Energy conservation in the residential sector

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Energy Conservation in the Residential Sector:

The Role of Policy and Market Forces

ERDAL AYDIN

13 January 2016

Energy Conservation in the Residential Sector: The Role of Policy and Market Forces

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Chapter 1

Introduction

In recent years, energy conservation has been a hot topic of debate among policy makers and researchers due to the concerns about global climate change and energy dependency. In the 1970s, the energy crisis has led to a growing attention on energy dependency and a possible depletion of fossil fuels. Currently, climate change has emerged as one of the most important policy issues, and energy conservation is promoted as a remedy to reduce greenhouse gas emissions. From a policy perspective, residential sector has been an important target for energy conservation policies as it is a major contributor to the total energy consumption and has a high potential for saving energy through efficiency measures.

Many countries have introduced regulations targeting the energy efficiency of the residential sector. However, whether these policies have been effective in reducing the total residential consumption of energy is still unclear. In the first chapter of this thesis, we analyze the impact of residential energy efficiency policies on household energy consumption across Europe for the period 1980-2009. We examine the electricity and non-electricity energy consumption separately, as these are generally used for different purposes (appliances and heating) by households and are subject to different energy efficiency policies. We focus on two distinct types of regulations – mandatory energy efficiency labels for household appliances and building standards. We find that after controlling for the county-specific effects and the changes in income, energy prices, demography and climate conditions over our sample period, both the energy labeling requirements for appliances and the stricter building codes lead up to lower residential energy consumption.

In the second chapter, we examine how households respond to energy efficiency measures. Policies designed to reduce energy consumption through energy efficiency measures in the residential sector are typically based upon engineering calculations, which may differ significantly from outcomes observed in practice. A widely acknowledged explanation for this gap between expected and realized energy savings is household behavior, as energy efficiency gains alter the perceived cost of comfort and may thereby generate shifts in consumption patterns – a "rebound effect". This chapter adds to the ongoing discussion about the method of identification and the magnitude of this effect, by examining the elasticity of energy consumption relative to a predicted measure of thermal efficiency, using a sample of 563,000 dwellings and their occupants in the Netherlands. The results show a rebound effect of 26.7 percent among homeowners, and 41.3 percent among tenants. There is significant heterogeneity in the rebound effect across households, determined by household wealth and income, and the actual energy use intensity (EUI). The effects are largest among the lower income and wealth cohorts, and among households that use more energy than the average household. We corroborate our findings through a quasi-experimental analysis, documenting that efficiency improvements following a large subsidy program lead to a rebound effect of about 56 percent. This confirms the important role of household behavior in determining the outcomes of energy efficiency improvement programs.

In the last chapter, we investigate financial aspects of energy efficiency investments in the housing market. Much of the current policy making hinges on the assumption that markets efficiently capitalize home energy performance into transaction prices. However, there is limited empirical evidence supporting this assumption. We use transaction data for a large sample of dwellings to examine the capitalization of energy efficiency in the housing market. Using the exogenous variation in energy efficiency generated by 1973-74 oil crisis, as well as the evolution of building codes as instruments, we document that a 50 percent increase in energy efficiency leads to an increase in the transaction price by around 11 percent for an average home in the Dutch housing market. Our findings indicate that the capitalization of energy efficiency does not vary significantly when Energy Performance

Certificates (EPC) are present. We document that the estimated value of energy efficiency varies over time, which might be a consequence of fluctuations in house prices, increased energy costs, and changing consumer awareness.

Chapter 2

The Impact of Policy on Residential Energy Consumption

2.1 Introduction

Residential energy consumption has returned to the top of the agenda in academia, business and policy. The first wave of residential energy debates of the early eighties succeeded a severe oil crisis, which stressed the importance of energy efficiency from a political point of view. Today, energy efficiency has regained importance, this time contending with the outlook of depleting energy resources and the harmful effects of climate change that result from increasing carbon dioxide emissions. Given that residential sector accounts for almost 40 percent of the EU's total energy consumption, the residential sector is an obvious target for energy conservation policies (Perez-Lombard et al., 2008). Within the EU, a wide collection of policy instruments has been implemented over the years, all with the aim of enhancing the energy efficiency of the residential sector. Among these, building standards and mandatory energy labels for household appliances are the most common policy tools that have been used by European countries over the last thirty years.

According to the Odyssee database, in 2012, nearly 67 percent of the total residential energy consumption in EU is used for space heating.[1] Therefore, minimum thermal efficiency standards for new buildings are considered as one of the most important energy

[1]See http://www.odyssee-indicators.org

conservation measures. Especially after the 1973-74 oil crisis, many countries have introduced their first national building standards or strengthened the existing codes. The importance of these standards also extends beyond their role in new dwellings. They are also expected to have spillover effects on the existing dwelling stock as these standards also serve as a benchmark for the energy efficiency refurbishments.

Energy efficiency in the appliance market is also an essential element in EU's portfolio of energy conservation policies. In order to facilitate the adoption of energy-efficient technologies, the EU Commission issued the Directive 92/75/EC requiring the member states to implement mandatory disclosure of energy labels in 1992. Following this directive, national governments have gradually introduced labeling schemes for different appliance groups. These energy-efficieny labeling regulations aim to remove the information barriers to the diffusion of energy efficient products in the market. The lack of sufficient information is generally accepted as one of the main reasons why households underinvest in energy efficient technologies (Gillingham et al., 2009). In the absence of information, consumers are not able to incorporate the operating costs into their purchasing decisions, which in return leads to lower investments in energy efficient products. The provision of energy labels may create market incentives for appliance manufacturers to design more energy-efficient products (Mills and Schleich, 2010). Newell et al. (1999) document that the mean energy efficiency of water heaters and air conditioners sold in the US increased significantly after the introduction of the labeling scheme in 1975. Therefore, greater transparency may enable both consumers and producers to incorporate energy efficiency in their decision-making process.

However, whether the building standards and the labeling schemes have been effective in reducing the total residential consumption of energy is still unclear. Thus far, the impact of these energy efficiency regulations has been mostly studied by use of the so-called bottom-up modeling approach, in which consumers are assumed to readily adopt new technologies without adjusting their energy behavior. While these studies provide useful ex-ante information on the potential impact of policies, they are not able to accurately assess the actual outcome. The uptake of building standards may be less than expected if they are poorly enforced or not stringent enough to be binding. Greening et al. (2000) argue that the voluntary uptake of energy efficiency innovations is modest, and part of the predicted efficiency gains are offset by a shift in energy demand through the so-called “rebound effect”. Considering the labeling regulations, even if the energy efficiency information is provided, price-driven temptation can lead to purchase of an energy-inefficient appliance with a low purchase price, in spite of its relatively high operating costs that will be incurred in the future (Tsvetanov and Segerson, 2013). As a consequence of these, the actual impact of energy efficiency regulations may well be lower than the expected.

The empirical evidence on the actual impact of these regulations is relatively scarce. There are only a couple of studies investigating the “actual” effects of building standards on residential energy consumption. Using a panel of 48 US states from 1970 to 2006, Aroonruengsawat et al. (2012) analyze the impact of the introduction of state level building codes. They find that the states, which adopted building codes, have experienced a reduction in electricity use by around 3-5 percent in 2006. In a recent study, Jacobsen and Kotchen (2013) find that the introduction of stricter building codes in Florida in 2002 has generated a 4 percent reduction in electricity use and 6 percent reduction in gas use for the dwellings that are constructed after the implementation of these regulations. As far as we know, there is not any study available in the literature, which investigates the actual impact of energy labeling schemes on residential energy use. Many ex-post evaluations of appliance labeling programs have focused on consumer awareness of the label and have not explicitly examined the impact of these programs on actual behavior (Vine et al., 2001).

Our study contributes to this literature by using actual data from a sample of EU countries and analyzing the impact of common policy indicators that are varying across these countries and over time. We explore and examine the time series of the largest real estate sector, the residential market across 13 EU countries (Austria, Belgium, Denmark, France, Finland, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, and the UK) using three decades of data. We analyze the importance of various factors identified by the available literature; income, energy prices, demography and climate. The main contribution of our paper, however, lies in our analysis of the impact of two distinct types of energy efficiency policies – the mandatory disclosure of energy labels for household appliances and the stringency of building standards.

Residential energy use can be mainly separated into two main components based on the purpose of use: the energy used for space heating and the energy used by household appliances (including lighting). We assume that non-electricity is mainly used for the first and electricity is mainly used by household appliances and lighting.[2] We track residential electricity and non-electricity energy consumption separately, as these are covered by different type of energy efficiency regulations. In order to examine the impact of building standards on non-electricity energy consumption, we developed a policy indicator based on the evolution of national U-value requirements, the measure for the thermal quality of construction materials in new construction. As these requirements vary over time, we are able to identify the impact of the building codes on residential energy consumption, while controlling for unobserved country-specific factors. Similarly, we constructed a policy indicator representing the extent of the mandatory labeling regulations. As the EU governments gradually increased the product coverage of the labeling schemes, we are able to identify the influence of the labeling requirements on residential electricity consumption.

Our results show that energy efficiency labeling policies in the appliance market and stricter building standards lead to significant reductions in residential energy consumption. According to the estimation results, if the government introduces mandatory disclosure of energy labels for an appliance group that represent ten percent of households' electricity use, this leads to a decrease in per capita electricity use by around 0.2 percent in the subsequent years. Similarly, given that U-values proxy the thermal quality of the new dwellings (the insulation level of outer walls), and is calibrated as an inverse index, which decreases as the thermal quality improves, we find that a 0.1 unit decrease in the U-value requirement triggers a lasting 0.3 percent annual decrease in residential non-electricity energy consumption. We also document that the impact of these regulations is stronger in countries with higher shares of new appliances and constructions.

The rest of this paper is organized as follows. We first introduce the data and provide the main statistics for our sample of countries. Section three explains the methodology employed in the study. In section four, we present our empirical results both for electricity

[2] In some of the EU countries electricity heating systems are still very common. We take this into account in the sample selection and the analysis.

and non-electricity energy consumption, and subsequently examine the validity of these results. In the final section, we conclude with a summary of our key findings and discuss their policy implications.

2.2 Data and Descriptive Statistics

Residential energy (electricity or non-electricity) consumption per capita for country i in year t, c_{it}, can be mainly described as a function of the energy price, p_{it}, per capita income, y_{it}, annual heating and cooling degree-days as measures of the annual climatological demand for heating and cooling, hdd_{it}, cdd_{it}, average demographic characteristics, d_{it}, and the energy efficiency level of the residential sector, ee_{it}:

$$c_{it} = f(p_{it}, y_{it}, hdd_{it}, cdd_{it}, d_{it}, ee_{it}) \tag{2.1}$$

for $i = 1, ..., N$ and $t = 1, ..., T$.

An increase in income and/or the demand for heating-cooling are expected to increase the consumption of residential energy. On the other hand, higher energy prices and improved energy efficiency are expected to have an opposite impact. Therefore, residential energy conservation policies are mostly designed in a way to alter these two factors. Increasing the tax rates on energy consumption, improving the thermal quality of the dwelling stock and the efficiency level of household appliances are the common policy instruments that many countries have been implementing over the last three decades.

In this study, we specifically examine the impact of two main energy efficiency regulations that are common across many EU countries: the stringency of building standards, and the energy label requirement for household appliances. We analyze the residential energy consumption by using a panel of 13 EU countries including Austria, Belgium, Denmark, France, Finland, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, and the UK, covering the period from 1980 to 2009. The sample is selected based on the availability of the data, and for the sake of comparability, we excluded the countries where electricity is used as the main source of residential heating.

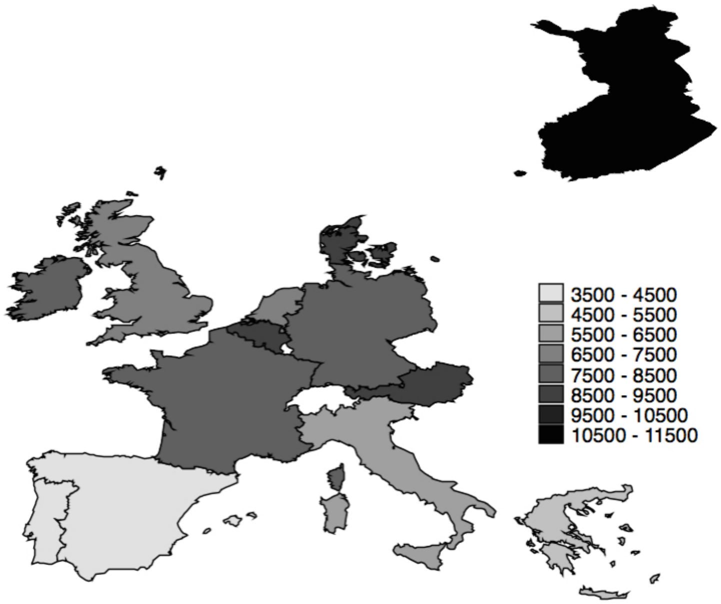
Our dataset is gathered from different sources. We obtained the energy consumption and tax-included real price data from the International Energy Agency (IEA). OECD provides the data for the annual Gross Domestic Product (GDP) that is used as a proxy for the per capita disposable income in the analysis. The series for heating degree-days, and demographics are obtained from EUROSTAT database. We calculated the annual cooling degree-days by using the average daily temperature data that is provided by Data Center of US National Oceanic and Atmospheric Administration (NOAA).[3] The policy variables are constructed based on the information provided by the MURE database and national sources.[4]

Figure 2.1 illustrates the cross-country variation of average per capita residential energy consumption in 2009. The higher level of residential energy use in Northern countries can be partly explained by the cold climate conditions. Besides that, the differences in socio-economic conditions and the energy-efficiency level of the residential sector may also explain the variation in the residential energy use for the countries with similar climate conditions (e.g., Belgium and the Netherlands). There might also exist some unobserved country-specific factors generating this variation. Therefore, in order to isolate the impact of regulations from these unobserved country-specific factors, we pay attention to the over-time variation instead of cross-country differences.

[3] According to the EUROSTAT, hdd is calculated as: $hdd = 18°C - T_m$ if $T_m \leq 15°C$ and $hdd = 0$ if $T_m > 15°C$, where T_m is the mean outdoor temperature realized during the day. cdd is calculated as: $cdd = T_m - 18.3°C$ if $T_m \geq 18.3°C$ and $cdd = 0$ if $T_m < 18,3°C$. Calculations are executed on a daily basis and added up to a year.

[4] See "http://www.muredatabase.org/" for a detailed information about MURE database.

