In contrast to the findings in this thesis, Brounen et al. (2012) report diminishing returns to insulation improvements, with small but statistically significant effects. However, insulation is not the primary focus of their study and is included only descriptively in the model. Moreover, their analysis lacks a causal framework, which limits the strength of their conclusions about the insulation effect. While their findings differ from the increasing savings suggested here, they should be interpreted with caution.

Additionally, Brounen et al. (2012) find that household characteristics explain more variance in gas consumption per capita than dwelling characteristics, whereas the opposite is found in this research. This discrepancy is likely due to differing dependent variables: their model uses gas consumption per capita (m^3capita^{-1}), while this thesis uses absolute gas consumption (m^3).

Finally, Zhivov and Lohse (2020) argue that shallow renovation projects may appear more effective than deep energy retrofits when evaluated against short-term objectives. While shallow renovations can generate immediate savings, their potential becomes quickly exhausted, leading to diminishing returns over time. In contrast, deep renovation paths yield smaller but more consistent savings, ultimately achieving significantly greater energy reductions in the long run.

This view contrasts with the findings of this thesis, which suggest that even in the short term, deep renovations, corresponding to substantial improvements in thermal quality, lead to larger gas savings than more modest upgrades. Nevertheless, both studies ultimately point to the same conclusion: deep energy renovations are essential for achieving long-term energy savings. As such, their findings provide additional support for prioritizing deep retrofit strategies as part of future energy policy.

In conclusion, this study's findings are largely consistent with existing research, particularly in confirming the modest yet statistically significant impact of energy renovations on gas consumption. While direct comparisons are complicated by differences in methodology, data vintage, and renovation definitions, the general alignment in effect sizes strengthens the credibility of the causal estimates reported here.

More importantly, this thesis offers several novel contributions. It provides empirical evidence of non-linear renovation effects using a causal regression framework that integrates behavioral controls alongside structural and demographic characteristics. It also relies on certified dwelling inspections, improving the measurement reliability of the causal variable of interest. Furthermore, the potential non-linearity of renovation effects is explicitly examined through robustness checks (see Section 6.3), offering greater confidence in the reliability of these results. To the author's knowledge, such an in-depth empirical analysis of non-linear effects is not present in existing Dutch studies. Together, these elements support a more nuanced understanding of gas consumption dynamics and strengthen the case for policies that prioritize comprehensive, deep renovations strategies over shallow, incremental upgrades.

6.2 Limitations

This study assesses the effect of energy renovations on gas consumption in Dutch residential buildings. However, several limitations should be considered when interpreting the findings. These relate to unobserved variables, behavioral responses, measurement challenges, and modeling decisions.

Despite controlling for various factors, some relevant variables may remain unobserved. Omitted variable bias arises when a variable that influences both thermal quality and gas consumption is excluded, leading to biased estimates. While not all unobserved variables introduce bias, those structurally related to both gas consumption (dependent variable) and thermal quality (independent variable) do. This issue is inherent in observational studies, where not all relevant variables are known or available. Nonetheless, it is important to consider which unobserved factors are likely to be most influential and how their omission may affect results.

6.2.1 Behavioral Factors

The relationship between thermal quality and gas consumption is not purely technical but also influenced by household behavior. Personal heating preferences and behavioral adjustments following renovations both play a role in shaping gas consumption, potentially introducing bias in the estimated effect of thermal quality. Heating behavior varies across households based on preferences, habits, and financial considerations. Some households prefer to set their thermostat higher or heat more rooms than others, directly influencing gas consumption.

These heating preferences may also influence the choice of dwelling, particularly its thermal quality. Households that prefer higher indoor temperatures might **self-select** into well-insulated dwellings, as these homes retain heat better and reduce heating costs. While frugal households may tolerate lower quality insulation but compensate through energy saving behaviors. These preferences are related to both the thermal quality, through the self-selection effect, and gas consumption, due to their preferred temperature.[1]

As a result, unobserved heating preferences might introduce bias in the estimated effect of thermal quality. Since a preference for higher temperatures is likely associated with both greater gas consumption and a higher likelihood of living in a well-insulated dwelling, omitting this factor leads to an underestimation of the true effect of thermal quality. The model may attribute part of the higher gas consumption to the thermal quality rather than recognizing that it stems from the pre-existing underlying preference for higher indoor temperatures.

Not controlling for temperature settings in the main model does lead to unobserved heating preferences, potentially leading to a biased estimate. However, including temperature would block the **rebound effect** and lead to unreliable estimates. The rebound effect is another important behavioral mechanism, where energy efficiency improvements lead to changes in consumption patterns. If improved thermal quality reduces heating costs, households may respond by increasing their indoor temperatures or heating additional rooms. This behavioral adjustment partially offsets the expected energy savings, resulting in less gas savings than if the rebound effect did not occur. As discussed in the robustness analysis, the rebound effect is not likely to play a large role in the causal estimates. By not controlling for temperature in

[1] The preferred temperature is not necessarily equal to the temperature set on their thermostat, as present within the data. The actual temperature can deviate from the preferred one due to for example financial constraints.

the main model, the effect estimate captures possible adjustments to target temperature that households make after renovations.[2]

6.2.2 Measurement of Thermal Quality

The **calculation of the energy index**, and by extension thermal quality, may introduce some inaccuracies in this study. For thermal quality to be a valid causal variable, it should accurately represent the energetic efficiency of a dwelling with respect to heating. In principle, the energy index efficiently summarizes multiple characteristics related to insulation and ventilation. However, some included variables do not directly reflect heat loss reduction or heating efficiency, introducing measurement error in the key explanatory variable. If these variables only affect the reported thermal quality, but not actual gas consumption, then they introduce random noise into the measurements. This leads to a measurement error, which typically causes attenuation bias, biasing the estimated effect of thermal quality toward zero but not creating a spurious relationship. If the variables also affect the gas consumption, they act as confounders, leading to omitted variable bias.

One example is the inclusion of solar panels in the energy index calculation. While a dwelling with extensive solar panels may be assigned a higher thermal quality, solar panels do not directly affect heat retention or gas consumption. If such factors are correlated with both the reported thermal quality and gas consumption, they could bias the estimated effect of thermal quality. For example, energy conscious households that install solar panels might also be more likely to adopt other energy saving behaviors. In this specific case, solar panels were controlled for in the model to prevent their influence on the estimates. However, other factors that are unaccounted for may similarly distort the thermal quality measure, leading to potential biased effect estimates. Notably, the exact methodology for computing the energy index is not freely available, and it is assumed that there are few or none other such factors. However, if there are, the causal estimate might be biased towards zero, underestimating the renovation effect.

Another critical source of measurement error is **installation quality**. The energy index records various dwelling characteristics, such as insulation type and thickness, but does not assess whether these materials were properly installed. A dwelling may have a high quality insulation on paper, but if installation defects are present, such as gaps around windows or doors, the expected improvements in heat retention may not materialize. In some cases, poor installation could even increase gas consumption by creating unintended drafts.

The extent to which installation quality is correlated with thermal quality determines the

[2] The model does account for some other variables related to attitudes and behavior. Even when household still consider themselves the same amount of frugal, they might still increase their thermostat temperature, because they might feel it will be offset by the reduced costs or greenhouse gas emissions. Therefore, controlling for these variables does not block the rebound effect.

impact on the estimated effect. If installation quality varies randomly across dwellings, it introduces measurement error, likely leading to attenuation bias. If installation quality is systematically related to thermal quality, for example if renovated dwellings tend to have lower installation quality, then the effect of thermal quality could be underestimated.

Whether this is problematic depends on the interpretation. If the goal is to estimate the theoretical potential of thermal quality, measurement error reduces validity. However, since this study focuses on real-world impacts of energy renovations as they are typically implemented, capturing the effect of imperfections is appropriate and enhances external validity.

6.2.3 Heating System

Households with different **heating systems** may exhibit distinct heating habits. Among the two included heating systems, gas heaters and central heating, the proportion of heated area relative to total floor area likely differs. Gas heaters typically provide localized heating, often installed in only a few rooms and without radiators, resulting in partially heated dwellings. In contrast, central heating systems may lead to broader heating coverage, not necessarily due to occupant preferences but due to system capabilities. For instance, homes with central heating are more likely to heat hallways or kitchens, whereas gas heaters may be physically unable to do so.

The type of heating system is included in the calculation that determines the thermal quality of a dwelling, and is also expected to influence the percentage of heated area, influencing the gas consumption. It is unknown whether the average occupant behavior the energy index is based on takes behavioral differences between heating systems into account. If it does not, the heating system influences both thermal quality and gas consumption, and its omission may lead to a biased estimate.

Including heating system type in the model could control for this variation. However, since system upgrades are part of many renovations, holding it constant may exclude an important part of the total renovation effect. As such, its omission reflects a deliberate modeling choice aimed at estimating the broader impact of renovations, including the system replacement.

6.2.4 Model Specifications and Data Limitations

The specification of the regression model plays a central role in estimating the effect of thermal quality on gas consumption. An inappropriate functional form may bias coefficient estimates or obscure meaningful relationships. While robustness checks address non-linearity to some extent, the optimal specification remains uncertain. It is possible that non-linear relationships between thermal quality and gas consumption are not fully captured.

Additionally, possible interaction effects between thermal quality and other variables, such as heating system type or household composition, are not explicitly included in the model. These interactions (e.g., number of residents × presence of a bath) may influence gas consumption and contribute to unexplained variation in the estimates.

Weather conditions in 2018, the year the gas consumption was measured, may also affect the results. For instance, a particularly cold winter could enlarge the role that financial constraints play.