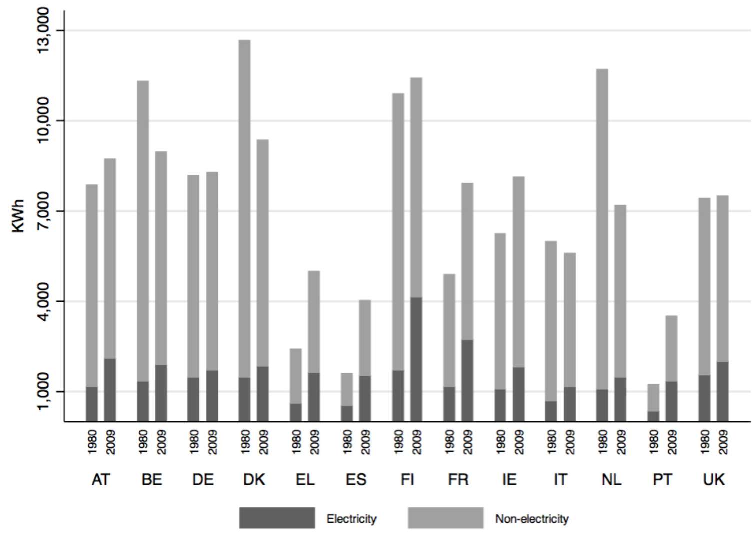
Figure 2.1: Residential Energy Consumption per Capita across Europe (Kwh, 2009)



Source: International Energy Agency

Residential energy use can be mainly specified as a combination of the energy used for space heating and the energy used by household appliances (including lighting). Due to the absence of proper data for these two types of energy use, we approximate these measures by separating the total residential energy use into two components: electricity and non-electricity energy consumption. Figure 2.2 exhibits the change in the use of these two energy sources from 1980 to 2009. For all countries in our sample, per capita residential electricity consumption has increased over the last three decades. This change might be a combined result of the socio-economic and technological developments that have drastically changed household lifestyles. Considering the non-electricity component of residential energy use, we observe that its use has increased for the Southern countries while it is the other way around for the Northern countries. The decrease of non-electricity consumption in Northern countries can be mainly explained by the change of climate conditions and the change in the energy efficiency level of the dwelling stock.[5]

Figure 2.2: Residential Electrcity and Non-electricity Consumption per Capita



Source: International Energy Agency

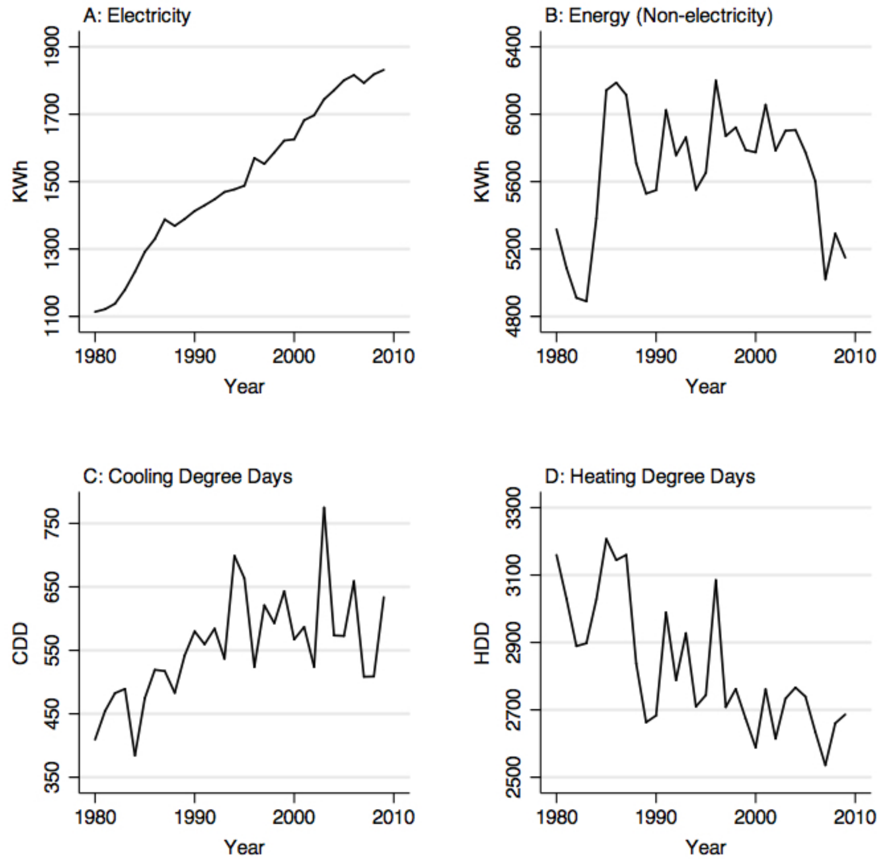
According to the ODYSSEE database, in 2008, nearly two-thirds of household energy consumption in EU-27 countries is used for space heating.[6] Therefore, one can expect a close relationship between climate conditions and the amount of energy consumed by households. In Figure 2.3, we plot the annual fluctuations in electricity and non-electricity consumption against heating and cooling degree-days (HDD and CDD). Although there appears to be some similarity between heating degree-days and non-electricity consumption volatility, no compelling evidence is provided for a relationship between cooling degree-days and residential electricity use. This can be expected since electrical cooling systems are not very common in the sampled European countries.[7]

[5]Haas and Schipper (1998) point out that after the substantial decrease in residential energy demand following the 1973-74 oil crisis, energy demand did not rebound when the energy prices declined considerably in 1985. They suggest that irreversible efficiency improvements, which took place after the 1973-74 oil crisis, might be a reason for this moderate change in energy demand in times of declining energy prices.

[6]See http://www.odyssee-indicators.org/

[7]According to the data provided by Odyssee database, in 2009, around 16 percent of households in our sample of EU countries uses air conditioning equipment, while this share is around 83 percent in the US according to the Residential Energy Consumption Survey (RECS).

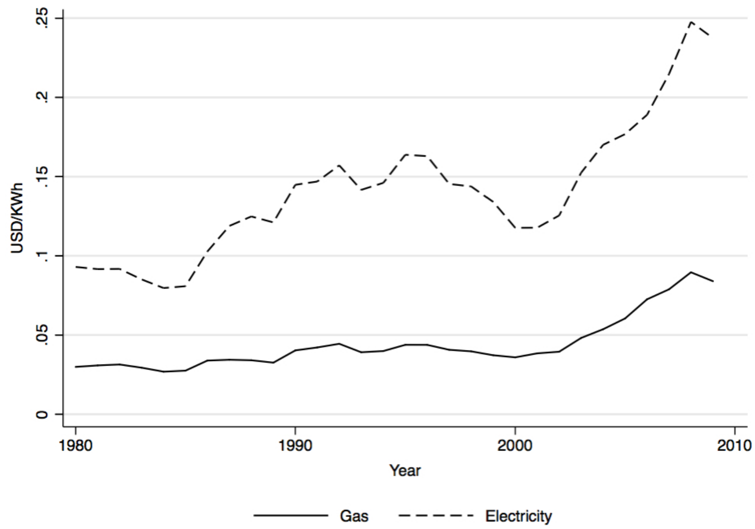
Figure 2.3: Climate Indicators and Residential Energy Consumption per Capita



Source: International Energy Agency & EUROSTAT & NOAA

While there are only a couple of studies in the literature investigating the relationship between energy efficiency regulations and residential energy consumption, there exist more which focus on the effect of economic factors, e.g. income and price, as determinants of residential energy demand. Over the time period we analyze, the average GDP level in European countries has increased from a level of 22,000 USD to 35,000 USD, and as pictured in Figure 2.4, the real energy prices have more than doubled over the last three decades. Economic theory suggests that household income affects residential energy demand positively, while the reverse is true regarding energy prices (Becker, 1965). Based on these income and price elasticity assumptions, many countries have implemented energy taxes as means of reducing consumption levels and carbon emissions. Therefore, in our analysis, in order to isolate the impact of energy efficiency regulations, we control for the changes in income and energy prices.

Figure 2.4: Residential Energy Prices in Europe



Source: International Energy Agency

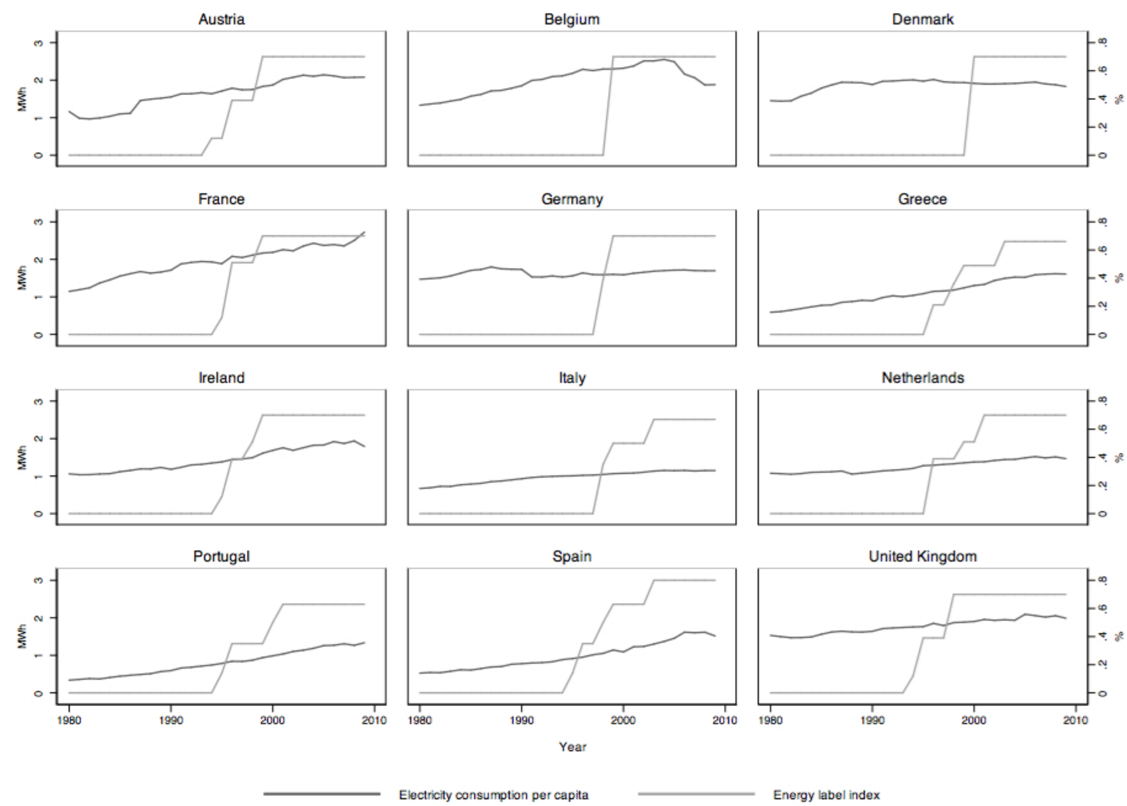
Over the last thirty years, many European countries have introduced regulations targeting the energy efficiency of household appliances and dwellings. In this study, we empirically estimate the impact of these energy efficiency regulations, and exploit the over-time variation associated with the implementation and diffusion process. Firstly, we analyze the impact of the introduction of energy labels on residential electricity consumption. In 1992, the EU Commission introduced a framework directive on energy labeling of electric appliances, which was followed by the introduction of implementing directives targeting specific appliance groups.[8] Based on these directives, each country issued national regulations in the subsequent years. For each country in our sample, we derived an index indicating the average electricity consumption share (in total residential electricity use) of appliances that are subject to a mandatory labeling regulation, benefiting from the over-time variation of the coverage of the labeling regulation.[9] This variable takes

[8]The implementing EU directives are introduced for refrigerators, frozen food storage cabinets, food freezers and their combinations in 1994, for washing machines and driers in 1995, for dishwashers in 1997, for lamps in 1998, for air-conditioners and ovens in 2002 and for televisions in 2010.

[9]Each country implemented the labeling regulations by extending the appliance coverage over time. We predicted the average electricity usage share of these appliances for each year based on the appliance-specific energy consumption statistics provided by Dubin and McFadden (1984), and Larsen and Nesbakken (2004) and the ownership statistics provided by Odyssee database.

a maximum value of one if all household appliances in the market have to be sold with a label according to legislations, and takes a minimum value zero if there is no regulation for the disclosure of energy labels. In Figure 2.5, we present the over-time variation of the label index and per-capita electricity consumption for each country in our sample of analysis. Although the general trends look similar, there exist cross-country differences in the evolution of the label index and electricity use. By exploiting these differences, we aim to identify the impact of appliance labeling regulations on per-capita residential energy demand in the following years.

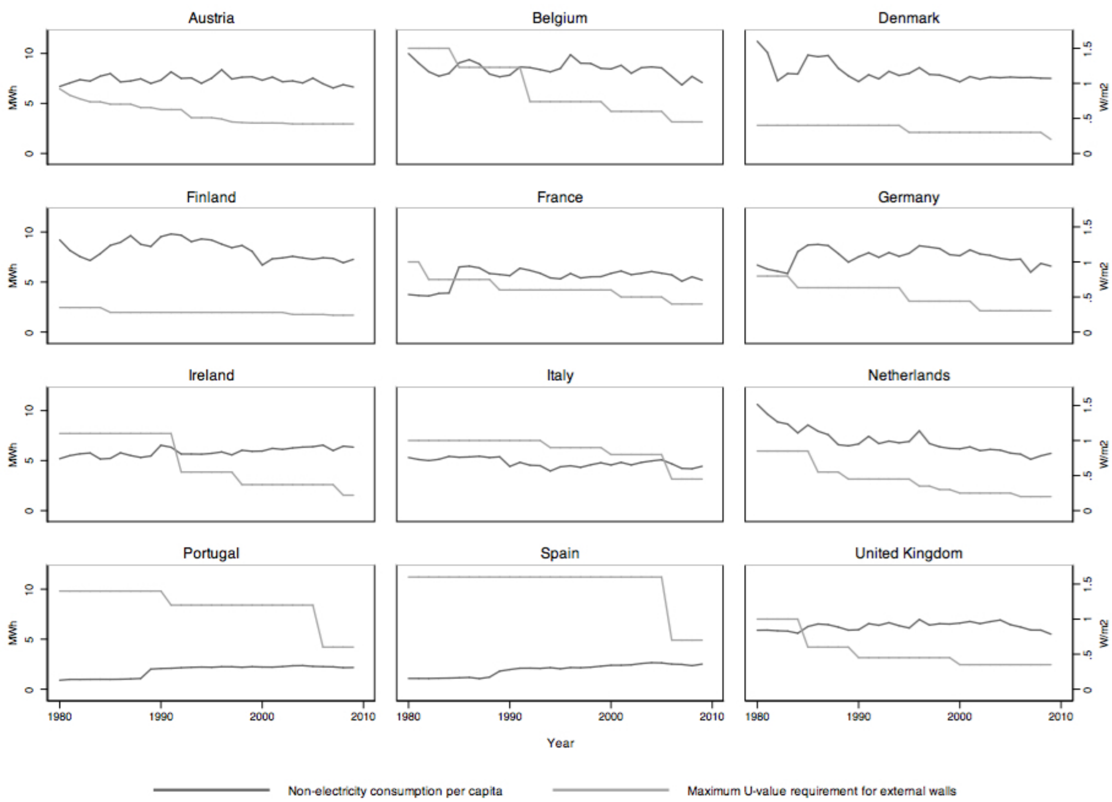
Figure 2.5: Residential electricity Consumption and Coverage of Mandatory Energy Labels



Source: International Energy Agency & MURE Database

As a policy measure targeting the thermal efficiency of new dwellings, we examine the influence of the stringency of building codes on the energy consumed for heating purpose (non-electricity energy). The maximum allowable U-value requirement for external walls is used as a proxy for the stringency of building codes. This U-value is consistently defined as the amount of heat loss through one square meter of the material for one-degree difference in temperature at the either side of the material.[10] The first U-value requirements were implemented in Northern European countries during the 1960s, and were motivated by the demand for thermal comfort. After the oil crisis in the early 1970s, many European countries set or raised U-value requirements in order to reduce the residential energy consumption and decrease their dependency to oil. Figure 2.6 plots the over-time variation of the U-value requirements for the external walls of new construction in the sample of analyzed countries, and clearly shows that the colder Northern European countries have the strictest U-value requirements.

Figure 2.6: Residential Non-electricity Consumption and U-value Requirements



Source: International Energy Agency & MURE Database

[10]As an example; one square meter of a standard single glazed window transmits about 5.6 watts of energy for each degree difference either side of the window and so has a U-Value of 5.6 W/m^2. On the other hand, a double glazed window has a U-value of 2.8 W/m^2.