The thermal quality variable is approximately normally distributed, resulting in relatively few observations at the lower and upper extremes. Since the effect of thermal quality on gas consumption is likely non-linear, this sparsity limits the reliability of estimates for dwellings with very poor or very high energy performance.

Another limitation concerns potential measurement error from unobserved electric heating. Although dwellings with known electric heating systems (e.g., heat pumps) are excluded from the sample, supplementary electric heating, such as mobile space heaters, is not accounted for. Analysis of the sample indicates that such heaters are more commonly used in poorly insulated dwellings. This suggests that some of these households may supplement their gas heating with electricity, leading to an underestimation of total heating energy use. As a result, the estimated effect of thermal quality on gas consumption may be biased downward. In particular, this substitution could contribute to an apparent pattern of increasing returns, where the gas savings from improving thermal quality appear to grow at higher levels of insulation. However, this possibility is examined in greater detail in the next section, which includes a robustness check excluding all households with electric space heaters.

Finally, the temporal context of the data introduces an important limitation. The analysis is based on data from 2018, before significant societal developments that likely altered household energy behavior. Most notably, the Covid-19 pandemic led to a structural increase in working from home, especially among higher-educated individuals with office jobs. This trend has increased the time people spend at home, potentially raising residential heating demand. In addition, the sharp rise in gas prices following the 2022 Russian invasion of Ukraine has heightened public awareness of energy consumption and prompted more frugal energy behavior. These developments may have changed both the level and pattern of gas usage, as well as the marginal value of thermal insulation. While the model controls for key factors such as income and occupancy as main effects, it does not fully capture the broader behavioral and economic changes that occurred after 2018. Therefore, the estimated effect of thermal quality should be interpreted as context-specific and may not fully generalize to current conditions. Nonetheless, later robustness checks by occupancy groups provide additional confidence that the core pattern of increasing returns to thermal quality is a reliable finding.

6.3 Reliability of the Increasing Returns Result

The finding that deeper renovations yield disproportionately higher gas savings challenges conventional wisdom underlying much of current energy policy, which generally prioritizes widespread renovation of the worst-performing homes. Given the potentially profound implications of this result, a critical examination of its reliability is essential to ensure that it is not an artifact of model specification, data limitations, or overlooked factors.

While the previous section addressed conceptual and methodological limitations, this section presents additional robustness checks and supplementary analyses, some of which are detailed in Appendix F, to rigorously assess the validity of the increasing returns pattern. This approach demonstrates that the surprising nature of the finding has been carefully scrutinized from multiple angles before informing policy-relevant conclusions.

Such a thorough investigation is crucial because current policy strategies often assume a relatively linear or diminishing relationship between renovation depth and energy savings, leading to a strong focus on upgrading the poorest-performing dwellings. The evidence suggests that this assumption may not hold, highlighting the need to reconsider and potentially reorient policy priorities. The extensive additional testing presented here aims to explore alternative explanations and confirm that the increasing returns effect is a robust and meaningful feature of the data, rather than a statistical anomaly.

6.3.1 Electric Space Heaters

Households with poor thermal quality may be more likely to supplement gas heating with electric space heaters, which would reduce their gas consumption independently of thermal quality. While the dataset lacks direct information on usage frequency, it does include whether a household owns an electric space heater. Ownership rates increase consistently with worsening energy labels, from 4.8% among label A homes to 14.4% among label G homes (see Table F.1).

This trend suggests that some of the gas savings attributed to thermal quality improvements may instead reflect fuel switching behavior. In such cases, gas consumption alone understates total energy use in inefficient dwellings, potentially exaggerating the slope of the thermal quality effect and producing an apparent pattern of increasing returns.

However, a robustness check excluding all households that reported owning an electric space heater showed that the increasing returns pattern remained unchanged.[3] This strengthens the interpretation that the pattern reflects real differences in gas consumption due to renovations, and is not driven by fuel switching behavior.

[3] For the quadratic model β_{TQ} changes from 0.393 to 0.390 and β_{TQ^2} changes from -0.097 to -0.098. For the categorical model, the gas consumption of dwellings with energy label G is still not statistically different from energy labels F, E, and D.

6.3.2 Robustness to Functional Form and Model Specification

Changing the Dependent Variable Specification

To test whether the observed increasing returns pattern holds when using absolute rather than relative gas use, the main regression was re-estimated with gas consumption in cubic meters per year (instead of its natural logarithm) as the dependent variable. The log-transformed model captures proportional (percentage) changes. However, higher percentage reductions at better thermal quality levels do not necessarily imply larger absolute savings, since households with more energy-efficient homes already consume less gas. For example, a 20% reduction from 600 m^3 saves more gas than a 25% reduction from 400 m^3.

By using absolute gas use directly, it is possible to verify whether deeper renovations yield larger actual energy savings in cubic meters. Interestingly, when estimating the model using absolute gas consumption, the difference between label D and label G becomes statistically significant at the 5% level (previously only at the 10% level in the logarithmic model). This suggests that label D may be more distinct from label G in terms of actual energy use than the relative model initially implied. Nonetheless, the estimated partial effect of thermal quality remains similar in shape (see Figure F.1). It is positive at the lower end of the scale (for part of label G), and increasingly negative at higher thermal quality levels, indicating greater savings. This provides additional support for the robustness of the increasing returns pattern, now validated both in relative and absolute terms.

Cubic Term for Thermal Quality

To assess whether the quadratic model might obscure further non-linearities or exaggerate the increasing returns pattern, a cubic specification of thermal quality was estimated. Unlike a linear or quadratic model, a cubic functional form allows the effect of thermal quality to vary flexibly across its range, capturing relationships that may initially flatten and then steepen, or vice versa. This is particularly useful when testing for increasing returns, as it does not impose symmetry or constant curvature.

The partial derivative of gas use with respect to thermal quality, calculated from the cubic specification, confirmed that gas savings increase at higher levels of thermal quality across the empirical range of values, supporting the main result (see Figure F.2). The partial effect is even steeper and indicates even higher increasing returns than the quadratic model. This suggests that deeper renovations indeed yield disproportionately larger reductions in gas consumption, rather than being an artifact of model specification.

Applying Survey Weights to the Non-Linear Model

The non-linear models were re-estimated using the survey weights. The results of the weighted analysis closely mirror those of the unweighted models. The estimated partial effect of thermal quality remains highly consistent in shape and magnitude, again showing a clear pattern of increasing returns.

However, some differences in statistical significance emerge. In the categorical model, the difference in gas consumption between label G and label D is no longer statistically significant at conventional levels (previously significant at the 10% level). Additionally, the differences between label G and labels C and B, and between label A and label C remain significant, but now only at the 5% level (previously at the 1% level). These shifts reflect increased uncertainty but do not alter the substantive interpretation that deeper renovations still yield larger and more reliable gas savings than shallow ones.

Overall, the weighted analysis confirms the robustness of the increasing returns pattern while providing more conservative estimates of statistical significance.

Robustness to Sample Composition

To further validate the main findings, the analysis was repeated on various restricted subsamples to test robustness to sample composition. These tests evaluate whether the main results are driven by extreme values at either end of the energy label distribution, by imbalanced label representation, by occupancy of the dwelling, or by heterogeneity in heating systems.

First, subsamples were constructed based on different segments of the energy label distribution, including dwellings with relatively poor, average, or good thermal quality. The linear model was re-estimated for several lower-bound samples. When restricting the data to labels D through G, representing homes with relatively poor thermal quality, the estimated coefficient on thermal quality fell substantially from −0.164 to −0.058 and was only statistically significant at the 10% level. Narrowing the range further to labels E through G yielded an even smaller coefficient of −0.057, which was no longer statistically significant at conventional thresholds. These results suggest that shallow renovations, such as upgrades from label G to D or E, are associated with smaller and less reliable reductions in gas consumption.

In the quadratic specification, the marginal effect of thermal quality remained consistent across all subsamples. Gas savings showed increasing returns throughout the observed range. While the slope and starting point varied somewhat across samples, the overall shape and direction of the curve were remarkably stable. This suggests that the increasing returns pattern is not driven by outliers in the full sample or skewed by the inclusion of certain energy labels.

To further assess the increasing returns finding, non-linear regressions were also conducted separately for subsets of the sample based on daytime occupancy patterns (i.e., households where occupants are always, sometimes, or never at home during the day). Interestingly, all three occupancy groups exhibited a consistent pattern of increasing returns to thermal quality improvements. This reinforces the interpretation that the observed non-linear relationship between thermal quality and gas consumption is not driven by differences in time spent at home. Consequently, even if societal trends such as increased working from home shift the overall distribution of occupancy in the future, changing occupancy distributions would likely only affect the average magnitude of gas savings but not the underlying shape of the returns curve. Therefore, this robustness check strengthens the credibility of the increasing returns finding and increases the likelihood that it remains relevant under current and future occupancy patterns.

Finally, the analysis was repeated on a subsample restricted to dwellings equipped with central heating systems only. Results from the quadratic model remained highly consistent with the main specification, again showing increasing returns to thermal quality improvements. A minor difference was observed in the significance of the gap between label D and label G, which became statistically significant at the 5% level (previously only at 10%).

Taken together, these subsample analyses reinforce two key conclusions. First, the pattern of increasing returns is not dependent on the inclusion of particular subgroups or outliers and holds across different portions of the energy label distribution and sample restrictions. Second, they underscore that substantial gas savings primarily emerge after surpassing a certain thermal quality threshold. Improvements limited to the lowest end of the scale, such as upgrades from label G to E, appear insufficient to generate large or reliable reductions in gas use.

Sensitivity to Cut-Off Year

The analysis focuses on estimating the impact of energy renovations on gas consumption in older Dutch residential buildings. To ensure that variation in thermal quality represents actual improvements due to renovations, rather than differences in initial construction quality, the main model restricts the sample to dwellings built before 1980. In older dwellings, high thermal quality reflects the result of energy renovation efforts, making them a suitable population for causal analysis.