2.3 Methodology

In order to analyze the dynamics of residential electricity and non-electricity energy consumption (based on a standard constant elasticity demand function which is specified in equation 2.1), we propose the following empirical model:

$$c_{it} = \beta_1 p_{it} + \beta_2 y_{it} + \beta_3 hdd_{it} + \beta_4 cdd_{it} + \beta_5 d_{it} + \beta_6 ee_{it} + \beta_{6i} t_{it} + \alpha_i + \epsilon_{it} \tag{2.2}$$

for $i = 1, ..., N$ and $t = 1, ..., T$, where c_{it} is the logarithm of per capita residential energy (electricity or non-electricity) consumption, p_{it} is the logarithm of tax-included real price (USD/kWh) of the corresponding energy type, y_{it} is the logarithm of income variable that is proxied by per capita Gross Domestic Product in real terms (USD), hdd_{it} and cdd_{it} are the logarithm of annual heating and cooling degree-days.[11] We include the share of elderly (age over 65) in the population, d_{it}, as one of the most important demographic characteristics expected to affect residential energy consumption, which is also verified by some of the household level studies (Baker et al., 1989; Brounen et al., 2012). α_i represents the individual country fixed-effects and ϵ_{it} is the error term assumed to be distributed independently across countries and years. In order to eliminate the unobserved country fixed-effects, we transform equation (2.2) into a first-difference model. The use of first-differenced variables also enables us to take the existence of non-stationary variables into account, which might lead to the estimation of spurious relationships between variables. The first-difference specification of equation (2.2) can be written as below:

$$\Delta c_{it} = \gamma_1 \Delta p_{it} + \gamma_2 \Delta y_{it} + \gamma_3 \Delta hdd_{it} + \gamma_4 \Delta cdd_{it} + \gamma_5 \Delta d_{it} + \gamma_6 \Delta ee_{it} + \Delta \epsilon_{it} \tag{2.3}$$

Our aim in this study is to identify the influence of energy efficiency regulations on per capita residential energy use. Since the energy efficiency regulations are expected to influence the energy efficiency level of the residential sector through the construction of new dwellings and the purchase of new appliances, they are expected to have a cumulative

[11] Due to the data limitations, we use the unit price of gas as a proxy for the price of non-electricity energy.

effect on the energy efficiency level (and on the energy consumption in the subsequent years). According to this, the impact of policy on residential energy efficiency level can be described as below:

$$\Delta ee_{it} = \theta_1 policy_{it} + \theta_2 \Delta x_{it} + \Delta \varepsilon_{it} \tag{2.4}$$

where, depending on the type of energy that is analyzed, $policy_{it}$ denotes either the legal maximum U-value requirement for the external walls of the new buildings, or the share of electricity that is used by the appliances that needs to be marketed with an energy label.[12] x_{it} is a vector of potential determinants of energy efficiency, which are also included in equation (2.3) as control variables (income, energy prices, climate conditions and demographics). ε_{it} represents the error term which captures the unobserved determinants of the residential energy efficiency. In order to measure the annual impact of energy efficiency regulations on residential energy consumption, we transform equation (2.3) by replacing the energy efficiency variable with equation (2.4):

$$\Delta c_{it} = \gamma_1 \Delta p_{it} + \gamma_2 \Delta y_{it} + \gamma_3 \Delta hdd_{it} + \gamma_4 \Delta cdd_{it} + \gamma_5 \Delta d_{it} + \gamma_6 policy_{it} + \Delta \xi_{it} \tag{2.5}$$

Our estimation methodology is based on the assumption that residential energy efficiency regulations are independent of the error term (ξ_{it}), which captures the unobserved determinants of residential energy efficiency (ε_{it}) and the other unobserved factors that might influence energy consumption (ϵ_{it}). Unfortunately, due to the data limitations, we are not able to test the validity of this assumption. However, we check the robustness of our findings by applying different approaches. First, we examine the impact of these regulations separately for sub-samples of countries having high or low shares of new appliances and new construction. We expect a larger impact of energy efficiency regulations for the countries with higher shares of new appliances and newly constructed dwellings. Second, as the

[12]In this model, we assume that the annual impacts of energy efficiency policies are constant during our period of analysis. This assumption might seem unrealistic in case of a longer time horizon. As the efficiency levels of the dwelling and appliance stocks increase over time, we can expect a decreasing impact of the regulations. That is why, the policy coefficients need to be interpreted as the average annual impacts of legislations between 1980 and 2009 for our sample of countries.

over-time change in the usage of heating systems might be correlated with the evolution of building standards, we include the share of electrical and gas heating systems in the analysis of non-electricity consumption as control variables.

2.4 Empirical Results

We first estimate the model in equation (2.5) to investigate the impact of labeling regulations on per capita residential electricity usage.[13] The first column of Table 2.1 reports the estimation results for the 12 countries in our sample.[14] Our results imply that the introduction of mandatory energy efficiency certificates for household appliances has a significant negative impact on residential electricity use. According to the estimated coefficient, if the government introduces mandatory disclosure of energy labels for the appliances that represent ten percent of households' electricity use, this leads to an annual decrease in per capita electricity use by around 0.2 percent in the subsequent years. This result can be explained by policy-induced changes in the demand and supply of energy-efficient products in the market. Given that consumers are willing to pay for energy-efficient products conditional on the provision of information (Galarraga et al., 2011), the mandatory disclosure of information on energy efficiency is expected to lead to a shift in the supply of more energy-efficient appliances, and thus lead to lower residential

[13]We also estimate the linear regression model based on levels instead of a first-differenced variables. In this model, we include country fixed-effects and country-specific linear time trends. We provide the estimation results in Appendix Table 2.A.1. The estimated coefficients of policy variables are significantly larger compared to first-differenced model. However, these coefficients are not easy to interpret as they do not represent the annual impact of the regulations. They indicate the average difference in per capita energy use between the time periods with different regulations. That is why, assuming that the policies have cumulative impacts, we prefer to use first-differenced model which provides us coefficients that represent the average annual impacts of legislations during our period of analysis.

[14]Due to the high share of electrical heating systems, and the extreme climate conditions, Finland has a relatively much higher per-capita electricity consumption level compared to the other EU countries in our sample (see Figure 2.2). Therefore, in order to avoid any distorting effects associated with the heating demand, we do not include Finland in our analysis of electricity. In Appendix Table 2.A.2, we also report the estimation results for electricity consumption including Finland. We do not find a significant difference in the estimated policy impact compared to the estimate based on the sample without Finland.

electricity use.[15]

Table 2.1: First-Difference Estimation Results

	Electricity	Non-Electricity
Coverage of Label Policy (between 0 and 1)	-0.019***	
	[0.006]	
Maximum U-value Requirement for External Walls		0.032***
		[0.010]
ΔLn(Price)	-0.015	0.018
	[0.017]	[0.033]
ΔLn(GDP)	0.216**	0.274
	[0.086]	[0.172]
ΔLn(Heating Degree-days)	0.122***	0.420***
	[0.024]	[0.049]
ΔLn(Cooling Degree-days)	0.002	
	[0.002]	
ΔShare of population over age 65	0.029**	-0.003
	[0.012]	[0.026]
Constant	0.020***	-0.024***
	[0.003]	[0.009]
R-square	0.116	0.203
Number of Observations	348	348

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Consumption per capita).
"Coverage of Label Policy" takes a maximum value of one if all household appliances in the market have to be sold with a label according to legislations, and takes a minimum value zero if there is no regulation for the disclosure of energy labels.
Since Finland has a relatively much higher per-capita electricity consumption level compared to the other EU countries in our sample, we do not include Finland in our analysis of electricity.
We do not include Greece in our analysis of non-electricity energy consumption as there is no available data indicating the over-time change in national U-value requirements.

We also find that electricity consumption is significantly affected by income (one percent increase in income leads to a 0.22 percent increase in per capita residential electricity use), a result which is plausible in light of previous studies for developed countries [the income elasticities reported by the available literature are in the range of: 0.2-0.4 for the G7

[15] The policy results, which are provided in Table 2.1, are based on the assumption that the policy indicators are not correlated with potential non-linear trends in unobserved determinants of residential electricity use. In order to examine how the results differ when we control for common year-specific effects, we introduce year fixed-effects in our model. In Appendix Table 2.A.3, when we include year fixed-effects in our estimations, the impact of label policy becomes statistically insignificant, while the coefficient of building standards remains significant. This indicates that the label policy might be correlated with other non-linear time-varying common factors that affect residential electricity use. Another explanation might be; as the evolution of coverage of label policy is very similar across our sample of countries, the impact of over-time variation in the label policy is mostly captured by the year fixed-effects. Since both explanations might be valid, we should be cautious while interpreting the estimated impact of label policy.

countries by Narayan et al. (2007), 0.5 for the U.S. by Silk and Joutz (1997)]. Within our sample, the price elasticity is found to be -0.15 (although not significant) which is within the range of previous findings (between -0.04 and -2.25) reported by Espey and Espey (2004).[16] We also find that the higher the number of heating degree-days, the higher the residential use of electricity. According to the estimated coefficient, an increase of heating degree-days of one percent results in an increase in residential energy demand of 0.12 percent. This effect is probably caused by the use of electrical heating systems, which is more intense during cold days. Considering the household cooling demand, we find that the number of cooling degree-days does not have a significant impact on residential electricity use for our sample of EU countries where the use of air conditioning is scarce. Finally, we document that as the share of elderly individuals in the population increases by one percentage point, per capita electricity consumption increases by around three percent, which is in line with the findings of Barnes et al. (1981) and Brounen et al. (2012). Elderly people are more inclined to spend time at home and use appliances during this time.[17]

In Column 2 of Table 2.1, we report the results for residential non-electricity energy consumption.[18] Here, we find significant evidence for the effect of stricter building standards on per capita residential energy consumption. The higher the allowable maximum U-value requirement for external walls, the higher the non-electricity energy consumption. Given that U-values proxy the thermal quality of the new dwellings (the insulation level of

[16] The literature also identifiy a long-run relationship between residential electricity consumption, income and energy prices (Narayan et al., 2007). Although our main objective in this study differs from this literature, we also apply the cointegration framework (described in Apenndix B) in order to see how the estimation results differ. According to the test statistics provided in Table 2.B.3, there is not a significant cointegrating relationship between non-stationary variables. Assuming that there exist a cointegrating relationship between consumption, income and energy prices as it is the case in Narayan et al. (2007), we estimate an error correction model. The results that are reported in Table 2.B.4 confirm that there is not a long run equilibrium between these variables, as the coefficients of the error correction terms are positive. Considering the other coefficient estimates, we see that there is a positive long run impact of income on residential electricity use. The results also imply that households respond to short run price changes in electricity. Although the signs of the coefficients of policy variables are in line with the OLS results, they are not statistically significant.

[17] We also examine whether the share of children and the share of female has a significant impact on residential energy use. The results provided in Appendix Table 2.A.4 imply that share of children significantly reduces the electricity use, while there is no evidence for the impact of share of females and elderly in the population. These results needs to be interpreted carefully as the population share of children and elderly are highly correlated.

[18] We do not include Greece in our analysis of non-electricity energy consumption as there is no available data indicating the over-time change in national U-value requirements.

outer walls), and is calibrated as an inverse index, which decreases as the thermal quality improves, this result is both intuitive and significant. We find that a 0.1 unit decrease in the U-value requirement results in a 0.3 percent annual decrease in residential non-electricity energy consumption in the subsequent years. This impact is close to the engineering expectations. For our sample of EU countries, the average annual dwelling construction rate during the period of analysis is nearly three percent, and the average U-value requirement in 1980 is around 1 W/m^2. We can assume that a 0.1 unit decrease in the U-value requirement generates a 10 percent reduction in the required heating energy for the new dwellings built after 1980 (ignoring the rebound effect). Multiplying this with the average rate of new dwellings entering to the dwelling stock, we can expect that the regulation leads to a 0.3 percent annual reduction in the total residential heating energy consumption. The prevalence of rebound and the spillover effects will have opposite effects on this expected impact.

In line with our assumption that non-electricity energy is mainly used for space heating purpose, we find stronger effects of heating degree-days on residential non-electricity energy consumption. According to the estimated coefficient, if the number of heating degree-days increases by one percent, per capita non-electricity energy consumption increases by around 0.4 percent. Our estimation results imply that non-electricity energy consumption is not significantly associated with contemporaneous income and price changes. We suspect that there might be a delay in households' response to changes in income and energy prices. As also pointed out by Ito (2014), households may receive energy bills at the end of billing periods, and thus they may respond to lagged prices rather than contemporaneous prices. It is also likely that energy prices have a lagged impact on residential energy efficiency investments (purchase of energy-efficient appliances and investment on energy efficiency retrofits), and thus on energy consumption. On the other hand, increased income might have a delayed positive effect on energy consumption through the purchase of additional appliances and/or the switch to more energy-consuming heating systems that provide higher thermal comfort (switch from one-room heating equipment to central heating systems). Therefore, in order to control for the lagged effects of income and energy prices, we estimate the same model by including one-year lagged variables instead of contemporaneous variables. According to the results provided in Table 2.2, non-electricity energy consumption is significantly affected by the lagged price and income changes. These results imply a price elasticity of around six percent and an income elasticity of around 70 percent, which are significantly larger than the elasticities that we reported for electricity usage. The other coefficient estimates are comparable to the estimates that are provided in Table 2.1. In the subsequent analyses, we continue to use the lagged price and income measures as control variables.[19]

Table 2.2: First-Difference Estimation Results: Including Laged Price and GDP

	Electricity	Non-Electricity
Coverage of Label Policy (between 0 and 1)	-0.023***	
	[0.006]	
Maximum U-value Requirement for External Walls		0.029***
		[0.010]
Lag.ΔLn(Price)	0.000	-0.059*
	[0.017]	[0.033]
Lag.ΔLn(GDP)	0.190*	0.733***
	[0.100]	[0.203]
ΔLn(Heating Degree-days)	0.109***	0.407***
	[0.023]	[0.048]
ΔLn(Cooling Degree-days)	0.002	
	[0.002]	
ΔShare of population over age 65	0.020*	-0.007
	[0.012]	[0.026]
Constant	0.023***	-0.028***
	[0.004]	[0.009]
R-square	0.116	0.203
Number of Observations	348	348

Notes:
* $P<0.05$. ** $P<0.01$. *** $P<0.001$
Dependent variable: ΔLn(Consumption per capita).
"Coverage of Label Policy" takes a maximum value of one if all household appliances in the market have to be sold with a label according to legislations, and takes a minimum value zero if there is no regulation for the disclosure of energy labels.
Since Finland has a relatively much higher per-capita electricity consumption level compared to the other EU countries in our sample, we do not include Finland in our analysis of electricity.
We do not include Greece in our analysis of non-electricity energy consumption as there is no available data indicating the over-time change in national U-value requirements.

[19]Additional analysis show that our findings regarding the impacts of regulations do not depend on whether lagged or current price and income variables are used as control variables. We also test the robustness of our policy results to the use of lagged policy measures, as there might be a delay in the implementation of regulations. When we include the lagged values of the policy measures instead of current variables, the estimated impact of regulations is found to be not significantly different from the previous estimates.

In order to verify the validity of our policy findings, we also examine the impact of regulations separately for countries having high and low shares of new appliances and construction. If we are able to identify the impact of these regulations, we expect to find a stronger impact for the countries where appliances and dwelling stock are rather new. We first examine the impact of labeling regulations on residential electricity consumption. Using the appliance ownership data provided by Odyssee, we separate our sample of countries into two groups based on the electricity consumption share of new appliances that are purchased by households after 2000.[20] Our results (see Table 2.3) imply that the impact of energy labeling schemes is indeed stronger (although not significantly different) for the countries in which households' adoption rate of new appliances between 2000-2009 is larger than the sample median.

[20]Odyssee provides annual data on the average share of appliance ownership for each type of appliance for each country starting from 2000. Using this database and the statistics provided by Dubin and McFadden (1984), and Larsen and Nesbakken (2004), we calculated the expected change in households' average electricity consumption from 1999 to 2009 for each country, which results from the purchase of new appliances. The median expected change in electricity consumption for our sample of countries is 812 KWh. Based on this median value, we divide the countries in our sample into two sub-samples. The countries for which the expected change is higher than the median level is considered as the countries having a high level of new appliance stock.

Table 2.3: First-Difference Estimation Results: Low-High Share of New Appliances

	Low	High
Coverage of Label Policy (between 0 and 1)	-0.017**	-0.029***
	(0.008)	(0.008)
Lag.ΔLn(Price)	-0.026	0.024
	(0.025)	(0.024)
Lag.ΔLn(GDP)	0.065	0.237**
	(0.187)	(0.117)
ΔLn(Heating Degree-days)	0.120***	0.098***
	(0.035)	(0.032)
ΔLn(Cooling Degree-days)	0.001	0.002
	(0.004)	(0.002)
ΔShare of population over age 65	0.014	0.025
	(0.018)	(0.016)
Constant	0.021***	0.025***
	(0.005)	(0.005)
R-square	0.096	0.154
Number of Observations	168	168

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Electricity consumption per capita).
We separate our sample of countries into two groups based on the electricity consumption share of new appliances that are purchased by households after 2000.
"Coverage of Label Policy" takes a maximum value of one if all household appliances in the market have to be sold with a label according to legislations, and takes a minimum value zero if there is no regulation for the disclosure of energy labels.
Since Finland has a relatively much higher per-capita electricity consumption level compared to the other EU countries in our sample, we do not include Finland in our analysis of electricity.

We employ a similar approach to examine the validity of our findings regarding the impact of building standards. We assign the countries into two sub-samples based on their average annual construction rates between 1980-2009. According to statistics provided by Entranze Project, the median share of dwellings constructed during this time period is 33 percent of the existing dwelling stock for the countries in our sample.[21] The countries having a rate above this value are considered as high-construction countries and the countries having a rate below this value are considered as low-construction countries. The results that are provided in Table 2.4 indicate that the building standards have a larger (although not significantly different) impact on residential energy use in high-construction countries. For the low-construction countries, the estimated impact of building standards is lower and

[21] See http://www.entranze.enerdata.eu/

statistically insignificant.[22]

Table 2.4: First-Difference Estimation Results: Low-High Share of New Constructions

	Low	High
Maximum U-value Requirement for External Walls	0.008	0.031**
	[0.014]	[0.015]
Lag.ΔLn(Price)	-0.098***	-0.021
	[0.033]	[0.055]
Lag.ΔLn(GDP)	0.556**	0.763***
	[0.269]	[0.282]
ΔLn(Heating Degree-days)	0.705***	0.209***
	[0.055]	[0.072]
ΔShare of population over age 65	-0.025	0.053
	(0.022)	(0.057)
Constant	-0.009	-0.038**
	[0.011]	[0.015]
R-square	0.541	0.139
Number of Observations	168	168

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Non-electricity energy consumption per capita).
We assign the countries into two sub-samples based on their average annual construction rates between 1980-2009. The countries having a rate above median construction rate are considered as high-construction countries and the countries having a rate below this value are considered as low-construction countries.
We do not include Greece in our analysis of non-electricity energy consumption as there is no available data indicating the over-time change in national U-value requirements.