To test the sensitivity of the results to the choice of cut-off year, the model was re-estimated for different subsamples: dwellings built before 1970, 1980 (baseline), and 1990, as well as using no cut-off at all. Across these specifications, the estimated linear effect of thermal quality on gas consumption remains negative and fairly stable, with coefficients of −0.175 for cut-off year 1970, and −0.199 for cut-off year 1990. In the full sample with no construction year restriction, the estimated coefficient is larger (−0.252), suggesting a steeper relationship between thermal quality and gas use. However, because good thermal quality levels no longer represents purely renovation efforts, but also higher construction standards, this estimate no longer isolates the effect of renovations alone. It therefore does not align with the research objective but is still useful as a robustness check.

Importantly, the quadratic specification estimated on the sample without a construction year restriction, as well as on samples using a different cut-off year, still shows a pattern of increasing gas savings with higher thermal quality, supporting the main conclusion of increasing returns to renovation quality. For the subsample with no cut-off year, label A and B now show a statistical difference. All other models find no difference, similar to the baseline model. For all of the modifications to the cut-off year, there is a statistically significant difference between the gas consumption of energy label G and D at the 5% level. These results lend further confidence to the result that deeper energy renovations yield progressively greater reductions in gas use.

6.3.3 Interpretation and Implications

Despite these robustness checks, some limitations remain. First, the risk of functional form misspecification and unobserved confounders cannot be fully ruled out. For example, if variables like dwelling size have non-linear effects and are also correlated with energy label (e.g., label G homes tend to be larger), then omitting squared or interaction terms could bias results. However, additional tests including higher-order terms (such as squared log(area)) show that the estimated effect of thermal quality remains largely unchanged, suggesting that such bias is limited.

In addition, several alternative model specifications were tested to examine differences in gas consumption between energy labels. In the main specification, gas consumption differences became statistically significant starting from label C compared to label G. However, models using different functional forms or subsamples provided stronger evidence that this threshold may actually begin at label D, with dwellings achieving label D consuming significantly less gas than those with label G, a difference only marginally significant in the main model. This suggests that relatively shallow renovations reaching label D can deliver more meaningful gas savings than initially concluded. However, these alternative specifications do not contradict the main finding of increasing returns to renovation depth. Instead, they refine the understanding of where significant gas savings begin to occur along the energy label scale.

While the overall pattern shows increasing marginal savings with higher thermal quality, there is no statistically significant difference in gas consumption between label A and label B in most models. This could indicate stagnating returns at the upper end of the energy label scale, where additional improvements yield smaller or negligible savings. However, this does not challenge the main finding of increasing returns up to label B. The non-linear pattern remains clear. Improvements from lower to intermediate labels are associated with progressively larger reductions in gas consumption.

Taken together, these additional analyses strengthen the credibility of the main finding that renovations yield increasing gas savings as thermal quality improves. While the cross-sectional nature of the data means that definitive causal claims cannot be made, the consistency of results across models and samples suggests the findings are robust. Therefore, the results provide credible support for policy measures that prioritize renovations aimed at achieving higher thermal quality.

Chapter 7

Conclusions

This thesis set out to address a critical question in the context of the Dutch energy transition: *"How do energy renovations influence the energy consumption of Dutch residential buildings?"*. Drawing on large-scale national survey data from WoON 2018, this study estimated how thermal quality, a proxy for renovation depth, affects natural gas consumption in dwellings built before 1980. The findings contribute both scientifically and practically, offering new insights into the relationship between building characteristics and household energy use, and providing guidance for policy aimed at reducing carbon emissions in the built environment.

Overall, the results suggests a need to shift policy focus from minimal upgrades toward deep, comprehensive renovations, while also recognizing the significant role of household behavior. This chapter summarizes the main findings, discusses their policy implications, and outlines possibilities for future research.

7.1 Summary of Findings

Descriptive analysis found that thermal quality is approximately normally distributed across the sample data, with majority of dwelling having energy label D. Comparing the gas usage of dwellings, worse energy labels consume consistently more gas than better labels. The causal effect of thermal quality on gas consumption is estimated by controlling for other factors related to thermal quality and gas consumption. The effect is precisely estimated and highly statistically significant across three model specifications: linear, non-linear, and categorical.

The main conclusion about how energy renovations influence the energy consumption of Dutch buildings is that, on average, energy renovations significantly reduce household gas consumption. Specifically, using the linear model, improving thermal quality by one unit, roughly equivalent to three energy label upgrades, leads to a 16.4% average reduction in gas use.

Additionally, using the quadratic model, increasing returns are found for higher thermal quality. Increasing returns mean that upgrading from label G to F reduces gas consumption less than upgrading from E to D, or from C to B. The partial effect is -0.20 at the mean of thermal quality (label D), corresponding to a gas reduction of 20%. This is larger than the effect found in the linear model. However, for energy labels E, F, and G, the effect is smaller than in the linear model. One possible explanation for the increasing returns is that comprehensive and well-planned renovations tend to occur at the higher end of the efficiency scale, and that these tend to yield larger savings than incremental improvements in poorly insulated homes.

The categorical model provides further insight into the distribution of effects across the thermal quality scale. It shows that the gas consumption in dwellings with energy labels F, E, and D is not statistically different from that of energy label G, indicating that energy savings from renovations in these lower ranges may be limited. This suggests that the average effect found in the linear model is primarily driven by improvements at the mid to high end of the thermal quality scale. The model also finds increasing returns, with gas reductions resulting from improving by one label increasing in magnitude for better labels.

Finally, the energy savings from upgrading all dwellings to at least energy label D are projected using the estimated causal effects of the three different models. The projections show that this would decrease the gas consumption from the sample data by between 1.4% and 2.4%. Compared to the gas consumption from the national housing stock, this corresponds to a decrease between 0.7% and 1.3%.

The findings contribute to the broader evidence base on the effectiveness of energy renovations. It is shown that while thermal quality improvements lead to meaningful reductions in gas use, the effect is non-linear and concentrated at higher thermal quality levels. Robustness checks, including alternate model specifications and subsample analysis, support the credibility of these findings.

Beyond its empirical contribution, this thesis also demonstrates the value of combining detailed technical dwelling data with behavioral survey responses. For example, the strong role of frugality in predicting energy energy use suggests that consumption is shaped not only by insulation levels or heating systems, but also by people's everyday practices and choices. Integrating these dimensions can strengthen future evaluations of energy policy and housing interventions.

7.2 Implications for Policy

The findings of this thesis offer several insights for policymakers seeking to accelerate the energy transition in the Dutch residential sector. While the overall message supports continued investment in energy renovations, the results call for a more refined and strategic approach.

From Minimal Upgrades to Meaningful Improvements

The evidence suggests that the current policy emphasis on bringing dwellings up to a minimum energy label, such as label D, may not be sufficient to achieve substantial reductions in natural gas consumption. Although upgrading all homes to label D leads to measurable savings at the aggregate level, up to 1.3% nationally, the effects are modest compared to the savings potential unlocked by deep renovations. The finding of increasing returns at higher levels of thermal quality indicates that policies focused solely on bringing the worst-performing homes up to a mediocre standard risk leaving much of the potential untapped.

To increase the impact of renovation policies, a shift is needed from encouraging the 'lowest-hanging fruit' toward enabling deeper, more comprehensive upgrades. Prioritizing deep renovations means not only supporting insulation and heating system improvements but also addressing the practical, financial, and psychological barriers that homeowners face in pursuing ambitious renovations. A key challenge is designing policies to motivate homeowners to renovate their dwellings further, after already achieving a relatively good energy label, as this may not seem worthwhile. More generous subsidies, zero-interest loans, or performance-based incentives could help bridge the gap between minimal upgrades and deeper interventions, and help to achieve more ambitious renovation goals.

Reconsidering Label Thresholds and Targets

Current policy benchmarks, such as the widespread use of energy label D as a renovation target, should be critically reassessed. Although label D homes perform slightly better than poorer labels, the difference is not very pronounced. The statistical insignificance of differences in gas consumption among labels G through D, as shown in this study, suggests that label D may not be a meaningful threshold for energy performance. This suggests that shallow renovations may have limited impact, while deeper renovations yield significantly more gas savings. Therefore, policymakers should consider revising performance benchmarks to better align with actual energy savings, such as targeting label C or even B, where gas reductions become clearly significant and progressively larger.

Combine Technical Upgrades with Behavioral Support

Another policy-relevant finding of this study is the large and significant impact of household frugality on gas consumption. Frugal households use 16.2% less gas than other households, keeping all other factors constant.[1] The savings of frugal behavior are thus approximately equal to the gas savings resulting from upgrading a dwelling by three energy labels. This highlights a crucial but often underutilized policy lever: behavior. Energy savings do not arise solely from improving insulation levels and upgrading heating systems, they are also a product of how people use their homes. Interventions aimed at reducing energy use should therefore not focus only on technology but also on habits, norms, and choices.

[1] Even after accounting for the thermostat temperature, frugal still had a highly significant effect with magnitude -0.111. Therefore, there is still a significant reduction due to frugality independent of temperature settings. This is important because many people might not be inclined to decrease the indoor temperature, but might be open to, for example, change their ventilation behavior.

Policymakers could complement physical renovation subsidies with behavioral programs such as energy coaching, personalized feedback, or community-based campaigns that promote energy-conscious living. Residents might also benefit from easier to find information about which behaviors can (easily) save heating energy. For example, existing campaigns from the Dutch government already provide information to residents on how to save energy by insulating their dwelling. However, information about behavior is hard to find, although some behaviors are mentioned on a page about insulation (Zet ook de knop om, n.d.). Even modest changes in everyday routines, such as heating only occupied rooms or closing curtains at night, can compound into substantial energy savings when adopted at scale.

Designing for Equity and Effectiveness

The finding that deeper renovations yield higher savings raises important questions of equity. Households in well-insulated homes are typically wealthier and better positioned to afford further upgrades, which may be encouraged by policies that reward performance. Meanwhile, lower-income households may struggle to meet even basic efficiency standards, let alone undertake deep renovations.

Policy design should therefore balance effectiveness with fairness. For example, tiered subsidy systems could provide higher rates for low-income homeowners or renters. 'Renovation-rights' approaches could give tenants more leverage in demanding energy improvements, while social housing providers could be supported in executing deep renovations with long-term climate and social goals in mind. Ultimately, an inclusive energy transition requires that no group is left behind, even as policies target greater efficiency.

Moreover, the results of the robustness checks incorporating average indoor temperature point to an important nuance: a potential rebound effect. As thermal quality improves, residents may choose to raise their thermostat settings to increase comfort rather than maximize energy savings. This behavioral shift suggests that for many households, especially those currently limiting heating due to financial constraints, renovations may first and foremost enhance living conditions rather than reduce emissions.

From this perspective, even modest renovations of poorly insulated homes, while less efficient in terms of carbon saved per euro invested, can deliver significant social value. They may lift households out of energy poverty, increase thermal comfort, and improve health and well-being. Policymakers should therefore recognize that efficiency and equity do not always align perfectly and that comfort gains can be a legitimate and necessary co-benefit of renovation policy, particularly for vulnerable groups.

Towards a Strategic Decarbonization Approach

This study adds a necessary note of realism to the role of energy renovations in the Dutch climate agenda. While their potential is substantial, their overall impact on national gas consumption remains incremental without both widespread adoption and substantial renovation depth. To unlock their full potential, renovations must be integrated with complementary measures such as the expansion of district heating, and programs that improve energy literacy and promote behavioral change.

The path forward is not a binary choice between building new or improving old, nor between technology and behavior. Rather, the findings suggest the need for a strategic approach to housing decarbonization: one that encourages deep, meaningful renovations; embraces behavioral interventions; aligns thresholds with actual performance; and evaluates trade-offs across different decarbonization strategies.

7.3 Recommendations for Future Research

This thesis provides robust empirical evidence on the effectiveness of energy renovations in older, gas-heated Dutch homes. However, questions remain about how energy renovations interact with behavior, costs, heating systems, and policy design. To deepen this understanding, future research can build upon these findings in several directions.

Broadening the Scope

The current study focuses on older, gas-heated dwellings. While the scope provides valuable insights, especially given that such homes are often prioritized in renovation efforts, it limits the generalizability of the findings. To inform nationwide policy, especially as the Netherlands is moving towards phasing out natural gas in the residential sector, the scope of analysis should be broadened.

Future research could incorporate more recently constructed buildings and homes with other heating types such as electric heating and district heating. Conducting similar analyses for different heating systems would help determine whether the renovation effect observed in gas-heated dwellings extends to other energy sources. For example, improving the energy label of an electrically heated dwellings by three classes might yield a comparable reduction in electricity consumption as it does for gas, a hypothesis that remains to be tested.

To support this, researchers could employ emerging data sources, including newer survey waves, smart meter data, or utility-provided consumption data. Such data would allow for a more precise estimation of thermal quality effects under varying energy mixes. For instance, one could compare electricity use for space heating between otherwise similar renovated and non-renovated dwellings. However, these analyses may require more complex data collection or model specifications, especially since heating consumption is often not separately metered from general household electricity use.

Moreover, broadening the scope enables deeper exploration of interactions between renovation measures and heating technologies. Are insulation and ventilation upgrades more effective in dwellings with certain systems, such as low-temperature radiators or heat pumps? Understanding such synergies could enhance the effectiveness of renovation strategies and support more targeted policy design.

Longitudinal and Panel Data Analysis

Longitudinal studies could contribute to a more reliable identification of the causal impact of renovations. Following the same households before and after renovation would help isolate changes in energy use and uncover time-varying behavioral adaptations. This could be done using panel survey data or by linking existing housing data to smart meter readings over time. It should be noted that study participation may alter the behavior of participants, known as the Hawthorne effect (Schwartz et al., 2013), which could bias results in renovation studies if the change in energy use due to participation is not accounted for. For example, households preparing for renovation or being surveyed may improve their energy awareness or change behavior, confounding estimates of the causal impact of renovations alone.

For this additional research, low-performing labels could be grouped. Because labels G through E are statistically indistinguishable in gas consumption, another study might group these labels together or redefine categories for better policy targeting.

Behavioral Effects: Studying Frugality More Closely

This thesis found that self-reported frugality has a practically large and statistically significant impact on gas consumption, highlighting the potential of behavioral interventions. Yet very little is known about what behaviors actually drive this effect. If specific actions that save a lot of energy can be identified, this can be used to design policies that support these behaviors. To investigate the effect of behavior further, research could take several forms:

- *Observational Studies:* Future research could use regression analysis on data similar to the data that was used in this thesis. Researchers could also conduct a home energy diary study where participants record heating, ventilation, and window-opening behavior for several weeks. This could be linked to hourly smart meter data to measure the real impact. Similar to the panel data research, such a design could also be influenced by the Hawthorne effect. Therefore it might be better to record the behavior using sensors, although this may be more expensive.

- *Experimental Studies:* A randomized control trial could assign participants to different behavioral interventions, such as a campaign encouraging them to open windows less in winter, and then track consumption changes.
- *Case Studies or Interviews:* In-depth case studies of households that identify as 'very frugal or 'not frugal' could reveal motivations, practices, and trade-offs.

Motivating Homeowners to Renovate

The finding of increasing returns for higher thermal quality raises a crucial behavioral and policy question. How do you motivate homeowners to improve already well-insulated homes? If households perceive their homes to be already efficient, they may not see the benefit of upgrading further, even if deeper savings can still be achieved.

Here, behavioral economics and policy experimentation are key. Research could explore the framing effects of communication, incentive design, or normative messaging. The goal should be to identify what kind of policies would make homeowners more likely to act. Furthermore, the support of policies should be evaluated. For example, bonuses for very high performance might be effective to make people renovate their dwellings, but this might not be equitable towards people with less resources. This line of inquiry would benefit from experimental surveys or discrete choice experiments.

Understanding Non-Linear Effects

The non-linear effect could be explored in more detail. While this study found robust results indicating increasing return at higher thermal quality, it is important to validate the results with additional research. As indicated by the absence of a statistical difference in gas consumption between energy labels A and B, there could be stagnating returns at the upper end of the label scale. The WoON 2018 data might not allow comparing good to very good labels, especially with heating system and construction year restrictions.

The 2021 reform of the energy label system introduced more granularity for the best-performing dwellings, offering a promising opportunity to analyze these very good dwellings in more detail. Another benefit of using more recent data combined with the new energy label is that it could provide valuable validation of the increasing results result. Such analyses would reflect post-pandemic occupancy patterns and heightened energy awareness due to rising gas prices. If the non-linear relationship between thermal quality and gas use persists under these new societal and policy conditions, this would strengthen confidence in the structural nature of the finding and its applicability beyond the 2018 context.

Furthermore, since this study used a one-dimensional measure for thermal quality, the effects of different renovation measures could not be differentiated. There might be diminishing returns for one type of renovation, and increasing returns for another. Researching the effect of different renovation measures separately might lead to a better understanding. However, renovation measures are often not implemented in isolation, which might limit the opportunities for research and the practical conclusions.

Integrating Renovation Costs and Carbon Savings

While this study quantified energy savings, future research could integrate economic and environmental performance metrics. Firstly, the cost per unit of thermal quality improvement should be estimated, using average renovations costs. Secondly, gas savings per euro invested can be calculated by combining these costs with the estimated savings from this or similar studies. Thirdly, gas savings can be converted to carbon savings using standard emission conversion factors. Lastly, above findings can be combined to determine the carbon saved per euro invested through renovation measures.

By linking renovation efforts to both costs and emissions, a cost-benefit analysis can be conducted. This allows for a direct comparison of renovation strategies with other climate mitigation measures, helping identify the most cost-effective approaches. Using the updated energy label from 2021 should support such an analysis, as the new standard is publicly available. This facilitates estimating how specific renovations affect the energy index or label.

System-Level Trade-Offs

This thesis highlights that while energy renovations can lead to meaningful reductions in households gas consumption, their overall impact may be modest, particularly in older, poorly insulated dwellings. For example, even an extensive renovation that upgrades a home from energy label G to label A reduces gas use by roughly 33%. While significant, achieving such savings requires deep and often expensive interventions, which may not always be cost-effective or practical.

Given these limitations, it is essential to consider the broader system-level trade-offs between renovation and alternative pathways such as demolition and new construction. In some cases, rebuilding may offer greater long-term benefits, especially if new dwellings can be designed to high energy standards, incorporate modern heating technologies, and avoid the architectural constraints of older housing stock. This is not only an economic question, but also an environmental one. The potential carbon and financial costs of deep renovations must be weighed against the life-cycle emissions and resource use of new construction. To properly evaluate this trade-off, several key questions must be addressed:

- Under what conditions is demolishing and rebuilding more cost-effective or sustainable than renovating?

- How do embodied emissions from materials and construction factor into the overall carbon footprint?
- Are there hybrid solutions, such as partial demolitions or facade upgrades?