Finally, as a robustness check, we also consider the transition between energy sources that are used for heating purposes. In some of the EU countries, the use of electricity as a heating source has varied over time, which led to a change in residential non-electricity consumption. In case this transition is correlated with the evolution of building standards, the estimated impact of building standards might be biased. Therefore, we include the over-time variation in the shares of heating systems as control variables in the analysis of non-electricity energy consumption.[23] According to the results provided in Table 2.5,

[22]Since there might be some differences in the energy consumption dynamics of low and high income countries, we also examine these countries separately based on the median GDP level in 1980. According to results provide in Appendix Table 2.A.5, the impact of building standards is only significant in low-income countries, which might be associated to the higher construction rates in these countries. We find that the impacts of price and heating degree days on residential non-electricity consumption is larger in high-income countries. This might be related to the higher heating demand in northern countries, which are included in the sample of high-income countries.

[23]Odyssee provides data on the shares of electrical and gas heating systems that are used by the households. However, this data is not available for all years and countries in our sample.

the estimated impact of building standards does not differ when we include the share of electrical and gas heating systems. [24]

Table 2.5: First-Difference Estimation Results: Controling for Share of Heating Systems

Dep. Variable: ΔLn(Non-electricity Consumption per Capita)	(1)	(2)
Maximum U-value Requirement for External Walls	0.032***	0.032***
	[0.011]	[0.011]
ΔShare of Dwellings with Electricity Heating	-0.522	-0.530
	[0.338]	[0.346]
ΔShare of Dwellings with Gas Heating		0.034
		[0.354]
Lag.ΔLn(Price)	-0.068*	-0.071*
	[0.039]	[0.040]
Lag.ΔLn(GDP)	0.267	0.259
	[0.222]	[0.226]
ΔLn(Heating Degree-days)	0.503***	0.493***
	[0.052]	[0.053]
ΔShare of population over age 65	0.017	0.018
	[0.029]	[0.029]
Constant	-0.022**	-0.022**
	[0.009]	[0.010]
R-square	0.445	0.432
Number of Observations	162	157

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Non-electricity energy consumption per capita).
We do not include Greece in our analysis of non-electricity energy consumption as there is no available data indicating the over-time change in national U-value requirements.
The number of observations decreases considerably as the data on heating equipment is missing for some countries and years.

2.5 Conclusions

Energy efficiency improvements in the residential sector can play an essential role in the reduction of global carbon emissions. Accordingly, over the last three decades, many countries have introduced regulations targeting the energy efficiency of the residential sector. Among these, stricter building codes and mandatory disclosure of energy efficiency information for household appliances have been the most common policy instruments.

[24] In Appendix, Table 2.A.6, we include the share of electricity heating systems as a control variable in our model for electricity consumption. The coefficient of share of electricity heating systems is not statistically significant.

However, whether these policies have been effective in reducing the total residential energy consumption is still unclear. Thus far, the impact of these energy efficiency regulations has been mostly studied by use of the so-called bottom-up modeling approach, in which market agents are assumed to readily adopt new standards without adjusting their energy behavior. While these studies provide useful ex-ante information on the potential impact of policies, they have some limitations to accurately assess the actual outcome. Their results might be misleading if the policies are not perfectly adopted by the target group or if households change their behavior as a response to the prospective efficiency improvements.

In this paper, using actual data from a sample of thirteen EU countries, we analyze the impact that energy efficiency policy has had on household energy consumption during the period 1980-2009. We measure and track the time variation of labeling requirements for household appliances and the stringency of building standards, and study their impact on the per capita residential energy use. We examine the electricity and non-electricity energy consumption separately, as these are generally used for different purposes (appliances and heating) and are subject to different energy efficiency policies.

Our results underline the importance of residential efficiency policies in reaching the EU policy targets regarding primary energy and CO2 emissions. We find that a ten percent increase in the coverage of mandatory labeling regulation (in terms of energy consumed by household appliances) results in a 0.2 percent annual reduction in the per capita residential electricity use in subsequent years. For policy makers, this result may help in stimulating more extensive dissemination of energy labels. Similarly, our results suggest that stricter building codes lead up to lower residential energy consumption. A 0.1 unit decrease in the maximum allowable U-value, which corresponds to a ten percent reduction in the energy required to heat a building constructed in 1980, leads up to a 0.3 percent annual decrease in total non-electricity energy use in the following period. This confirms that the residential sector in EU countries has a high potential for saving energy by lowering the heating demand through insulation measures. We also document that, in markets where the share of new appliance and new construction is high, the effects of these regulations are stronger.

Although we provide some evidence on the impact of residential energy efficiency regulations on actual energy consumption, we are not able to explore the underlying mechanism through which the regulations influence the residential energy use. Detailed information on market agents' preferences, decisions and actions would allow us to further disentangle the influence of these regulations. This is left for future research.

Appendix

2.A Suplementary Tables

Table 2.A.1: OLS Estimation Results: Models in Levels

	Electricity	Non-Electricity
Coverage of Label Policy (between 0 and 1)	-0.120***	
	[0.025]	
Maximum U-value Requirement for External Walls		0.122**
		[0.052]
Ln(Price)	-0.019	-0.045*
	[0.020]	[0.027]
Ln(GDP)	0.514***	0.746***
	[0.078]	[0.144]
Ln(Heating Degree-days)	0.113**	0.320***
	[0.048]	[0.087]
Ln(Cooling Degree-days)	0.003	
	[0.004]	
Share of population over age 65	-0.003	-0.023
	[0.007]	[0.014]
Constant	0.020***	-0.024***
	[0.003]	[0.009]
Country fixed-effects	Yes	Yes
Country-specific liner time trends	Yes	Yes
R-square	0.980	0.966
Number of Observations	360	360

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: Ln(Consumption per capita).

Table 2.A.2: First-Difference Estimation Results: Sample Including Finland

	Electricity
Coverage of Label Policy (between 0 and 1)	-0.022***
	[0.006]
ΔLn(Price)	-0.016
	[0.016]]
ΔLn(GDP)	0.173**
	[0.079]
ΔLn(Heating Degree-days)	0.137***
	[0.023]
ΔLn(Cooling Degree-days)	0.001
	[0.002]
ΔShare of population over age 65	0.028**
	[0.012]
Constant	0.023***
	[0.003]]
R-square	0.128
Number of Observations	377

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Consumption per capita).

Table 2.A.3: First-Difference Estimation Results: Including Year Fixed-effects

	Electricity	Non-Electricity
Coverage of Label Policy (between 0 and 1)	0.021	
	[0.023]	
Maximum U-value Requirement for External Walls		0.031***
		[0.011]
ΔLn(Price)	-0.022	0.021
	[0.029]	[0.045]
ΔLn(GDP)	0.103	0.401
	[0.125]	[0.258]
ΔLn(Heating Degree-days)	0.047	0.263***
	[0.034]	[0.073]
ΔLn(Cooling Degree-days)	0.000	
	[0.002]	
ΔShare of population over age 65	0.040***	-0.012
	[0.012]	[0.028]
Year fixed-effects	Yes	Yes
Constant	0.022*	-0.046*
	[0.011]	[0.024]
R-square	0.260	0.312
Number of Observations	348	348

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Consumption per capita).

Table 2.A.4: First-Difference Estimation Results: Additional Demographic Controls

	Electricity	Non-Electricity
Coverage of Label Policy (between 0 and 1)	-0.012*	
	[0.006]	
Maximum U-value Requirement for External Walls		0.030***
		[0.011]
ΔLn(Price)	0.007	-0.047
	[0.017]	[0.031]
ΔLn(GDP)	0.120	0.818***
	[0.101]	[0.199]
ΔLn(Heating Degree-days)	0.099***	0.386***
	[0.023]	[0.046]
ΔLn(Cooling Degree-days)	0.002	
	[0.002]	
ΔShare of population over age 65	0.009	-0.000
	[0.012]	[0.025]
ΔShare of population below age 15	-0.036***	0.007
	[0.009]	[0.020]
ΔShare of female	-0.023	0.054
	[0.048]	[0.103]
Constant	0.013***	-0.031***
	[0.004]	[0.009]
R-square	0.150	0.256
Number of Observations	326	326

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Consumption per capita).

Table 2.A.5: First-Difference Estimation Results: High-Low Income Countries

	Electricity		Non-electricity	
	Low-income	High-income	Low-income	High-income
Coverage of Label Policy (between 0 and 1)	-0.024***	-0.029***		
	[0.008]	[0.009]		
Maximum U-value Requirement for External Walls			0.030**	0.006
			[0.013]	[0.020]
Lag.ΔLn(Price)	-0.030	0.008	-0.008	-0.133***
	[0.021]	[0.025]	[0.048]	[0.041]
Lag.ΔLn(GDP)	0.149	0.062	0.719***	0.548
	[0.100]	[0.214]	[0.243]	[0.359]
ΔLn(Heating Degree-days)	0.101***	0.164***	0.144**	0.728***
	[0.029]	[0.037]	[0.067]	[0.062]
ΔLn(Cooling Degree-days)	0.002	0.002		
	[0.002]	[0.003]		
ΔShare of population over age 65	0.011	0.018	0.036	-0.031
	[0.017]	[0.018]	[0.043]	[0.030]
Constant	0.032***	0.021***	-0.038***	-0.005
	[0.005]	[0.006]	[0.014]	[0.015]
R-square	0.124	0.160	0.124	0.499
Number of Observations	196	168	168	168

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Consumption per capita).

Table 2.A.6: First-Difference Estimation Results: Including Heating Type

	Electricity
Coverage of Label Policy (between 0 and 1)	-0.008
	[0.007]
ΔShare of Dwellings with Electricity Heating	0.302
	[0.203]
ΔLn(Price)	-0.020
	[0.023]
ΔLn(GDP)	0.292**
	[0.126]
ΔLn(Heating Degree-days)	0.088***
	[0.031]
ΔLn(Cooling Degree-days)	0.002
	[0.002]
ΔShare of population over age 65	0.302
	[0.203]
Constant	0.011**
	[0.005]
R-square	0.100
Number of Observations	181

Notes:
* P<0.05. ** P<0.01. *** P<0.001
Dependent variable: ΔLn(Consumption per capita).
The number of observations decreases considerably as the data on heating equipment is missing for some countries and years.
Finland is included in the sample as we control for share of electricity heating.

2.B Cointegration Analysis

We also estimate our model using recently developed panel data econometric techniques, which allow us to deal with the existence of non-stationary variables, with heterogeneous effects, and with the cross sectional dependence across panel members. We first test for the existence of cross-country dependence of time series. In light of the results of this test, we apply the proper panel unit root tests to identify the non-stationary variables. As a next step, we test for the existence of any cointegrating relationship among the non-stationary variables. Finally, assuming the existence of a long-run cointegrating relationship, we estimate the long-run and short-run effects.

2.B.1 Cross Section Dependence Tests

Due to the geographic proximity and the socioeconomic connections which can lead to common shocks or spillover effects, there is a possibility that the variables are correlated across countries. This correlation should be taken into account in the test and estimation procedures, since it can lead to imprecise estimates or identification problems. Therefore, as a first step in the analysis, we examine the existence of this correlation by using the cross-sectional dependence (CD) test proposed by Pesaran (2004), which tests the null hypothesis of independence of variables across the panel members. The test is based on an average of all pairwise correlations of the raw variables. The CD statistic can be defined as:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \to N(0,1) \tag{2.B.1}$$

where $\hat{\rho}_{ij}$ is the estimate of the pairwise correlation.

Table 2.B.1 reports the CD test statistics and the corresponding p-values for the variables we use. According to these results, the independence hypothesis is rejected for all of variables. Therefore, cross sectional dependence should be taken into account in the further steps of the analysis.

Table 2.B.1: Cross Section Dependence Tests

Variable	CD-test	p-value	Correlation
Ln (Non-electricity consumption per capita)	4.83	0.000	0.393
Ln (Electricity consumption per capita)	35.57	0.000	0.799
Ln (Gas price)	35.21	0.000	0.791
Ln (Electricity price)	37.25	0.000	0.837
Ln (GDP)	43.21	0.000	0.971
Ln (Heating degree-days)	29.89	0.000	0.672
Ln (Cooling degree-days)	17.35	0.000	0.691
Share of population over age 65	30.55	0.000	0.454
Maximum U-value requirement for external walls	33.60	0.000	0.755
Coverage of label policy	42.16	0.003	0.947

Notes:
Under The null hypothesis of cross-section independence CD N(0,1)

2.B.2 Unit Root Tests

As a next step in the analysis, we examine whether we are dealing with non-stationary variables in our demand model. This we test using the alternative unit root method of Pesaran (2007), which accounts for the cross sectional dependence:

$$\Delta y_{it} = \alpha_i + \beta_{1i} y_{i,t-1} + \beta_{2i} \bar{y}_{t-1} + \beta_{3i} \Delta \bar{y}_{t-1} + \epsilon_{it} \tag{2.B.2}$$

where i represents the panel member, t is the time period and $\bar{y}_{t-1}$ is the cross section average of the lagged variable and ϵ_{it} is the error term. The test statistic is based on the mean of individual Augmented Dickey Fuller (ADF) t-statistics of each unit in the panel. To eliminate the cross dependence, the standard ADF regressions are augmented with the cross section averages of lagged levels and first-differences of the individual series. The null hypothesis claims that all series are non-stationary.

Table 2.B.2 reports the panel unit root test results based on the specifications with and without trend variable. The test statistics suggest that most of the variables, except the heating degree days, cooling degree days and the coverage of label policy contain unit roots. On the other hand, the hypothesis of unit root is rejected for all of the first-differenced variables except share of elderly. Thus, we can conclude that the consumption, prices, GDP and U-value variables are integrated of order one, which leads us to examine the existence

of any long run equilibrium relationship between these variables.

Table 2.B.2: Panel Unit Root test (CIPS)

	Raw Data				First-differenced Data			
	Without trend		With trend		Without trend		With trend	
Variables	Zt-bar	p-value	Zt-bar	p-value	Zt-bar	p-value	Zt-bar	p-value
Ln (Non-electricity cons.)	-1.187	0.118	1.367	0.914	-7.878	0.000	-6.456	0.000
Ln (Electricity cons.)	-1.193	0.117	0.498	0.691	-5.563	0.000	-3.706	0.000
Ln (Gas price)	-0.429	0.334	2.146	0.984	-6.379	0.000	-6.033	0.000
Ln (Electricity price)	0.807	0.790	-1.126	0.130	-5.771	0.000	-4.580	0.000
Ln (GDP)	-2.237	0.013	0.262	0.603	-3.977	0.003	-2.852	0.002
Ln (Heating degree-days)	-3.933	0.000	-2.116	0.017	-7.025	0.000	-5.092	0.000
Ln (Cooling degree-days)	-2.278	0.011	-2.499	0.006	-11.379	0.000	-9.765	0.000
Share of elderly	1.145	0.874	2.427	0.992	o.990	0.839	1.604	0.946
Maximum U-value requirement	-0.981	0.163	1.703	0.956	-7.302	0.000	-6.853	0.000
Coverage of label policy	-9.087	0.000	-7.876	0.000	-10.052	0.000	-8.109	0.000

Notes:
Under the null hypothesis series are I (1).
CIPS test assumes cross-section dependence is in form of a single unobserved common factor.
Number of lags included in ADF regressions is (2).

2.B.3 Cointegration Tests

After confirming that there exist unit roots in some of the series, we check whether there is a long run equilibrium relationship between these variables. For this purpose, we benefit from four different panel cointegration test statistics proposed by Westerlund (2007), which are based on the test of error correction. Considering the following error correction model where all variables are I(1),

$$\Delta y_{it} = \delta_i d_t + \theta_i (y_{i,t-1} - \beta_i x_{i,t-1}) + \sum_{j=1}^{p_i} \lambda_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it} \tag{2.B.3}$$

the θ_i determines the speed at which the system corrects back to the equilibrium relationship $(y_{i,t-1} - \beta_i x_{i,t-1})$after a sudden shock. If $\theta_i < 0$, then there exist error correction which implies that y_{it} and x_{it} are cointegrated; if $\theta_i = 0$, then the null hypothesis of no cointegration for all panel members is true. The statement of the alternative hypothesis depends on the homogeneity assumption regarding the error correction parameter θ_i. Two of the proposed tests which are named as "Group-Mean Tests" assume heterogeneity of θ while the other two, called "Panel Tests", assume that θ_i is equal for all panel members. In all of these test procedures, the cross-section dependence is accounted for by the use of bootstrap approach of Westerlund (2007).

After carrying out the cointegration tests for different combinations of the non-stationary variables, we concluded that there do not exist a long run equilibrium relationship between any group of non-stationary variables. Table 2.B.3 reports the results of Westerlund (2007) panel cointegration tests for residential energy consumption and the economic factors (GDP and energy prices). According to these results, both mean-group test statistics G_t and G_a statistics verify the null hypothesis of no cointegration between variables.

Table 2.B.3: Error Correction Model Panel Cointegration Tests

	"Ln(Gas Cons.)& Ln(Gas Price)& Ln(GDP)"				"Ln(Elec. Cons.)& Ln(Elec. Price)& Ln(GDP)"			
Statistic	Value	Z-value	P-value	Robust P-value	Value	Z-value	P-value	Robust P-value
Gt	-1.321	0.201	0.580	0.333	-1.312	0.231	0.591	0.300
Ga	-5.071	0.477	0.683	0.347	-3.276	1.614	0.947	0.497
Pt	-4.262	-0.765	0.222	0.237	-3.526	-0.211	0.417	0.313
Pa	-3.478	-0.692	0.244	0.267	-2.225	-0.193	0.577	0.310

Notes:
Bootstrapping critical values under H0: no cointegration
Number of lags included in ECM is (2).

2.B.4 Estimation Methodology and Results

Assuming that long run stable relationships between variables exist, we now employ an error correction model of which the parameters are estimated using the Mean Group (MG) estimator as it is developed by Pesaran et al. (1997, 1999). This estimator allows for heterogeneous short run and long run dynamics. The error correction parameterization of our energy demand model can be written as;

$$\begin{aligned} \Delta ln(c_{it}) = \theta_i \left[ln(c_{i,t-1}) - \beta_{0i} - \beta_{1i} ln(y_{it}) - \beta_{2i} ln(p_{it})\right] + \lambda_{1i}\Delta ln(y_{it}) + \lambda_{2i}\Delta ln(p_{it}) \\ + \lambda_{3i}\Delta ln(hdd_{it}) + \lambda_{4i}\Delta ln(cdd_{it}) + \lambda_{5i}\Delta d_{it} + \lambda_{6i} policy_{it} + \epsilon_{it} \end{aligned} \tag{2.B.4}$$

where θ_i is the error correction speed of adjustment parameter, β_{1i} and β_{2i} are the long run income and price elasticities respectively.

The results that are reported in Table 2.B.4 indicate that there is not a long run equilibrium between energy prices, income and energy consumption, as the coefficients of the error correction terms are positive. Assuming that these variables are cointegrated, we find that there is a positive long run relationship between income and electricity use. The results also imply that households respond to short run price changes in electricity. The signs of the coefficients of policy variables are in line with the previous results although statistically insignificant.

Table 2.B.4: "Mean Group" Estimation Results

	Electricity	Non-electricity
Long run Estimates		
Ln(Price)	0.024	0.225
	[0.125]	[0.142]
Ln(GDP)	0.837**	0.239
	[0.368]	[0.261]
Short run Estimates		
EC	0.308***	0.383***
	[0.058]	[0.064]
Δ Ln(Price)	-0.031*	-0.019
	[-0.016]	[-0.036]
Δ Ln(GDP)	-0.152	0.297
	[0.155]	[0.206]
Δ Ln(Heating Degree-days)	0.146***	0.467***
	[0.034]	[0.080]
Δ Ln(Cooling Degree-days)	-0.005	
	[0.010]	
Δ Share of population over age 65	0.008	-0.019
	[0.027]	[0.044]
Coverage of label policy (between 0 and 1)	-0.025	
	[0.028]	
Maximum U-value Requirement for External Walls		0.086
		[0.094]
Observations	348	348

Notes:
* $P<0.05$. ** $P<0.01$. *** $P<0.001$
Dependent variable: ΔLn(Consumption per capita).

Chapter 3

Energy Efficiency and Household Behavior: The Rebound Effect in the Residential Sector

3.1 Introduction

Energy consumption in the durable building stock has, once again, returned to the agenda of policy makers. Around the world, regulatory measures are introduced to reduce and mitigate the harmful effects of climate change that result, in part, from the carbon emission externality of energy consumption in buildings. While stricter building codes seem to have reduced the energy consumption of newly constructed dwellings (Jacobsen and Kotchen, 2013), codes as a policy instrument alone may be insufficient to meet broader energy reduction targets for the built environment (Majcen et al., 2013). Irrespective of the effectiveness of policies in increasing the thermal quality of the building stock, a critical debate focuses on how households respond to these improvements in energy efficiency.

Research has shown that, as a consequence of the associated changes in consumer behavior, technological improvements may lead to lower energy savings than expected (Jevons, 1906; Brookes, 1990; Khazzoom, 1980, 1987; Wirl, 1997). The mechanism underlying this behavioral change can be derived from the neoclassical economic theory. As described by the "household production" model of Becker (1965), households use energy as one of the inputs in the production of services – such as driving, space heating, and cooking. Households acquire utility from consuming energy services, rather than from consuming energy itself. When the energy efficiency of a particular service is improved, without leading to an offsetting change in the price of energy, households realize a reduction in the effective price of that service due to the decrease in the amount of energy that is required for its production. Consequently, under the condition that the demand for the energy service is price-elastic, improved energy efficiency leads to an increase in its demand, so the amount of energy that is required for its production. This implicit price mechanism generates the so-called "rebound effect" as it partially offsets the initial efficiency gains.[1]

While the existence of such rebound effect is widely acknowledged, the real debate lies in the identification and the size of the effect (Gillingham et al., 2013; Greening et al., 2000). The discussion on the extent of rebound effect has led to different views on the role of energy efficiency policies in addressing climate change (Borenstein, 2015). So far, due to the uncertainty regarding its actual size, the rebound effect has been disregarded in ex-ante impact assessments of energy conservation measures (e.g. building regulations and energy efficiency subsidy programs), leading to higher expectations about their role in saving energy (Jacobsen and Kotchen, 2013). This is of importance, as it determines the success of energy efficiency policies in reducing energy consumption and carbon emissions. Incorporating the rebound effect into policy evaluations can help to develop cost-effective energy conservation policies.[2]

Furthermore, as the size of the rebound effect may vary across different socio-economic segments of the society, identification of the heterogeneity in the rebound effect may

[1]The literature identifies three types of rebound effects that encompass both the microeconomic and macroeconomic perspectives (Greening et al., 2000; Sorrell et al., 2009): the direct rebound effect, the indirect rebound effect and the economy-wide effects. The direct rebound effect occurs when an improvement in energy efficiency for a particular energy service reduces the effective cost of the service, which subsequently leads to increased consumption.The indirect rebound effect occurs when the reduction of the effective cost of the energy service leads to changes in demand of other goods, services and productive services that also require energy. The sum of direct and indirect rebound effects represents the economy-wide rebound effect. In this study, we focus on direct rebound effect.

[2]It is important to note that, since rebound effect is a re-optimization as a response to implicit price changes, it can be seen as welfare improving according to the neoclassical economic theory. On the other hand, its extend has important implications on the outcomes of energy conservation policies.

also contribute to the assessment of potential outcomes of energy efficiency policies. As Borenstein (2015) mentions, the size of the rebound effect might be different for the households who are targeted by energy efficiency regulations. For instance, low-income households, who are more likely to accommodate in poorly insulated houses, might be more responsive to the efficiency improvements as they are expected to be more cost-sensitive. In that case, the regulations, which are specifically targeting energy-inefficient dwelling stock, will result with a higher rebound effect than the average. Another source of heterogeneity might be the variation in energy use intensity level of the households. Since the cost of heating is higher for the households who are more energy dependent, these households might show a stronger response to energy efficiency changes. Identification of household level heterogeneity can also guide us to form policy expectations for different regions of the world with different income and energy use intensity levels, and for the other residential energy services that require different amounts of energy input. Thus, for policy purposes, an important question is how rebound effect differs by income and energy use intensity.

Measuring the rebound effect is not straightforward, as it involves an estimation of the elasticity of the demand for a particular energy service with respect to energy efficiency. Instead of using this definition, the majority of studies on the topic have estimated the rebound effect using price elasticity, since data on energy efficiency measurements is generally limited. In principle, under neoclassical assumptions, rational consumers should respond in the same way to a decrease in energy prices as they would respond to an improvement in energy efficiency. This symmetry assumption, however, does not always hold, as consumers may respond differently to these alternatives due to the "bounded rationality". While making consumption decisions, as a result of cognitive limitations and attention scarcity, households may overweight information that is prominent (Simon, 1955; Tversky and Kahneman, 1974). For instance, Sexton et al. (2015) documents that, for a sample of consumers who are enrolled in an automatic bill payment program, perceived energy costs decline, and the electricity consumption significantly increases after the change of payment method. The difference between the perceived persistence of price changes and the efficiency changes might also lead to asymmetric responses. Li et al. (2014) report that households' response to gasoline tax changes is six times as large as that from tax-exclusive price changes, which might be a result of the difference in the perception of longevity of these changes. Finally, even if the symmetry assumption is satisfied, many studies estimating price elasticity of energy demand fail to address endogeneity concerns, as the adoption of energy-efficient technologies itself may be affected by changes in energy prices (Sorrell et al., 2009).[3]

In the literature, the transport sector and the residential sector are the two main areas where improvements in energy efficiency have previously been studied, as energy consumption levels are high in both sectors, and technological innovations are fast-evolving.[4] However, due to limited availability of data, the literature on the housing market has been relatively scant. For the housing market, residential heating is of key interest, since there are many ways in which consumer behavior may influence the level of this energy demand, for example, by means of choosing temperature levels, share of space heated, ventilation rates, etc.

One strand of the available literature on the topic is based upon cross-section analysis of household survey data (Dubin et al., 1986; Hsueh and Gerner, 1993; Haas and Biermayr, 2000). Dubin et al. (1986) study the relationship between actual electricity consumed for heating and the cost of heating for 252 single-family dwellings in Florida. Using the variations in energy price and energy efficiency indicators, the authors report a price elasticity of heating demand ranging from 52 to 81 percent. Similarly, Hsueh and Gerner (1993) use data from 1,281 single-family homes in the U.S., and document that the engineering estimates are two to eight times as large as the realized savings for different insulation measures (roof, wall and windows), depending on region and type of fuel. Using a cross-section database of about 500 Austrian households, Haas and Biermayr (2000) estimate a rebound effect about 30 percent based on the variation in the thermal characteristics of the dwellings. Although this literature provides more reliable estimates of

[3]Sorrell et al. (2009) also mentions that, due to the irreversibility of efficiency improvements and regulations, energy price elasticities are found to be higher for periods with rising prices than those for falling prices. Given that reduction in energy prices is the appropriate proxy for efficiency improvements, studies that are based on time series data including periods of rising prices may overestimate the rebound effect.

[4]See, for example, Wheaton (1982) and Small and Van Dender (2007) for the case of vehicle fuel economy, Hausman (1979) for the case of air conditioners, Davis et al. (2014) for the case of refrigirators, and Davis (2008) for the case of clothes washers.

the rebound effect compared to the evidence based upon price elasticities only, it also has some drawbacks in terms of data and methodology used in the estimations. These studies are based on small samples which lead to imprecise (or even statistically insignificant) estimates of the rebound effect. Besides, given the lack of detailed information on dwelling and household characteristics, the use of cross-sectional analysis may lead to a bias arising due to unobserved heterogeneity. Finally, since an analysis of efficiency measures require detailed information regarding the technical characteristics of dwellings, which is not easy to measure with survey questions, the measurement error in calculated (or self-reported) efficiency indicators potentially leads to a bias in the estimated rebound effect.

Another methodological approach in the literature is to compare the demand for heating before and after an energy efficiency improvement (Hirst et al., 1985; Milne and Boardman, 2000; Haas and Biermayr, 2000). For instance, Hirst et al. (1985) compares the internal temperature settings before and after efficiency improvements for 79 U.S. households who received subsidies. They document that 11 percent of the potential savings is not achieved (although not statistically significant) due to the change in internal temperature. Milne and Boardman (2000) examine the average change of internal temperature after efficiency improvements using data from 13 UK efficiency projects, and conclude that the average rebound effect observed in these projects is around 30 percent. Haas and Biermayr (2000) study the gap between theoretically calculated and realized energy savings after energy retrofit measures for 12 large multi-family dwellings in Austria. They document that the actual savings are 40 to 100 percent less than the expected savings. However, as well as the problems associated with the limited sample size, there are also some concerns regarding the methodological quality of these studies. The results provided by these studies are based upon simple before-after comparisons, without use of a control group. Since there might be other factors which may also have affected the observed outcome (e.g. thermostat settings), the use of simple before-after comparisons might lead to biased results (Meyer, 1995). Besides, these studies potentially suffer from sampling bias, resulting from non-random selection of the project participants (Hartman, 1988). Finally, the thermostat setting might be a poor proxy for the heating demand, since it does not take the other determinants of thermal comfort (such as the share of heated area, humidity, and airflow) into account.

In this study, we address some of the methodological limitations in the current literature on the identification of rebound effect. This is the first study in the literature that is based on a large representative sample of dwellings using a continuous energy efficiency measure. We analyze a detailed panel dataset that covers both the engineering estimations and the actual energy consumption of 560,000 households in the Dutch housing market. Exploiting the widespread diffusion of home energy performance certificates (EPCs), which are mandatory in all Member states of the European Union, we investigate the elasticity of actual energy consumption relative to the engineering predictions of energy performance. In order to account for the potential measurement error in engineering estimates, we use an instrumental variable approach by including the year of construction as an instrument. Although we control for the observed household characteristics such as income, size, employment status, gender and age, we also estimate a fixed-effects model to control for unobserved household characteristics that might be correlated with the thermal quality of the dwelling.

Using the large number of covariates in our dataset, we then explore the heterogeneity of the rebound effect, which may help to better understand the findings. We separately estimate the model for cohorts of households with different income and/or wealth levels and differences in tenure (i.e., households that own a home versus households that rent a place). Using a quantile regression approach, we also examine whether the magnitude of the rebound effect depends upon the actual energy use intensity of households. Finally, as a robustness check, we estimate the rebound effect based on a quasi-experimental design for a subsample of dwellings that benefited from an energy efficiency subsidy program initiated by Dutch government.

Our findings suggest that, on average, the rebound effect for residential heating is 41.3 percent for tenants and 26.7 percent for the homeowners. We document that the rebound effect is strongest among lower income groups – these households are further from their satiation in consumption of energy services, including thermal comfort (Milne and Boardman, 2000). Based on the results of quantile regression analysis, we also report that the rebound effect is larger among consumers with relatively high energy consumption. For the dwellings that benefited from an energy efficiency subsidy program, we show that the efficiency improvements lead to a rebound effect of around 55 percent. The relative large size of this estimated rebound effect for these households supports our findings, as well as the heterogeneity hypothesis. Households that invest in the efficiency improvements are at the upper quantiles of the actual gas consumption distribution in the population. Clearly, income and usage patterns are key aspects to take into account in the design and implementation of energy efficiency policies.

The results of this paper have some implications for policy makers. There is much excitement about the potential for energy savings, and thus reductions of carbon emissions, from the residential and commercial building sectors. Some estimates indicate that it is the built environment where such savings come at a financial return rather than just a capital cost (Enkvist et al., 2007). But in the current debate on energy efficiency, program evaluations on for example the effects of subsidies and rebates are often based on engineering calculations of energy savings. While the behavioral response of consumers through a rebound effect should be ”no excuse for inaction” (Gillingham et al., 2013), it needs to be incorporated in models of projected energy savings through energy efficiency measures that governments and public policy outfits often use. Using these adjusted, more realistic models may increase the effectiveness of policies regarding energy efficiency measures. This holds for governments in EU Member States when it comes to, for example, the deployment of mandatory disclosure schemes through Energy Performance Certificates, but also more generally for countries outside the European Union when designing (incentive) programs for improving energy efficiency.