These questions require life-cycle assessment methodologies that account for all phases of the building life, from material extraction to demolition and disposal. But technical factors alone are not enough. Social dimensions, such as residents' attachment to their homes and neighborhoods, cultural heritage, and urban planning constraints, must also be taken into account. In some communities, the value of place and continuity may outweigh the technical or environmental rationale for demolition.

Crucially, this trade-off between renovating and rebuilding should not be examined in isolation. It must be situated within the broader ecosystem of decarbonization options, including the electrification of heating, photovoltaic systems, and behavioral demand reduction. Likewise, housing interventions should be compared to mitigation options in other sectors, such as transportation, industry, or agriculture, where emissions reductions might be achieved more cost-effectively or quickly.

In the context of limited resources and urgent climate targets, careful prioritization is needed. This means not only assessing which strategies reduce emissions most effectively, but also which align with broader societal goals of equity, resilience, and livability. Understanding when to renovate, when to rebuild, and how to integrate these choices into a coherent, cross-sectoral climate strategy is therefore a critical agenda for future policy and research.

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Appendix A

Thermal Quality Including Full Range of Construction Years

This Appendix complements the main analysis by presenting the thermal quality plotted against the full range of construction years in Figure A.1, including 118 additional observations that were excluded from Figure 4.1.

While the main text limited the figure to dwellings built after 1900, this figure includes all available data from the full energy module. Notably, dwellings recorded as having been built between the year 1000 and 1900 significantly distort the readability of the scatterplot due to the wide timespan and sparse distribution of data in this period.

The regression line provides a smoothed view of the general trend over time. It suggest a slight decline in thermal quality up to the 1500s, followed by a relatively stable pattern until the late 1900s. However, given the limited number of observations for earlier periods, this trend should be interpreted with caution.

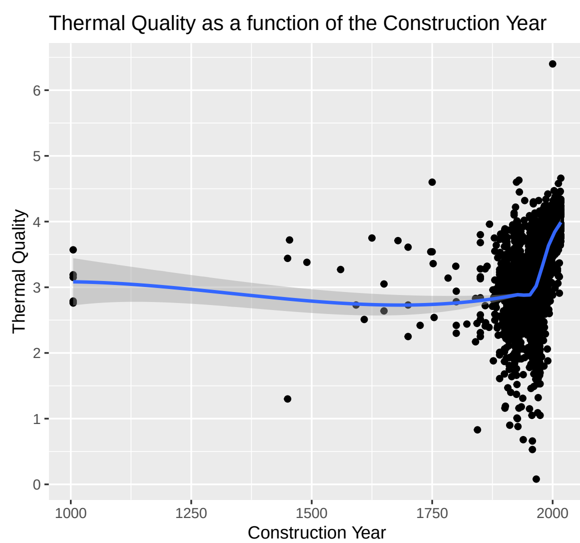

Figure A.1: Thermal Quality as a Function of the Construction Year, Including Full Dataset

The thermal quality values of all dwellings included in the energy module are plotted against their construction year. The blue line is a LOESS regression line, a local regression/estimation similar to a moving average.

Appendix B

Overview of the Used WoON Variables

Table B.1 shows the used variables from the WoON dataset. If a variable is constructed using multiple variables from the original dataset, they are all listed in the rightmost column.

Table B.1: Overview of the Used WoON Variables

Variable	Description (in Dutch from WoON dataset)	Variable name
age	Leeftijd respondent (7 klassen)	leeftijd
areaHome	Oppervlakte van de huidige woning (Bron: BAG peildatum 1 januari 2017)	gebruiksopp
bath	(Enquête) Heeft uw woning een ligbad, een douche of beide?	bad
centralHeating-Boiler	(10.1.1) Soort verwarming - CV-ketel	verwarm1
constrYear	Bouwjaar van de huidige woning (Bron: BAG peildatum 1 januari 2017)	bjaarbag
dispIncome	Besteedbaar inkomen huishouden (definitie VROM/BZK), voorlopig inkomen 2017, na revisie	vromhh_r
dwellingType	Een-/meergezins en type eengezins (6 klassen)	woontype
educ	Hoogst behaalde onderwijsniveau respondent	vltoplop5
	Hoogst behaald onderwijsniveau partner respondent 5-deling	vltoplpa5
electricHeater	(Enquête) Een elektrische straalkachel?	e_straal
energyIndex	(Afleiding) Energieindex, berekend op basis van resultaten woningopname	ei_insp
energyLabel	(Afleiding) Het energielabel op basis van de berekende energie index (ei_insp)	label_ins
frugal	Hoe zuinig vindt u dat uw huishouden omgaat met energie voor het verwarmen van uw woning?	zuingas
gasHeater	(10.1.4) Soort verwarming - gaskachel	verwarm4
gasStove	(Enquête) Wat voor soort fornuis of kookplaat heeft u thuis?	koken
gasUsage	Gasverbruik (Bron: Net bedrijven)	gasv
important	Hoe belangrijk of onbelangrijk vindt u energiezuinig gedrag?	belangener.y
loweredGas	(Enquête) Bewust geprobeerd minder gas te gebruiken, bijvoorbeeld door de verwarming lager te zetten	act_gas
nrChild	Aantal kinderen in het huishouden (4 klassen)	aantkind4
nrResidents	Uit hoeveel personen bestaat uw huishouden (uzelf meegerekend)?	aantalpp3
occup	(Enquête) Op welke momenten is er doordeweeks (van maandag t/m vrijdag) meestal iemand thuis?	morgenlaat, middagvroeg, middaglaat
ownership	Beheervorm huidige woning	bhvorm
partner	Respondent heeft partner	partner
province	Provincie (12)	prov
respNr	Respondentnummer	respnr
solarPanel	(Opname) Zonnepanelen (PV-systemen) aanwezig	zonnecel
temp	(Enquête) Hoe hoog staat de temperatuur dan ingesteld op doordeweekse dagen?	wt_morgenvroeg, wt_morgenlaat, wt_middagvroeg, wt_middaglaat, wt_avond, wt_nacht
weight	Weegfactor huishouden	ew_huis

Appendix C

Descriptive Statistics for the Estimation Sample

The descriptive statistics of the estimation sample are presented in this Appendix. This includes 2,062 observations that are strictly gas-heated and built before 1980. Descriptive statistics of the whole estimation sample are given, and supplied by statistics stratified by energy label.

Table C.1 presents summary statistics of the numerical variables. Table C.2 shows the mean and standard deviation of the numerical variables per energy label. Table C.3 presents summary statistics for the categorical variables. Table C.4 shows the frequencies of the categorical variables per energy label.

Table C.3: Descriptive Statistics of the Categorical Variables (Estimation Sample)

		N	%
energyLabel	A	63	3.1
	B	138	6.7
	C	668	32.4
	D	558	27.1
	E	311	15.1
	F	206	10.0
	G	118	5.7
constrYear	bef_1945	702	34.0
	1945-1969	709	34.4
	after_1969	651	31.6
dwellingType	apartment	524	25.4
	corner	320	15.5
	detached	298	14.5
	semiDetached	267	12.9
	terraced	653	31.7
province	Groningen	58	2.8
	Friesland	69	3.3
	Drenthe	46	2.2
	Overijssel	135	6.5
	Flevoland	34	1.6

Table C.3: Descriptive statistics (continued)

		N	%
	Gelderland	293	14.2
	Utrecht	129	6.3
	Noord-Holland	298	14.5
	Zuid-Holland	580	28.1
	Zeeland	61	3.0
	Noord-Brabant	256	12.4
	Limburg	103	5.0
age	17-34	233	11.3
	35-64	993	48.2
	65+	836	40.5
nrChildren	0	1549	75.1
	1	236	11.4
	2	204	9.9
	3+	73	3.5
ownership	owner	1316	63.8
	privateRent	211	10.2
	socialRent	535	25.9
occup	always	943	45.7
	depends	788	38.2
	never	331	16.1
opinionEEBehavior	ambivalent	121	5.9
	doNotKnow	12	0.6
	important	1294	62.8
	refuses	1	0.0
	unimportant	20	1.0
	veryImportant	611	29.6
	veryUnimportant	3	0.1
ownSparsityHeatingEnergy	average	1012	49.1
	frugal	788	38.2
	nonFrugal	117	5.7
	refuses	13	0.6
	veryFrugal	118	5.7
	veryNonFrugal	14	0.7

Table C.1: Descriptive Statistics of the Numerical Variables (Estimation Sample)

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
gasUsage	1402	0	1537.68	802.67	44.00	1389.00	8583.00
gasPerArea	2025	0	13.54	6.43	0.75	12.78	113.53
thermalQuality	248	0	3.06	0.47	0.88	3.12	4.60
energyIndex	248	0	1.94	0.47	0.40	1.88	4.12
areaHome	259	0	121.27	64.71	15.00	111.00	1000.00
bath	2	0	0.38	0.48	0.00	0.00	1.00
gasStove	2	0	0.77	0.42	0.00	1.00	1.00
centralHeatingBoiler	2	0	0.97	0.18	0.00	1.00	1.00
gasHeater	2	0	0.05	0.22	0.00	0.00	1.00
solarPanel	2	0	0.15	0.35	0.00	0.00	1.00
dispIncome	2023	0	39.18	25.98	0.01	33.33	429.74
higherEduc	2	0	0.51	0.50	0.00	1.00	1.00
nrResidents	8	0	2.07	1.12	1.00	2.00	9.00
partner	2	0	0.59	0.49	0.00	1.00	1.00
frugal	2	0	0.44	0.50	0.00	0.00	1.00
important	2	0	0.30	0.46	0.00	0.00	1.00
loweredGas	2	0	0.61	0.49	0.00	1.00	1.00
avgTemp	81	40	18.35	1.74	5.00	18.50	23.00

Table C.2: Mean and Standard Deviation of Numerical Variables per Energy Label (Estimation Sample)