The remainder of this paper is organized as follows. The next section discusses the engineering models used to predict residential energy efficiency. Section 3 describes the data, and provides some descriptive statistics. In section 4, we present the methodology and the results. Section 5 provides a brief conclusion.

3.2 Energy Labels and Consumption Predictions

Mandated by EU regulation, all leasing and sales transactions in the housing market of every EU Member State need to be accompanied by an energy performance certificate

(EPC). Based on an energy index, the energy performance certificates range from "A++" for exceptionally energy-efficient dwellings, to "G" for highly inefficient buildings. The energy index measures the energy efficiency level, based on thermal characteristics of the building. Professionally trained and certified assessors issue the certificates using standardized software. In order to classify the dwelling into one of the energy classes; an engineer visits a dwelling and inspects its physical characteristics (e.g., size, quality of insulation, type of windows, etc.). The collected information is then used to predict the total energy consumption of the dwelling.[5] After scaling by the size and the heating loss area of the dwelling, the prediction is transformed into an energy index, which corresponds to a certain label class, and this information is reported to a government managed database. Once the information has been verified, the certificate is registered and issued to the seller. Appendix 3.A provides a stylized example of the energy label in the Netherlands, which is comparable across the EU. Obtaining the certificate requires an investment of approximately €200, which is incurred by the seller of the dwelling. Dwellings that have been constructed after 1999, or that are classified as monuments, are exempted from mandatory disclosure of the energy performance certificate.[6]

In this study, we use predicted gas consumption, which is provided by EPC, as a measure of thermal efficiency. In Appendix 3.B, we briefly describe the framework of the engineering model that is used to predict the amount of residential gas that is required to achieve a fixed level of thermal comfort.[7] As mentioned by Pérez-Lombard et al. (2009), these "asset rating" engineering models are based on standard usage patterns, standard set of operating parameters (e.g., for thermostat settings) and climatic conditions that do not depend on occupant behavior, actual weather and indoor conditions, and are developed to rate the

[5]The predicted total energy consumption based on the EPC is a combination of predicted gas and electricity consumption. However, the electricity component does not include the electricity consumption from household appliances, which are expected to make up nearly 40 percent of total residential electricity consumption (Majcen et al., 2013). Therefore, since the predicted electricity consumption is not comparable with actual electricity use, we focus on residential heating only.

[6]Importantly, if the buyer of the dwelling signs a waiver, the seller is also exempt from providing the certificate. The sell-side real estate agent typically offers such a waiver.

[7]The engineering model and software tool that are used in the calculations comply with "BRL 9501" describing the quality of the calculation method according to ISSO-publication 54 "Energy Diagnosis Reference (EDR)". EDR describes the test procedures (case studies etc.) that need to be carried out to check the validity of the calculations, and it serves as a guarantee of quality for the tested application.

building and not the occupant. Use of asset rating model enables us to compare different houses using a consistent methodology (SENTECH, Inc., 2010). For instance, these models assume that the occupants heat the complete usable floor area of the dwelling at a fixed level of temperature. This assumption may seem unrealistic, since occupants can opt to heat only some of the rooms (because of the higher cost of heating the complete space). However, in the context of our model, this assumption is acceptable and even required, as we estimate the response of the occupants to the changing cost of thermal comfort. So, if the occupant prefers to heat only part of the dwelling, we interpret this as a behavioral response to the higher cost of heating the complete space. Therefore, we do not consider these standard assumptions to represent a source of systematic measurement error in the predicted energy efficiency; instead, these assumptions are necessary in order to obtain a correct measure of energy efficiency.

In the engineering literature, there are also some studies examining whether engineering predictions of energy consumption fit with the actual energy consumption. For example, comparing the predictions of different engineering models with the utility bills, Edwards et al. (2013) report that engineering models over-predict the average actual gas consumption. However, since average actual gas consumption is also determined by average occupant behavior which is preferably not included in the asset rating models, this comparison do not provide any evidence for a systematic mistake in the energy efficiency rating models.[8] In this study, we benefit from this occupant-independent characteristic of gas use predictions. In order to identify the rebound effect, instead of investigating the gap between average predicted and actual gas use, we focus on the gap between relative changes in these variables. Thus, what is of importance for this study is the systematic accuracy of the asset rating model.

The accuracy of asset rating models is typically based upon evaluations of tools against accepted baseline standards. National Laboratory of the U.S. Department of Energy has developed a number of building energy simulation test (BESTEST) instruments for

[8] It should be noted that the standard occupant behavior and standard set of operating parameters are not determined based on average behaviour observed in the population. They are chosen based on a set of conditions that satisfy a sufficient level of thermal comfort.

assessment and identification of errors in engineering software that is used for analysis of energy efficiency in building sector (Judkoff et al., 2011).[9] Given the fact that the engineering model that is used in the calculation procedure is examined through energy simulation tests (Judkoff and Neymark, 1995; Neymark and Judkoff, 2004) and verified by pilot studies in each EU country which are implementing a similar labeling policy (Poel et al., 2007), we assume that there is not a systematic measurement error that is related to the engineering model.

On the other side, although the predicted energy efficiency is based on an advanced engineering model using detailed information on thermal characteristics of the dwelling, it is still based on some assumptions regarding some characteristics of the dwelling, which are not easy to observe. Especially for older dwellings, the inspector has to make assumptions regarding the thermal quality (U-value) of building envelope and the rates of ventilation and infiltration. Besides that, the installation quality of insulation might be lower than expected because of the moral hazard problem. However, Maldonado (2013) reports that when analyzing the housing stock in the Netherlands, 184 reference buildings were used to verify the assumptions made on the components of buildings. These reference dwellings are used to determine the energy saving potential of dwellings' technical installations. Furthermore, a sample of reference houses were used the check the validity for packages (combinations of thermal envelope and technical systems improvements) of energy saving measures. Therefore, while we acknowledge the presence of measurement error through engineering assumptions, we do not expect this to be significantly correlated with the degree of efficiency of a dwelling.

The other potential source of measurement error is the quality of the inspection. In 2011, it was documented that 16.7 percent of the labeled dwellings exceeded the maximum acceptable level of the deviation from the real energy index (VROM-Inspectie, 2011). These

[9] There is also a discussion on the effectiveness of these instruments (SENTECH, Inc., 2010). However, the debate stems from the observed differences between predicted and realized energy consumption levels, which might be explained by the behavioral factors that are preferably not included in the asset rating models. For instance, Hendron et al. (2003) suggest incorporating a set of operational assumptions that mimic realistic occupant behavior into engineering models. As this example represents, most of the discussion relates to the accuracy of the models in predicting realized energy consumption, which is not the main objective of the asset rating models.

labels, which deviate from the real energy index more than eight percent, are considered as labels with a critical defect. However, examination of the data on re-inspection of a sample of labeled dwellings indicates that this inspection error is not systematically and significantly correlated with the true efficiency value. By using the data on 47 re-inspections, provided by VROM-Inspectie (2011), we found that there is not a significant relationship between the true energy index and the inspection error.[10]

3.3 Data

AgencyNL, a government agency, maintains a repository with information on the characteristics of the certified dwellings as well as their predicted gas consumption. We merge the dwelling information with information on occupant characteristics and their actual gas consumption, provided by the Bureau of Statistics in the Netherlands (CBS). This leads to a panel of 610,000 dwellings and their occupants, which adopted an Energy Performance Certificate (EPC) in the years 2011 and 2012. Additionally, in order to assess whether there are significant differences between the characteristics of the dwellings with and without label, we also use a sample of 122,119 dwellings that are not labeled. These are the dwellings that were sold in years 2011 and 2012, and registered by the National Association of Realtors (NVM). The final dataset includes information on the dwelling characteristics, household characteristics and the household's annual gas consumption from 2008 to 2011.

We exclude the years in which occupants change their address, since it is not possible to exactly identify the amount of energy used by the occupant in that year. We also drop the observations with a gas or electricity consumption of zero, and we exclude outliers that are detected based on the sample distribution of house size, actual and predicted energy consumption (electricity and gas) – the upper and lower boundaries for the outliers are set at the first and 99th percentile. The complete dataset includes an unbalanced panel of 563,010 dwellings.

According to CBS statistics, 59.3 percent of the housing stock consisted of

[10]The estimated correlation coefficient is equal to 0.105 with a p-value 0.482.

owner-occupied dwellings in 2011. However, since the diffusion of energy labels among owner-occupied dwellings in the Netherlands is relatively slow, the share of owner-occupied dwellings in our sample is only around eight percent, which is below the population average. Therefore, the rental housing stock is overrepresented in our sample. Since this might cause a sampling bias in the estimation of the average rebound effect, we analyze the owner-occupied and rental sample separately.

Table 3.1 presents the summary statistics for dwelling and household characteristics. The sample statistics indicate that there are only few differences in the average characteristics of the two samples (rental versus owner-occupied dwellings). The gas consumption in the owner-occupied market seems to exceed the consumption in the rental market, but once correcting for the variation in dwelling size, the differences disappear. For both the rental and owner-occupied homes in our sample, we find that gas consumption predictions that are based on the labels are higher than the actual gas bills.[11] This difference is 17 percent for the rental dwellings, and about 16 percent for the owner-occupied dwellings. Regarding the distribution of energy label categories, we find almost no difference between the subsamples. The other variables indicate that there is overrepresentation of apartments in our rental sample, that rental homes are typically more recently constructed, are smaller in size and accommodate households that are more often elderly with lower income and wealth. We also compare the labeled owner-occupied dwellings with the owner-occupied dwellings that are not labeled. The average actual gas consumption and the occupant characteristics are quite similar for both samples. However, the non-labeled sample contains more dwellings that are built after the year 2000. This is in line with expectations, as the energy label is not mandatory for the dwellings constructed after 1999.

[11] Since the predicted gas use is calculated based on a fixed number of heating degree days (212 days with an average outside temperature equal to 5.64 degree Celsius), in order to provide comparable descriptive statistics, the actual gas consumption in each year is corrected for the annual heating degree days (HDD) in that year. We multiply the actual gas consumption of the household by the ratio of the “fixed HDD” to the “actual HDD” of that year. Fixed HDD, which is used in engineering predictions, is equal to $212 * (18 - 5.64) = 1,620$. We apply this correction in order to better evaluate the average gap between engineering predictions and realized consumption in Table 3.1. In the analysis, we do not apply this correction as we include year and location dummies in our model, which control for varying climatic conditions.

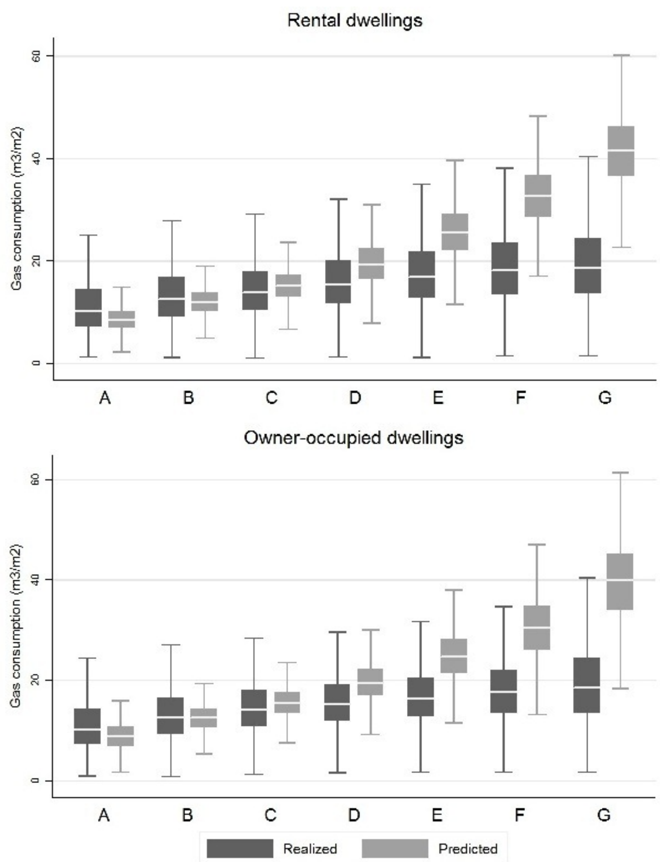
Table 3.1: Descriptive Statistics

Number of Observations	Rental (With Label) *519,512*		Owner-Occupied (With Label) *43,498*		Owner-Occupied (Without Label) *122,119*	
Variables	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Actual Gas Consumption (m^3)	1,245	(526)	1,588	(665)	1,573	(632)
Predicted Gas Consumption (m^3)	1,492	(624)	1,887	(759)		
Actual Gas Consumption (m^3/m^2)	15.7	(7.1)	15.3	(6.2)		
Predicted Gas Consumption (m^3/m^2)	18.7	(8.1)	18.2	(7.1)		
Size (m^2)	82.2	(21.6)	106.7	(34.7)		
Label:						
Label-A (EI<1.06)	0.02		0.03			
Label-B (1.05<EI<1.31)	0.16		0.17			
Label-C (1.30<EI<1.61)	0.33		0.32			
Label-D (1.60<EI<2.01)	0.25		0.24			
Label-E (2.00<EI<2.41)	0.14		0.14			
Label-F (2.40<EI<2.91)	0.07		0.08			
Label-G (2.90<EI)	0.03		0.02			
Dwelling Type:						
Apartment	0.49		0.27		0.21	
Semi-detached	0.32		0.21		0.32	
Corner	0.19		0.32		0.32	
Detached	0.00		0.20		0.15	
Construction Period:						
1900-1929	0.07		0.10		0.12	
1930-1944	0.03		0.08		0.09	
1945-1959	0.17		0.14		0.08	
1960-1969	0.20		0.19		0.15	
1970-1979	0.19		0.25		0.17	
1980-1989	0.20		0.12		0.14	
1990-1999	0.11		0.09		0.16	
>2000	0.03		0.03		0.09	
Household Characteristics:						
Number of Household Members	1.91	(1.12)	2.36	(1.21)	2.28	(1.21)
Number of Elderly (Age>64)	0.46	(0.68)	0.29	(0.62)	0.31	(0.61)
Number of Children (<18)	0.34	(0.78)	0.50	(0.89)	0.53	(0.91)
Number of Females in Household	1.01	(0.74)	1.16	(0.77)	1.13	(0.79)
Number of Working Household Members	0.84	(0.94)	1.48	(0.99)	1.35	(0.96)
Household Annual Net Income (1000 Euro)	23.8	(11.5)	36.9	(17.1)	37.3	(26.2)
Household Wealth (1000 Euro)	22.6	(91.6)	177.8	(393.8)	191.3	(531.5)
Share of Households Receiving Rent Subsidy	0.41					

Notes:
The sample of labeled dwellings consists of the dwellings that have adopted an EPC in 2011 or 2012. The sample of dwellings without a label includes dwellings that have been sold in years 2011 and 2012. Since the label categories "A+" and "A++" have a small share in the full sample, we merged these categories with label "A".
The statistics on actual gas consumption and household characteristics are calculated based on both the cross-sectional and the time-series variation (2008, 2009, 2010, 2011) in the sample.
"Apartment" category is a combination of four different apartment types which are reported in the AgentschapNL data.

Figure 3.1 shows the descriptive statistics of actual versus predicted energy consumption across label categories, in cubic meters per unit of floor area, measured in square meters. The figure also includes the 95-percent confidence interval. On average, gas consumption predictions correspond quite precisely with the label categorization. Of course, this is a result by design, as these predictions determine the categorization. When comparing the descriptives with the box-plots that represent actual gas consumption, we observe a similar trend, but also clear deviations in the tails. The predictions of consumption are lower than the realized gas consumption for efficient dwellings and the reverse is true for inefficient dwellings. Moreover, we also observe that the variation in actual gas consumption is much larger than for the predictions. The higher variation in actual gas consumption may be explained by behavioral factors, such as time at home, comfort preferences, etc., that are not included in the engineering predictions.