	A (N=63)		B (N=138)		C (N=668)		D (N=558)		E (N=311)		F (N=206)		G (N=118)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
gasUsage	1118.35	627.05	1358.46	885.89	1445.12	673.82	1528.26	760.09	1632.87	805.91	1768.42	930.75	1885.94	1105.56
gasPerArea	11.28	8.43	11.38	5.43	12.49	5.17	14.02	7.41	14.64	5.99	15.08	6.58	15.43	6.74
thermalQuality	3.95	0.14	3.69	0.06	3.38	0.11	3.05	0.09	2.76	0.08	2.46	0.08	1.95	0.35
energyIndex	1.05	0.14	1.31	0.06	1.62	0.11	1.95	0.09	2.24	0.08	2.54	0.08	3.05	0.35
areaHome	111.68	49.32	122.61	50.28	122.92	62.20	116.90	64.22	117.00	52.38	127.63	75.96	136.34	99.64
bath	0.27	0.45	0.38	0.49	0.36	0.48	0.39	0.49	0.38	0.49	0.43	0.50	0.33	0.47
gasStove	0.70	0.46	0.70	0.46	0.74	0.44	0.78	0.41	0.82	0.38	0.83	0.38	0.81	0.40
centralHeatingBoiler	1.00	0.00	1.00	0.00	1.00	0.05	0.99	0.10	0.96	0.19	0.92	0.28	0.72	0.45
gasHeater	0.03	0.18	0.02	0.15	0.02	0.15	0.02	0.15	0.06	0.23	0.11	0.31	0.29	0.45
solarPanel	0.52	0.50	0.43	0.50	0.19	0.40	0.08	0.28	0.05	0.22	0.05	0.22	0.06	0.24
dispIncome	37.44	24.42	41.43	39.05	39.96	24.74	39.37	23.90	36.86	22.13	40.66	29.86	35.74	26.10
higherEduc	0.43	0.50	0.51	0.50	0.50	0.50	0.55	0.50	0.52	0.50	0.50	0.50	0.44	0.50
nrResidents	2.02	1.13	1.89	0.83	2.12	1.11	2.16	1.21	2.00	1.11	2.11	1.16	1.68	0.79
partner	0.56	0.50	0.62	0.49	0.65	0.48	0.58	0.49	0.53	0.50	0.57	0.50	0.44	0.50
frugal	0.59	0.50	0.48	0.50	0.47	0.50	0.42	0.49	0.42	0.49	0.40	0.49	0.38	0.49
important	0.38	0.49	0.38	0.49	0.30	0.46	0.28	0.45	0.28	0.45	0.27	0.45	0.31	0.47
loweredGas	0.57	0.50	0.60	0.49	0.61	0.49	0.63	0.48	0.59	0.49	0.65	0.48	0.60	0.49
avgTemp	17.89	2.61	18.54	1.75	18.37	1.59	18.47	1.48	18.21	1.86	18.28	2.10	17.93	2.05

Table C.4: Frequencies of Categorical Variables per Energy Label (Estimation Sample)

		A (N=63)		B (N=138)		C (N=668)		D (N=558)		E (N=311)		F (N=206)		G (N=118)	
		N	Pct.	N	Pct.	N	Pct.	N	Pct.	N	Pct.	N	Pct.	N	Pct.
constrYear	bef_1945	16	25.4	36	26.1	144	21.6	189	33.9	126	40.5	121	58.7	70	59.3
	1945-1969	23	36.5	35	25.4	179	26.8	218	39.1	142	45.7	71	34.5	41	34.7
	after_1969	24	38.1	67	48.6	345	51.6	151	27.1	43	13.8	14	6.8	7	5.9
dwellingType	apartment	13	20.6	30	21.7	146	21.9	155	27.8	81	26.0	56	27.2	43	36.4
	corner	10	15.9	23	16.7	108	16.2	78	14.0	52	16.7	38	18.4	11	9.3
	detached	8	12.7	25	18.1	75	11.2	65	11.6	51	16.4	44	21.4	30	25.4
	semiDetached	5	7.9	11	8.0	94	14.1	78	14.0	38	12.2	23	11.2	18	15.3
	terraced	27	42.9	49	35.5	245	36.7	182	32.6	89	28.6	45	21.8	16	13.6
province	Groningen	2	3.2	7	5.1	23	3.4	10	1.8	9	2.9	6	2.9	1	0.8
	Friesland	1	1.6	8	5.8	25	3.7	18	3.2	6	1.9	7	3.4	4	3.4
	Drenthe	1	1.6	3	2.2	15	2.2	10	1.8	12	3.9	3	1.5	2	1.7
	Overijssel	13	20.6	9	6.5	43	6.4	38	6.8	19	6.1	6	2.9	7	5.9
	Flevoland	2	3.2	8	5.8	14	2.1	7	1.3	3	1.0	0	0.0	0	0.0
	Gelderland	10	15.9	21	15.2	100	15.0	87	15.6	39	12.5	28	13.6	8	6.8
	Utrecht	5	7.9	3	2.2	44	6.6	36	6.5	22	7.1	14	6.8	5	4.2
	Noord-Holland	6	9.5	17	12.3	99	14.8	81	14.5	50	16.1	24	11.7	21	17.8
	Zuid-Holland	11	17.5	33	23.9	173	25.9	153	27.4	94	30.2	71	34.5	45	38.1
	Zeeland	2	3.2	5	3.6	15	2.2	18	3.2	8	2.6	9	4.4	4	3.4
	Noord-Brabant	4	6.3	16	11.6	94	14.1	74	13.3	34	10.9	26	12.6	8	6.8
	Limburg	6	9.5	8	5.8	23	3.4	26	4.7	15	4.8	12	5.8	13	11.0
age	17-34	5	7.9	10	7.2	70	10.5	82	14.7	42	13.5	18	8.7	6	5.1
	35-64	32	50.8	78	56.5	315	47.2	273	48.9	146	46.9	106	51.5	43	36.4
	65+	26	41.3	50	36.2	283	42.4	203	36.4	123	39.5	82	39.8	69	58.5
nrChildren	0	46	73.0	111	80.4	512	76.6	397	71.1	234	75.2	148	71.8	101	85.6
	1	8	12.7	17	12.3	61	9.1	68	12.2	43	13.8	29	14.1	10	8.5
	2	7	11.1	8	5.8	64	9.6	72	12.9	25	8.0	23	11.2	5	4.2
	3+	2	3.2	2	1.4	31	4.6	21	3.8	9	2.9	6	2.9	2	1.7
ownership	owner	29	46.0	92	66.7	446	66.8	368	65.9	186	59.8	134	65.0	61	51.7
	privateRent	4	6.3	7	5.1	36	5.4	44	7.9	44	14.1	35	17.0	41	34.7
	socialRent	30	47.6	39	28.3	186	27.8	146	26.2	81	26.0	37	18.0	16	13.6
occup	always	23	36.5	60	43.5	312	46.7	231	41.4	144	46.3	112	54.4	61	51.7
	depends	32	50.8	60	43.5	253	37.9	229	41.0	109	35.0	62	30.1	43	36.4
	never	8	12.7	18	13.0	103	15.4	98	17.6	58	18.6	32	15.5	14	11.9
opinionEEBehavior	ambivalent	3	4.8	4	2.9	40	6.0	34	6.1	22	7.1	9	4.4	9	7.6
	doNotKnow	0	0.0	1	0.7	4	0.6	4	0.7	2	0.6	1	0.5	0	0.0
	important	35	55.6	81	58.7	415	62.1	360	64.5	196	63.0	136	66.0	71	60.2
	refuses	0	0.0	0	0.0	0	0.0	1	0.2	0	0.0	0	0.0	0	0.0
	unimportant	0	0.0	0	0.0	7	1.0	4	0.7	5	1.6	4	1.9	0	0.0
	veryImportant	24	38.1	52	37.7	201	30.1	155	27.8	86	27.7	56	27.2	37	31.4
	veryUnimportant	1	1.6	0	0.0	1	0.1	0	0.0	0	0.0	0	0.0	1	0.8
ownSparsityHeatingEnergy	average	26	41.3	67	48.6	325	48.7	286	51.3	149	47.9	99	48.1	60	50.8
	frugal	31	49.2	57	41.3	269	40.3	210	37.6	113	36.3	70	34.0	38	32.2
	nonFrugal	0	0.0	4	2.9	24	3.6	32	5.7	26	8.4	21	10.2	10	8.5
	refuses	0	0.0	0	0.0	4	0.6	3	0.5	4	1.3	2	1.0	0	0.0
	veryFrugal	6	9.5	9	6.5	43	6.4	23	4.1	18	5.8	12	5.8	7	5.9
	veryNonFrugal	0	0.0	1	0.7	3	0.4	4	0.7	1	0.3	2	1.0	3	2.5

Appendix D

Descriptive Statistics for the Full Energy Module

The descriptive statistics of the full energy module are presented in this Appendix, including 4,447 observations. Descriptive statistics of the whole energy module are given, and supplied by statistics stratified by energy label.

Table D.1 presents summary statistics of the numerical variables. Table D.2 shows the mean and standard deviation of the numerical variables per energy label. Table D.3 presents summary statistics for the categorical variables. Table D.4 shows the frequencies of the categorical variables per energy label.

Table D.3: Descriptive Statistics of the Categorical Variables (Full Energy Module)

		N	%
energyLabel	A	731	16.4
	B	796	17.9
	C	1325	29.8
	D	699	15.7
	E	403	9.1
	F	263	5.9
	G	230	5.2
constrYear	bef_1945	812	18.3
	1945-1969	888	20.0
	after_1969	2747	61.8
dwellingType	apartment	1424	32.0
	corner	567	12.8
	detached	680	15.3
	semiDetached	594	13.4
	terraced	1182	26.6
province	Groningen	125	2.8
	Friesland	140	3.1
	Drenthe	96	2.2
	Overijssel	300	6.7
	Flevoland	147	3.3

Table D.3: Descriptive statistics (continued)

		N	%
	Gelderland	613	13.8
	Utrecht	294	6.6
	Noord-Holland	564	12.7
	Zuid-Holland	1266	28.5
	Zeeland	117	2.6
	Noord-Brabant	589	13.2
	Limburg	196	4.4
age	17-34	490	11.0
	35-64	2156	48.5
	65+	1801	40.5
nrChildren	0	3351	75.4
	1	478	10.7
	2	446	10.0
	3+	172	3.9
ownership	owner	2847	64.0
	privateRent	457	10.3
	socialRent	1143	25.7
occup	always	1958	44.0
	depends	1759	39.6
	never	730	16.4
opinionEEBehavior	ambivalent	284	6.4
	doNotKnow	22	0.5
	important	2728	61.3
	refuses	2	0.0
	unimportant	41	0.9
	veryImportant	1364	30.7
	veryUnimportant	6	0.1
ownSparsityHeatingEnergy	average	2065	46.4
	frugal	1794	40.3
	nonFrugal	211	4.7
	refuses	16	0.4
	veryFrugal	343	7.7
	veryNonFrugal	18	0.4

Table D.1: Descriptive Statistics of the Numerical Values (Full Energy Module)

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
gasUsage	2048	0	1363.19	757.70	6.00	1235.00	8583.00
gasPerArea	4298	0	11.90	6.29	0.05	10.92	113.53
thermalQuality	304	0	3.31	0.55	0.08	3.41	6.40
energyIndex	304	0	1.69	0.55	−1.40	1.59	4.92
areaHome	323	0	122.72	62.50	15.00	111.00	1000.00
bath	2	0	0.40	0.49	0.00	0.00	1.00
gasStove	2	0	0.69	0.46	0.00	1.00	1.00
centralHeatingBoiler	2	0	0.87	0.34	0.00	1.00	1.00
gasHeater	2	0	0.04	0.18	0.00	0.00	1.00
solarPanel	2	0	0.17	0.38	0.00	0.00	1.00
dispIncome	4289	0	40.42	31.35	0.01	34.52	1255.00
higherEduc	2	0	0.52	0.50	0.00	1.00	1.00
nrResidents	9	0	2.07	1.13	1.00	2.00	11.00
partner	2	0	0.59	0.49	0.00	1.00	1.00
frugal	2	0	0.48	0.50	0.00	0.00	1.00
important	2	0	0.31	0.46	0.00	0.00	1.00
loweredGas	2	0	0.58	0.49	0.00	1.00	1.00
avgTemp	97	41	18.52	1.84	0.00	18.75	26.00

Table D.2: Mean and Standard Deviation of Numerical Variables per Energy Label (Full Energy Module)

	A (N=731)		B (N=796)		C (N=1325)		D (N=699)		E (N=403)		F (N=263)		G (N=230)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
gasUsage	1174.21	685.56	1161.16	688.85	1375.34	684.15	1489.01	785.64	1548.65	789.27	1634.91	894.90	1574.94	952.88
gasPerArea	9.37	5.30	10.04	5.78	11.79	5.27	13.54	7.28	14.28	6.40	14.73	7.05	14.61	6.59
thermalQuality	3.97	0.17	3.70	0.06	3.41	0.11	3.06	0.08	2.76	0.08	2.46	0.08	1.94	0.37
energyIndex	1.03	0.17	1.30	0.06	1.59	0.11	1.94	0.08	2.24	0.08	2.54	0.08	3.06	0.37
areaHome	133.50	59.75	120.70	55.66	123.09	57.95	118.27	64.08	115.28	53.94	121.91	72.94	120.82	100.15
bath	0.47	0.50	0.42	0.49	0.40	0.49	0.38	0.49	0.36	0.48	0.37	0.48	0.30	0.46
gasStove	0.52	0.50	0.66	0.47	0.73	0.45	0.75	0.43	0.78	0.42	0.78	0.41	0.77	0.42
centralHeatingBoiler	0.79	0.41	0.91	0.28	0.96	0.20	0.92	0.27	0.85	0.36	0.76	0.43	0.42	0.49
gasHeater	0.02	0.16	0.02	0.13	0.02	0.15	0.02	0.15	0.05	0.21	0.08	0.28	0.17	0.37
solarPanel	0.41	0.49	0.21	0.41	0.15	0.36	0.08	0.27	0.06	0.24	0.05	0.21	0.03	0.18
dispIncome	47.97	52.91	40.06	26.27	40.08	24.84	39.08	23.58	36.30	21.94	38.52	28.02	33.00	22.00
higherEduc	0.58	0.49	0.50	0.50	0.51	0.50	0.53	0.50	0.49	0.50	0.50	0.50	0.47	0.50
nrResidents	2.26	1.19	2.01	1.05	2.08	1.11	2.13	1.23	2.01	1.13	1.96	1.12	1.66	0.81
partner	0.67	0.47	0.60	0.49	0.63	0.48	0.57	0.49	0.52	0.50	0.51	0.50	0.41	0.49
frugal	0.56	0.50	0.50	0.50	0.46	0.50	0.44	0.50	0.45	0.50	0.46	0.50	0.50	0.50
important	0.36	0.48	0.29	0.46	0.31	0.46	0.28	0.45	0.30	0.46	0.30	0.46	0.29	0.45
loweredGas	0.51	0.50	0.57	0.50	0.60	0.49	0.62	0.49	0.59	0.49	0.62	0.49	0.58	0.49
avgTemp	18.95	1.85	18.71	1.64	18.39	1.84	18.43	1.56	18.17	2.16	18.26	2.03	17.99	2.53

Table D.4: Frequency of Categorical Variables, per Energy Label (Full Energy Module)

		A (N=731)		B (N=796)		C (N=1325)		D (N=699)		E (N=403)		F (N=263)		G (N=230)	
		N	Pct.	N	Pct.	N	Pct.	N	Pct.	N	Pct.	N	Pct.	N	Pct.
constrYear	bef_1945	28	3.8	40	5.0	173	13.1	213	30.5	143	35.5	130	49.4	85	37.0
	1945-1969	32	4.4	45	5.7	203	15.3	244	34.9	175	43.4	94	35.7	95	41.3
	after_1969	671	91.8	711	89.3	949	71.6	242	34.6	85	21.1	39	14.8	50	21.7
dwellingType	apartment	208	28.5	283	35.6	347	26.2	211	30.2	136	33.7	101	38.4	138	60.0
	corner	80	10.9	88	11.1	192	14.5	97	13.9	59	14.6	39	14.8	12	5.2
	detached	129	17.6	113	14.2	192	14.5	88	12.6	66	16.4	51	19.4	41	17.8
	semiDetached	100	13.7	110	13.8	188	14.2	100	14.3	48	11.9	26	9.9	22	9.6
	terraced	214	29.3	202	25.4	406	30.6	203	29.0	94	23.3	46	17.5	17	7.4
province	Groningen	18	2.5	24	3.0	53	4.0	11	1.6	11	2.7	6	2.3	2	0.9
	Friesland	32	4.4	21	2.6	43	3.2	21	3.0	10	2.5	9	3.4	4	1.7
	Drenthe	19	2.6	20	2.5	26	2.0	12	1.7	14	3.5	3	1.1	2	0.9
	Overijssel	58	7.9	58	7.3	90	6.8	48	6.9	24	6.0	12	4.6	10	4.3
	Flevoland	32	4.4	56	7.0	43	3.2	11	1.6	5	1.2	0	0.0	0	0.0
	Gelderland	119	16.3	106	13.3	186	14.0	106	15.2	45	11.2	34	12.9	17	7.4
	Utrecht	60	8.2	40	5.0	85	6.4	51	7.3	30	7.4	18	6.8	10	4.3
	Noord-Holland	68	9.3	100	12.6	173	13.1	102	14.6	57	14.1	30	11.4	34	14.8
	Zuid-Holland	166	22.7	211	26.5	365	27.5	185	26.5	126	31.3	98	37.3	115	50.0
	Zeeland	26	3.6	21	2.6	27	2.0	20	2.9	9	2.2	10	3.8	4	1.7
	Noord-Brabant	109	14.9	105	13.2	179	13.5	98	14.0	54	13.4	30	11.4	14	6.1
	Limburg	24	3.3	34	4.3	55	4.2	34	4.9	18	4.5	13	4.9	18	7.8
age	17-34	99	13.5	72	9.0	122	9.2	96	13.7	50	12.4	27	10.3	24	10.4
	35-64	358	49.0	416	52.3	637	48.1	340	48.6	187	46.4	131	49.8	87	37.8
	65+	274	37.5	308	38.7	566	42.7	263	37.6	166	41.2	105	39.9	119	51.7
nrChildren	0	513	70.2	609	76.5	1018	76.8	510	73.0	301	74.7	200	76.0	200	87.0
	1	85	11.6	88	11.1	128	9.7	78	11.2	53	13.2	30	11.4	16	7.0
	2	91	12.4	78	9.8	122	9.2	83	11.9	34	8.4	27	10.3	11	4.8
	3+	42	5.7	21	2.6	57	4.3	28	4.0	15	3.7	6	2.3	3	1.3
ownership	owner	504	68.9	513	64.4	884	66.7	455	65.1	230	57.1	158	60.1	103	44.8
	privateRent	64	8.8	66	8.3	93	7.0	59	8.4	62	15.4	47	17.9	66	28.7
	socialRent	163	22.3	217	27.3	348	26.3	185	26.5	111	27.5	58	22.1	61	26.5
occup	always	287	39.3	345	43.3	618	46.6	294	42.1	185	45.9	132	50.2	97	42.2
	depends	305	41.7	334	42.0	510	38.5	287	41.1	145	36.0	87	33.1	91	39.6
	never	139	19.0	117	14.7	197	14.9	118	16.9	73	18.1	44	16.7	42	18.3
opinionEEBehavior	ambivalent	41	5.6	52	6.5	93	7.0	43	6.2	30	7.4	11	4.2	14	6.1
	doNotKnow	4	0.5	5	0.6	5	0.4	4	0.6	3	0.7	1	0.4	0	0.0
	important	420	57.5	497	62.4	803	60.6	449	64.2	244	60.5	168	63.9	147	63.9
	refuses	0	0.0	1	0.1	0	0.0	1	0.1	0	0.0	0	0.0	0	0.0
	unimportant	4	0.5	7	0.9	14	1.1	4	0.6	7	1.7	4	1.5	1	0.4
	veryImportant	261	35.7	234	29.4	407	30.7	198	28.3	119	29.5	79	30.0	66	28.7
	veryUnimportant	1	0.1	0	0.0	3	0.2	0	0.0	0	0.0	0	0.0	2	0.9
ownSparsityHeatingEnergy	average	304	41.6	363	45.6	651	49.1	348	49.8	186	46.2	114	43.3	99	43.0
	frugal	329	45.0	341	42.8	515	38.9	268	38.3	152	37.7	103	39.2	86	37.4
	nonFrugal	18	2.5	32	4.0	57	4.3	39	5.6	29	7.2	23	8.7	13	5.7
	refuses	0	0.0	0	0.0	7	0.5	3	0.4	4	1.0	2	0.8	0	0.0
	veryFrugal	79	10.8	58	7.3	91	6.9	37	5.3	30	7.4	19	7.2	29	12.6
	veryNonFrugal	1	0.1	2	0.3	4	0.3	4	0.6	2	0.5	2	0.8	3	1.3