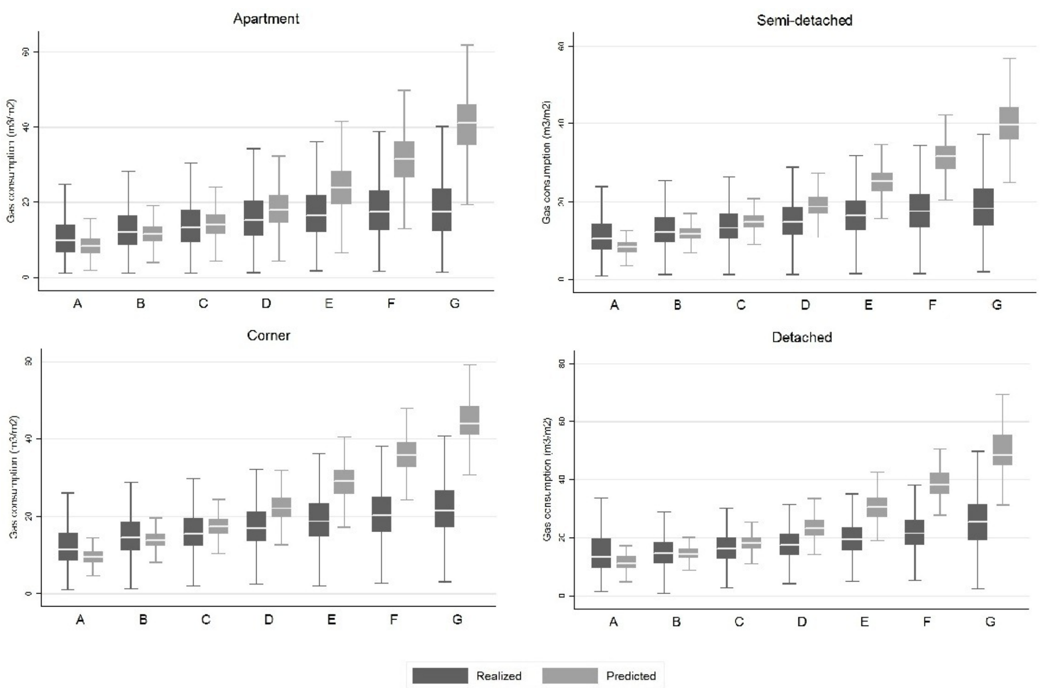
Figure 3.1: Predicted versus Actual Gas consumption



Source: Bureau of Statistics in the Netherlands (CBS), AgentschapNL, authors' calculations

We also stratify the sample across dwelling types, to assess whether the deviations between predicted and actual consumption are common across dwellings or whether they are type-specific. Comparing the statistics plotted in Figure 3.2, we document quite similar patterns. The dwelling type cannot explain why actual gas consumption is so different from what would be expected from the label. For all different dwelling types (apartments, semi-detached dwelling, corner dwelling and detached dwellings), we find underestimations of gas consumption for energy-efficient dwellings, and overestimations for inefficient dwellings.

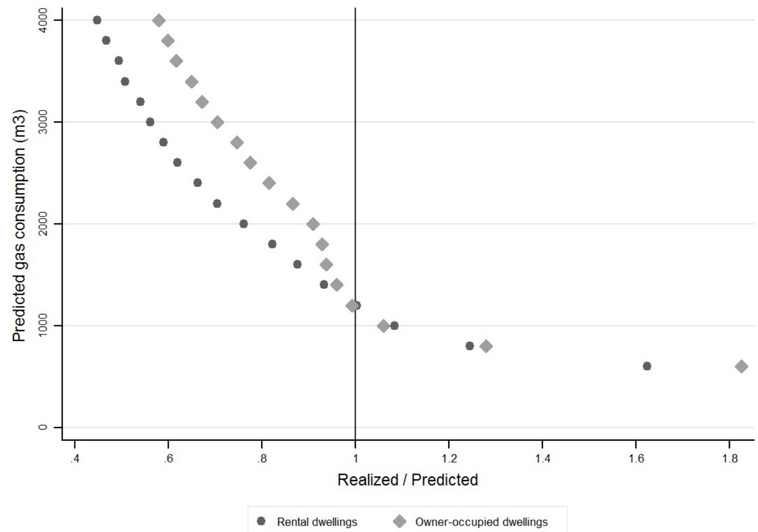
Figure 3.2: Predicted versus Realized Gas consumption by Dwelling Type



Source: Bureau of Statistics in the Netherlands (CBS), AgentschapNL, authors' calculations

In Figure 3.3, we plot the relationship between the predicted gas consumption and the ratio of actual versus predicted gas consumption. Here, we can consider the "predicted gas consumption" as the cost of heating the whole area of the dwelling at a fixed temperature, and the "actual/predicted" ratio can be considered as an indicator of the household demand for heating. The graph shows that as the cost of heating decreases (efficiency increases), the "actual/predicted" ratio increases, which provides some support for the rebound effect hypothesis. Moreover, the deviations between predicted and realized gas consumption are larger for tenants. This difference may be explained by the income and wealth differences between the two subsamples, as we expect the households with lower income and wealth levels to be more sensitive to cost changes from energy efficiency.

Figure 3.3: Realized/Predicted Gas Consumption



Source: Bureau of Statistics in the Netherlands (CBS), AgentschapNL, authors' calculations

Finally, we compare the most energy-efficient and inefficient houses, and their residents based on their observable characteristics. Table 3.2 documents the descriptive statistics for the houses that are at the lower (below 10th) and upper (above 90th) quantiles of the energy index distribution, which represent the energy-efficient and inefficient houses respectively. The statistics indicate that the percentage difference in actual gas consumption between these samples is significantly smaller than the percentage difference in their predicted gas consumption. Considering the other house characteristics, we observe that, as a main determinant of energy efficiency, the distribution of year of construction is significantly different between energy-efficient and inefficient houses. Examining the household characteristics, we do not observe significant differences between the households who are residing in these houses. On the other hand, we should note that the households who are accommodating in energy-efficient houses are wealthier compared to the households in energy-inefficient houses, although not statistically significant.

Table 3.2: Descriptive Statistics for Energy-efficient and Inefficient Houses

	Rental		Owner-occupied	
	Efficient (EI<1.2)	Inefficient (EI>2.3)	Efficient (EI<1.2)	Inefficient (EI>2.3)
Number of Observations	*59,595*	*53,502*	*4,381*	*4,713*
Actual Gas Consumption (m^3)	1,046	1,396	1,391	1,546
	(499)	(567)	(688)	(601)
Predicted Gas Consumption (m^3)	873	2,513	1,240	2,598
	(249)	(639)	(538)	(771)
Actual Gas Consumption (m^3/m^2)	12.9	19.1	12.3	18.2
	(6.3)	(7.9)	(6.0)	(7.1)
Predicted Gas Consumption (m^3/m^2)	10.7	34.3	10.6	30.8
	(2.8)	(8.0)	(2.9)	(8.3)
Size (m^2)	84.0	75.2	117.4	87.5
	(22.6)	(18.8)	(40.3)	(25.6)
Dwelling Type:				
Apartment	0.58	0.54	0.37	0.48
Semi-detached	0.27	0.24	0.17	0.20
Corner	0.15	0.22	0.25	0.27
Detached	0.00	0.00	0.21	0.05
Construction Period:				
1900-1929	0.03	0.13	0.06	0.15
1930-1944	0.01	0.07	0.03	0.14
1945-1959	0.06	0.39	0.08	0.26
1960-1969	0.08	0.27	0.10	0.21
1970-1979	0.09	0.12	0.12	0.23
1980-1989	0.14	0.02	0.07	0.01
1990-1999	0.31	0.00	0.19	0.00
>2000	0.28	0.00	0.35	0.00
Household Characteristics:				
Number of Household Members	1.80	1.92	2.36	2.04
	(1.04)	(1.14)	(1.23)	(1.12)
Number of Elderly (Age>64)	0.55	0.44	0.33	0.32
	(0.55)	(0.68)	(0.65)	(0.62)
Number of Children (<18)	0.29	0.35	0.53	0.33
	(0.72)	(0.80)	(0.93)	(0.73)
Number of Females in Household	0.99	1.00	1.16	1.02
	(0.69)	(0.76)	(0.77)	(0.71)
Number of Working Household Members	0.75	0.82	1.43	1.30
	(0.88)	(0.90)	(1.00)	(0.93)
Household Annual Net Income (1000 Euro)	23.7	23.0	38.0	32.9
	(11.0)	(11.1)	(18.1)	(16.4)
Household Wealth (1000 Euro)	30.3	20.4	220.3	135.7
	(110.9)	(69.6)	(310.1)	(120.5)
Share of Households Receiving Rent Subsidy	0.40	0.38		

Notes:
Energy-efficient and inefficient houses are selected based on the distribution of energy index (EI). Energy-efficient houses are the houses having an energy index lower than the 10^{th} quantile of the distribution (EI<1.2), and energy-inefficient houses are the houses with an energy index higher than the 90^{th} quantile of the distribution (EI>2.3).
The statistics on actual gas consumption and household characteristics are calculated based on both the cross-sectional and the time-series variation (2008, 2009, 2010, 2011) in the sample.
"Apartment" category is a combination of four different apartment types which are reported in the AgentschapNL data.

3.4 Methodology and Results

The rebound effect can be described as the elasticity of demand for a particular energy service with respect to energy efficiency. In this paper, the energy service is represented by the "thermal comfort" (heating), which is a combination of occupant's preferences regarding the temperature level, the share of heated space, the heating duration, and the shower duration. Thus, we can define the rebound effect for residential heating as:

$$\tau_G = \partial ln(H)/\partial ln(\mu_H) \tag{3.4.1}$$

where H denotes the residential heating that is consumed by households (the temperature level, percentage of the heated space and heating duration, quantity of hot water used per person in a day) and μ_H is the heating efficiency of the dwelling (heating system, dwelling characteristics, size, etc.) The heating efficiency can be defined as the heating level that can be achieved with one m^3 of gas:

$$\mu_H = H_r/G^* \tag{3.4.2}$$

In equation (3.4.2), H_r is the reference heating level that is taken as fixed in the calculation of the EPC and G^* is the amount of gas that is required in order to reach that heating level. This reference heating level can be described by: indoor temperature fixed at 18 degree Celsius for the complete space of the dwelling during the heating season (212 days), and a fixed amount of hot water per person per day. Assuming there is one-to-one relationship between the actual gas consumption and the actual residential heating consumption, we can define the actual level of heating that is consumed by households as follows:

$$H = H_r(G^a/G^*) \tag{3.4.3}$$

where G^a denotes the actual gas consumption. By using Equations (3.4.2) and (3.4.3), the rebound effect (3.4.1) can be redefined as:

$$\tau_G = \partial ln[H_r(G^a/G^*)]/\partial ln[H_r/G^*] \tag{3.4.4}$$

Since H_r is fixed in the above equation, the rebound effect is equal to:

$$\tau_G = 1 - \partial ln(G^a)/\partial ln(G^*) \tag{3.4.5}$$

which describes the relationship between actual and theoretical gas use.

3.4.1 Empirical Results

In order to identify the rebound effect in residential heating demand, we estimate the relationship between actual and theoretical gas use by applying a set of different estimation methods. The standard econometric model used to estimate this relationship can be defined as:

$$ln(G^a_{it}) = \beta_0 + \beta_1 ln(G^p_{it}) + \sum_{j=2}^{j} \beta_j Z_{jit} + \alpha_i + \varepsilon_{it} \tag{3.4.6}$$

where i is the household identifier, t is year, and G^p is the predicted gas consumption, which is used as the measure of theoretical gas use (G^*). Z is a vector of observed control variables that are not included in the calculation of EPC, but that are affecting the household's gas consumption, such as household size and composition, province, year, income, employment status of the household members, and ownership of the house. The composite error term is a combination of α_i which denotes the unobserved household-specific effects and the independent and normally distributed error term; ε_{it}. The coefficient of interest is:

$$\beta_1 = \partial ln(G^a)/\partial ln(G^p) \tag{3.4.7}$$

which is used to estimate the rebound effect formulated in equation (3.4.5):

$$\tau_G = 1 - \beta_1 \tag{3.4.8}$$

We first estimate this model using pooled ordinary least squares (OLS), assuming that G_{it}^{p} is independent of $(\alpha_i + \varepsilon_{it})$. The results of these estimations are presented in Table 3.3. When explaining actual gas consumption by the predicted gas consumption and the province and year fixed effects (column 1), the explanatory power of our model is about 21 percent of the variation in the residential gas use of the rental dwellings. The explanatory power of the model for the owner-occupied dwellings is 36 percent. The explanatory power increases to 25 and 40 percent, respectively, when we include the household characteristics.

The signs and magnitudes of the estimated effects for our control variables are in line with expectations. We find that, as the household size increases by one person, there is an increase in residential gas consumption by about 10 percent, with a decreasing marginal effect in larger households. In line with the findings of Brounen et al. (2012), demographics such as the number of elderly people and the number of females in the household also have a positive effect on residential gas consumption. We also control for the employment status of the household members. By including a dummy variable that indicates whether all household members are working or not, we aim to control for the time spent at home. The estimated coefficient indicates that if all household members are working, the gas consumption of that household decreases by six percent in rental units and by four percent in owner-occupied dwellings.

The income elasticity of residential gas consumption is about five percent for tenants and eight percent for homeowners. This is comparable to results obtained by Meier and Rehdanz (2010). Analyzing a sample of UK households, the authors document an income elasticity of residential heating of three percent for tenants and four percent for homeowners. In line with this income effect, for the rental sample we also document that receiving a rent subsidy (which is only available for the lowest income groups) is also related to lower gas consumption.

Importantly, β_1 ranges between 0.441 and 0.589, depending on the model specification and the ownership status. In columns (3) and (4), we control for household characteristics, leading to a decrease in the estimated coefficient. These estimates indicate a quite sizable difference between relative changes in actual energy consumption and engineering predictions.[12] We interpret this as evidence on the influence of household behavior on residential energy consumption.

Table 3.3: Pooled OLS Estimations

	(1) Rental	(2) Owner-Occupied	(3) Rental	(4) Owner-Occupied
Log (Predicted Gas Consumption)	0.485***	0.589***	0.441***	0.528***
	[0.011]	[0.011]	[0.010]	[0.010]
Number of Household Members			0.118***	0.132***
			[0.003]	[0.008]
Number of Household Members^2			-0.012***	-0.014***
			[0.000]	[0.001]
Number of Children (<18)			-0.009***	0.001
			[0.001]	[0.003]
Number of Elderly (Age>64)			0.031***	0.049***
			[0.002]	[0.005]
Number of Female			0.037***	0.016***
			[0.001]	[0.002]
All Household Members Are Working (1=yes)			-0.060***	-0.042***
			[0.002]	[0.004]
Log (Household Income)			0.054***	0.075***
			[0.003]	[0.007]
Receiving Rent Subsidy (1=yes)			-0.032***	
			[0.002]	
Province Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Constant	3.725***	3.038***	3.295***	2.481***
	[0.080]	[0.083]	[0.058]	[0.089]
R^2	0.210	0.361	0.255	0.402
Number of observations	1,664,113	87,282	1,664,113	87,282
Number of dwellings	519,512	43,498	519,512	43,498

Notes:
Dependent variable: Log (Actual Gas Consumption)
Years included in the analysis: 2008, 2009, 2010, and 2011
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by province and year.
* P<0.05. ** P<0.01. *** P<0.001

[12] In order to check whether this gap is mainly driven by a systematic error that is related to the unobserved characteristics of the older houses, we also estimate our model for a restricted sample including the houses that are constructed after 1999. The estimates of β_1, which are provided in Appendix Table 3.C.1, are slightly larger compared to the full sample estimates, which might be associated to the heterogeneity of the rebound effect. We examine the heterogeneity issue in more detail in the further sections of the paper.

3.4.2 Measurement Error in Engineering Predictions

Although we use a large representative sample and control for the household characteristics in the OLS estimations, there is a potential for bias in the estimated rebound effect, which originates from the measurement error in engineering predictions. As a next step, we therefore explicitly take this measurement error into account.

The assumption that G^p_{it} is independent of the error term may not be valid, due to the potential error in engineering predictions. It can be expected that the engineering prediction includes a measurement error, because of the assumptions made in the calculation procedure, and the potential mistakes made during the inspection. Therefore, we assume that the predicted theoretical gas use (G^p) is a combination of the true value (G^*) and a random multiplicative error component (e) as shown below:

$$G^p = G^* e \tag{3.4.9}$$

As discussed previously, the allowable inspection error is described by percentage values (8 percent) by the engineers, which means that the inspection error is expected to be multiplicative (proportional). We also assume that the error is not correlated with the true theoretical gas consumption level.

The presence of this random measurement error leads to a downward bias in the OLS estimate of β_1. In order to overcome this bias, a common approach is to use an instrumental variable (IV) method. Such an IV needs to be correlated with the predicted gas use (G^p), but has to be independent of the measurement error (e). In our case, the year of construction (T) can be considered as an instrument satisfying both of these conditions. We assume that there is a significant correlation between predicted gas consumption and construction year. This assumption relies on the improvements in the quality of building materials and introduction of stricter building codes. Besides, we can expect that the mean measurement error does not depend on the year of construction, unless there is a systematic mistake in the prediction model. If these assumptions are satisfied, we are able to disentangle the true variation in theoretical gas use (G^*).