Appendix E

Alternative Categorizations of Frugality Variable

The main regression model is re-estimated using alternative categorizations of the frugality variables. Because frugality has a highly significant effect, which is also meaningful in magnitude, it is investigated further. The result is shown in Table E.1. Frugal originally had five categories: from 'very non frugal' to 'very frugal'.

Table E.1: Multiple Regression Model using Different Specifications for Frugal

	Dependent variable:		
	log(gasUsage)		
	(1)	(2)	(3)
thermalQuality	-0.164^{***} (0.025)	-0.162^{***} (0.025)	-0.158^{***} (0.025)
occupdepends	-0.037^{*} (0.021)	-0.036^{*} (0.021)	-0.034^{*} (0.021)
occupnever	-0.055^{*} (0.033)	-0.056^{*} (0.033)	-0.051 (0.033)
1-frugal	-0.162^{***} (0.020)		
3-frugal		-0.148^{***} (0.020)	
3-veryFrugal		-0.287^{***} (0.056)	
5-veryNonFrugal			-0.052 (0.124)
5-nonFrugal			0.139^{***} (0.036)
5-frugal			-0.136^{***} (0.020)
5-veryFrugal			-0.276^{***} (0.056)
important	-0.004 (0.022)	0.006 (0.022)	0.007 (0.023)
loweredGas	-0.007 (0.020)	-0.005 (0.020)	0.001 (0.020)
Constant	6.229^{***} (0.206)	6.232^{***} (0.205)	6.197^{***} (0.204)
Observations	2,049	2,049	2,049
R^2	0.449	0.452	0.455
Adjusted R^2	0.438	0.441	0.444
Residual Std. Error	0.412 (df = 2009)	0.411 (df = 2008)	0.410 (df = 2006)
F Statistic	41.953^{***} (df = 39; 2009)	41.393^{***} (df = 40; 2008)	39.897^{***} (df = 42; 2006)
Note:			*p<0.1; **p<0.05; ***p<0.01
Additional Note:	All other control variables are included in the model, but omitted from the table.		

In the estimation model from the main text, a household is considered frugal when they answered 'frugal' or 'very frugal' to the question whether they think they are frugal with respect to heating their home. This model is repeated as **Model 1**. For this model, frugal households consume 16.2% less gas than non-frugal ones.

In **Model 2**, frugal is made into a categorical variable with three categories. Compared to the reference category, households answering from ‘very non frugal’ to ‘neutral’, frugal households use 14.8% less gas. Very non frugal households even save 28.7% gas.

Model 3 uses the original categorization using five categories. Compared to the reference category of people who answered ‘neutral’, frugal and very frugal household save approximately the same gas as in Model 2. The new category of non-frugal households uses 13.9% more gas than neutral ones. Very non-frugal households consume a bit less than average, but the difference is not statistically significant, probably due to the low number of observations (N=14).

Overall, the causal estimate of thermal quality stays approximately the same, and the explained variation only improves by a small amount. Therefore, the categorization is not expected to influence the estimate significantly. What the results do show it that the extent to which households think they are frugal (or not) matters as well as the binary distinction. People who consider themselves very frugal save approximately twice as much gas as those who only consider themselves frugal (compared to neutral households). Furthermore, when non-frugality is added as a category as well, it shows that households that consider themselves non-frugal use significantly more gas than average.

Appendix F

Supplements to the Reliability Analysis

Electric Space Heaters

Table F.1 shows the answers given to the question “Do you own an electric space heater?”. The table clearly shows that households living in dwellings with poorer energy labels more often own an electric space heater. However, the overall prevalence remains modest, with a maximum of 14.4% owning an electric space heater for energy label G.

Table F.1: Occurrence of Electric Space Heaters

Electric Space Heater	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Yes	3	8	43	44	35	20	17
No	60	130	620	508	276	185	101
Refuses	0	0	5	6	0	1	0
Percentage	4.8	5.8	6.4	7.9	11.3	9.7	14.4

Partial Effect of Model Using Absolute Gas Consumption

The MLR model is estimated while adding the cubed thermal quality, according to equation F.1. This resulted in the following coefficients: $\beta_{\mathrm{TQ}} = 305.890$ and $\beta_{\mathrm{TQ}^2} = -95.127$. The partial effect can then be calculated as: Partial Effect $= 305.890 - 95.127 \cdot 2 \cdot \mathrm{TQ}$, and is plotted in Figure F.1. The partial effect shows increasing returns, similar to the quadratic model. The tipping point where the effect turns negative is still a bit below 2.

$$\mathrm{gas}_i = \beta_0 + \beta_1 \cdot TQ_i + \beta_2 \cdot TQ_i{}^2 + \vec{\gamma} \cdot \vec{B}_i + \vec{\delta} \cdot \vec{H}_i + \vec{\zeta} \cdot \vec{A}_i + \epsilon_i \tag{F.1}$$

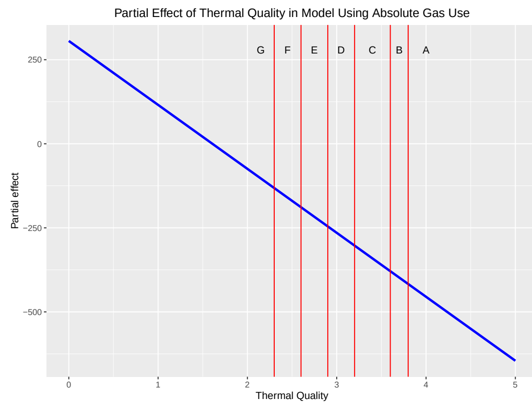

Figure F.1: Partial Effect of Thermal Quality for Model Using Absolute Gas Use
The partial effect shows increasing returns to renovations.

Partial Effect of Cubed Model

The MLR model is estimated while adding the cubed thermal quality, according to equation F.2. This resulted in the following coefficients: $\beta_{\text{TQ}} = 0.064$, $\beta_{\text{TQ}^2} = 0.030$, and $\beta_{\text{TQ}^3} = -0.016$. The partial effect can then be calculated as: Partial Effect $= 0.064 + 0.060 \cdot \text{TQ} - 0.048 \cdot \text{TQ}^2$, and is plotted in Figure F.2. The partial effect shows increasing returns, similar to the quadratic model. The positive effect of renovation (i.e., renovations increasing gas consumption), is very minimally present. The tipping point where the effect turns negative is still around a thermal quality of 2. The effect is steeper than for the model quadratic in thermal quality.

$$\log(\text{gas})_i = \beta_0 + \beta_1 \cdot TQ_i + \beta_2 \cdot TQ_i{}^2 + \beta_3 \cdot TQ_i{}^3 + \vec{\gamma} \cdot \vec{B}_i + \vec{\delta} \cdot \vec{H}_i + \vec{\zeta} \cdot \vec{A}_i + \epsilon_i \tag{F.2}$$

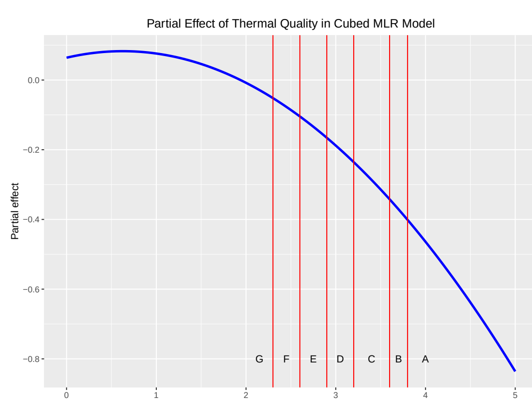

Figure F.2: Partial Effect of Thermal Quality for the Cubed Model
The partial effect shows increasing returns to renovations.