We estimate the model in equation (3.4.6) using two-stage least squares (2SLS) estimation approach, with year of construction (specified as dummy variables) as an instrument for theoretical gas consumption. Table 3.4 reports the results of the IV estimations.[13] Compared to OLS estimates that are provided in Table 3.3, we now document β_1 estimates of 0.587 and 0.733 for the rental and owner-occupied samples, respectively.[14] While the coefficients of control variables all remain comparable in sign and size, the use of IV estimators significantly reduces the rebound effect estimates, to 41.3 percent and 26.7 percent for the rental and owner-occupied samples, respectively. According to these results, if the efficiency of an average dwelling is increased by 100 percent, this will lead to a 59 percent energy saving in rental dwellings and 73 percent energy saving in owner-occupied dwellings, *ceteris paribus*. The difference between the estimated rebound effects for rental and owner-occupied dwellings is also in line with expectations that more wealthy households are less sensitive to changes in the cost of thermal comfort. Madlener and Hauertmann (2011) analyze the price elasticity of the residential heating for tenants and homeowners and find similar results for German households. In the following sections, we further analyze the heterogeneity of the rebound effect based on the wealth and income levels.

[13]When we estimate the first stage model by using the the year of construction as the only explanatory variable (specified as dummy variables), the estimated R^2 is 0.225 for the rental houses and 0.256 for the owner-occupied houses. This implies that our instrument satisfies the relevance assumption. The total R^2 for the first stage model (including the other control variables) is 0.323 for the rental houses, and 0.378 for the owner-occupied houses.

[14]Including the houses that are constructed before 1900 in the analysis leads to comparable results. We estimate the same IV model by grouping these houses in one age category in our IV estimations. The total share of these houses in our sample is nearly 0.26 percent. The estimated coefficient becomes 0.597 for rental houses and 0.743 for owner-occupied houses. The results are not significantly different compared to the estimates that are based on the restricted sample

Table 3.4: Pooled OLS-Instrumental Variable Estimations

	(1) Rental	(2) Owner-Occupied
Log (Predicted Gas Consumption)	0.587***	0.733***
	[0.012]	[0.016]
Number of Household Members	0.093***	0.105***
	[0.004]	[0.009]
Number of Household Members^2	-0.010***	-0.011***
	[0.001]	[0.001]
Number of Children (<18)	-0.004***	0.001
	[0.001]	[0.003]
Number of Elderly (Age>64)	0.034***	0.043***
	[0.002]	[0.004]
Number of Female	0.037***	0.015***
	[0.001]	[0.002]
All Household Members Are Working (1=yes)	-0.056***	-0.038***
	[0.002]	[0.004]
Log (Household income)	0.052***	0.051***
	[0.002]	[0.006]
Receiving Rent Subsidy (1=yes)	-0.034***	
	[0.002]	
Province Dummy	Yes	Yes
Year Dummy	Yes	Yes
Constant	2.276***	1.208***
	[0.078]	[0.130]
R^2	0.239	0.375
R^2 (First stage regression)	0.225	0.256
First-stage F-statistic on the excluded IVs	34123	1191
Number of observations	1,664,113	87,282
Number of dwellings	519,512	43,498

Notes:
Dependent variable: Log (Actual Gas Consumption)
Years included in the analysis: 2008, 2009, 2010, and 2011
"Predicted Gas Consumption" is instrumented by "Year of Construction"
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by province and year.
* P<0.05. ** P<0.01. *** P<0.001

In order to test the robustness of our IV results, we also estimate the 2SLS model based on an alternative instrument – the stringency of the building codes at the time of construction. Starting in 1965, the Dutch government introduced minimum legal requirements for the thermal efficiency level of new constructions. These legislations set a maximum allowable U-value for each component (walls, windows, floor and roof) of the constructions. U-value is defined as a measure of heat loss through one square meter of the material for one-degree difference in temperature at the either side of the material. The maximum allowable U-value for external walls decreased over-time from 2.00 W/m^2 to 0.25 W/m^2 by the regulations that were introduced in 1965, 1974, 1978, 1981, 1986, 1989, 1995, 2000, 2002, and 2006. Using this variation in the legal U-value requirement for external walls as an instrument for the predicted gas consumption, we estimate the IV model.[15] The results provided in Appendix Table 3.C.2 are comparable to the IV results that are estimated using the year of construction as an instrument.

Finally, we check whether our results are robust to inclusion of house size as a control variable. Households might respond the changing cost of thermal comfort through different mechanisms. One potential response might be changing the share of heated area. In order test whether our results are mainly driven by this kind of behavioral response, we control for the size of the house in the estimations. This also enables us to test the robustness of our findings regarding the engineering assumptions on the size of heating area. In Appendix Table 3.C.3, we report the estimation results for the models including the size of the house as a control variable (both linear and quadratic specifications). The results indicate that, keeping the house size constant, the estimated rebound effect is not significantly different than the results provided in Table 3.4. This implies that the estimated average rebound effect is not driven by the engineering assumptions on the size of heated space.

3.4.3 Endogeneity

Another econometric issue that may cause a biased estimate is the potential presence of household-specific factors that affect both the actual gas consumption and thermal quality of the dwelling. One reason for this potential correlation is that energy-efficient households sort into energy-efficient dwellings. This sorting may lead to an overestimation of β_1, and thus an underestimation of the rebound effect. On the other hand, low-wealth households might be sorting into more affordable housing, that has a lower thermal quality and is thus less efficient (this is sometimes referred to as “energy poverty”). In this case, there will be a downward bias in the estimation of β_1. Thus, our estimate will be biased if there

[15] Based on the statistics provided by AgentschapNL, we assume that the average U-value for the external walls of the houses constructed before 1965 is equal to 2.5 W/m^2.

exists any correlation between the theoretical gas use and unobserved household-specific factors. In order to account for this correlation, we use a fixed-effects instrumental variable (FE-IV) estimator, benefiting from the panel structure of our dataset. By tracking the same households over time, we are able to identify their movements from one address to another. The address change generates a variation in theoretical gas consumption due to the change of the characteristics of the dwelling in which the household resides. So, we can observe the change in the energy efficiency of the dwelling, and the resulting change in actual gas consumption, keeping the characteristics of the household fixed. By using a FE estimator, we are able to eliminate any unobserved household-specific effects (α_i) that are correlated with the thermal quality of the house. This allows us to obtain consistent estimates of β_1 under the presence of a relationship between household-specific effects and the thermal efficiency of the dwelling.

According to the FE estimation results, in Table 5, the rebound effect for rental dwellings is nearly the same as the pooled OLS estimates.[16] The rebound effect for homeowners is higher as compared to the OLS estimations. However, the standard error of this point estimate is relatively large due to the limited number of homeowners who have changed their addresses. This leads to a larger confidence interval for the estimated rebound effect for homeowners. When we test the differences between OLS and FE estimates, we conclude that there is no systematic difference between these estimates, according to Hausman test statistics. We also estimate a random-effects model, assuming that the household-specific effects are randomly distributed and are independent of the theoretical gas consumption. In Appendix Table C.4, the results show that the RE estimates of the rebound effect are quite comparable to the pooled OLS results.

[16] When we restrict the sample of fixed-effects estimation to those households that changed their address (i.e., moved) during the sample period (12,919 tenants and 475 homeowners), the estimated effect (0.586 for tenants and 0.658 for homeowners) is found to be very close to the fixed-effects estimate based on the unrestricted sample.

Table 3.5: Fixed-Effects (IV) Estimations

	Rental occupied	Owner-occupied
Log (Predicted Gas Consumption)	0.584***	0.663***
	[0.011]	[0.051]
All Household Members Are Working(1=yes)	0.000	0.004
	[0.001]	[0.006]
Log (Household income)	0.001	0.008
	[0.002]	[0.007]
Receiving Rent Subsidy (1=yes)	0.001	
	[0.001]	
Province Dummy	Yes	Yes
Year Dummy	Yes	Yes
Constant	3.961***	2.138***
	[0.110]	[0.423]
R^2	0.165	0.243
R^2 (within)	0.024	0.021
R^2 (between)	0.176	0.249
Number of observations	994,804	44,876
Number of households	351,462	21,595

Notes:
Dependent variable: Log (Actual Gas Consumption)
Years included in the analysis: 2008, 2009, 2010, and 2011
"Predicted Gas Consumption" is instrumented by "Year of Construction"
We exclude the households that had a change in their composition between 2008 and 2011.
* $P<0.05$. ** $P<0.01$. *** $P<0.001$

3.4.4 Heterogeneous Effects

Another important issue regarding the identification of the rebound effect relates to the heterogeneity of the effect within the population. As shown by the results, the rebound effect differs by tenure – households that rent are more prone to behavioral changes than homeowners. In this section, we further analyze the effects of wealth and income on the magnitude of the rebound effect. The literature on price elasticity of energy indicates that the price elasticity parameter strongly depends on the socio-economic characteristics of the consumers (Madlener and Hauertmann, 2011; Ida et al., 2013). We expect that wealthier households are less sensitive to cost changes, and the rebound effect may thus be lower for these households. Besides, it can be expected that these households already maximize their comfort from residential heating. So, the utility that can be gained from heating the dwelling above a comfortable room temperature will be lower. In order to test for the impact of wealth on the rebound effect, we estimate our model separately for different wealth cohorts, and analyze whether there is a significant difference between the estimated rebound effects.

In Panel A of Table 3.6, we provide the results for different wealth cohorts among homeowners. We divide the sample into quantiles, based on the position of each household in the wealth distribution. The results show that as household becomes richer, the estimated rebound effect decreases. The rebound effect for the lowest quantile is nearly 40 percent, while it is "just" 19 percent for the upper quantile.[17]

We also analyze the heterogeneity of the rebound effect among tenants with different income levels. We classify the households in rental units according to their income level, since there is limited variation in the wealth levels of tenants. The results provided in Panel B of Table 3.6 indicate that the rebound effect is heterogeneous among different income groups. For the lowest quantile, the rebound effect is nearly 49 percent, while it is in the range of 38-40 percent for the upper quantiles. These results imply that wealth and income matter for the behavioral response of homeowners and tenants to the energy efficiency of a dwelling.

[17]Note that the average rebound effect for the homeowners in the lowest quantile is nearly the same as the estimated rebound effect for the average household living in a rental dwelling.

Table 3.6: Pooled OLS-IV Estimations for Wealth and Income Cohorts

Panel A: Wealth Cohorts (Owners)					
Wealth Interval (€1000)	0-20% (< 10)	20-40% (10 – 69)	40-60% (69 – 171)	60-80% (171 – 300)	80-100% (> 300)
Log (Predicted Gas Consumption)	0.602***	0.676***	0.724***	0.811***	0.811***
	[0.040]	[0.028]	[0.033]	[0.022]	[0.027]
R^2	0.300	0.330	0.352	0.335	0.339
Number of observations	11,342	11,342	11,342	11,342	11,342

Panel B: Income Cohorts (Tenants)					
Income Interval (€1000)	0-20% (< 16)	20-40% (16 – 20)	40-60% (20 – 24)	60-80% (24 – 32)	80-100% (> 32)
Log (Predicted Gas Consumption)	0.515***	0.597***	0.599***	0.625***	0.598***
	[0.020]	[0.014]	[0.012]	[0.010]	[0.011]
R^2	0.169	0.213	0.245	0.243	0.243
Number of observations	332,299	332,225	332,275	332,284	332,305

Notes:
Dependent variable: Log (Actual Gas Consumption).Control variables are included in all regressions.
Years included in the analysis: 2008, 2009, 2010 and 2011. 2010, 2011 are excluded from the analysis of wealth cohorts, since the information is not available for these years.
“Predicted Gas Consumption” is instrumented by “Year of Construction”.
Households are assigned to the groups based on their wealth and income levels (percentiles).
Standard errors are clustered by province and year.
* P<0.05. ** P<0.01. *** P<0.001

Another source of heterogeneity relates to the actual gas consumption level of the household. Using OLS-IV and FE-IV estimators, we obtain the conditional mean of β_1, which leads to the estimation of a uniform rebound effect for all households. However, the rebound effect may vary depending on the actual gas use intensity of the household. For example, we expect that households that use more gas because of lower efficiency levels (including dwelling size) are more sensitive to changes in efficiency. Therefore, the rebound effect might be larger for these households. In order to capture this heterogeneity, we use a quantile regression approach (using instrumental variable). This enables estimating the model for different quantiles of the actual gas use distribution. The linear conditional quantile function can be estimated by minimizing the sum of absolute residuals at quantile k for the model specified in Equations (3.4.10)-(3.4.11) as follows:

$$min_{\beta_j} \sum_{i=1}^{n} \sum_{t=1}^{t} |\alpha_i + \varepsilon_{it}| \tag{3.4.10}$$

which can be also written as:

$$min_{\beta_j} \sum_{i=1}^{n} \sum_{t=1}^{t} |ln(G_{it}^{a}) - [\beta_0 + \beta_1 \widehat{ln(G_{it}^{p})} + \sum_{j=2}^{j} \beta_j Z_{jit}]| \tag{3.4.11}$$

Another advantage of the quantile regression approach is its robustness in the presence of outliers. Therefore, we are also able to check any potential effect of outliers by comparing the conditional mean estimate of β_1 with the quantile regression estimate for the 50th quantile (median) of actual gas consumption.

In Table 3.7, we estimate the rebound effect for different quantiles of the actual gas consumption distribution. The 50th quantile (median) estimates of the rebound effect are quite similar to the conditional mean estimates. We therefore conclude that outliers do not significantly affect our results. Considering the other quantiles of the distribution, we observe that as the actual gas consumption intensity of the household increases, the rebound effect becomes more noticeable. Moving from the 10th quantile to 90th quantile of the actual gas consumption distribution, the effect increases from 30 percent to 50 percent for rental dwellings, and from eight percent to 51 percent for owner-occupied dwellings.[18] These results imply that the response of households to improvements in energy efficiency depends on their actual gas consumption intensity level. This can be partly explained by the non-linear characteristic of the rebound effect – if a household resides in a highly inefficient dwelling (with a higher theoretical and actual gas consumption level), we can expect that this household will have a stronger behavioral response to energy efficiency improvements.

[18]In Appendix Table 3.C.5, we report the non-IV quantile regression estimation results. As expected, the coefficient estimates are lower compared to the IV estimates because of the potential measurement error in the predicted gas consumption variable. For the sample of homeowners, the relative magnitudes of the quantile coefficients is similar to the IV estimation results. However, we do not observe the same order for the rental sample, although the estimated rebound effect is still lower for the lowest quantile of the distribution. This might be associated to the unknown differences in the relative magnitudes of the measurement error bias.

Table 3.7: Quantile Regression-IV Estimations for Actual Gas Consumption Levels

Panel A: Sample of Owners					
	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Actual Gas Consumption (m^3)	*(707)*	*(1,039)*	*(1,481)*	*(2,003)*	*(2,454)*
Log (Predicted Gas Consumption)	0.922***	0.826***	0.750***	0.644***	0.492***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]

Panel B: Sample of Tenants					
	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Actual Gas Consumption (m^3)	*(590)*	*(846)*	*(1,166)*	*(1,539)*	*(1,917)*
Log (Predicted Gas Consumption)	0.699***	0.647***	0.599***	0.553***	0.494***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]

Notes:
Dependent variable: Log (Actual Gas Consumption). Control variables are included in all regressions.
The values in parentheses represent the actual gas consumption (m^3) level for each quantile.
Years included in the analysis: 2008, 2009, 2010 and 2011.
"Predicted Gas Consumption" is instrumented by "Year of Construction".
Quantiles are chosen based on the actual gas use level of the households.
* P<0.05. ** P<0.01. *** P<0.001

3.4.5 Quasi-Experimental Evidence

Thus far, we examined the rebound effect in the residential sector based either on the cross-sectional variation in energy efficiency levels, or on the over-time variation that is created by households changing their address. Although the fixed-effect estimation results indicate there is no evidence of omitted variable bias, we further examine the rebound effect from energy efficiency improvements by using a quasi-experimental setting.

In 2008, the Dutch government initiated a program named "Meer met Minder" (more with less), to stimulate energy efficiency improvements in the residential sector. In this program, homeowners received tailored advice on energy saving measures, and in addition, those homeowners increasing the energy label of their dwelling by one or two steps received a premium of €300 or €750, respectively. Based on data provided by the program administrator, AgentschapNL, we estimate the realized savings for these dwellings by using a standard difference-in-differences (DID) approach. Using a sample of 605 owner-occupied dwellings that benefited from the subsidy program in 2010, we compare the realized savings with predicted savings on the consumption levels of these dwellings between 2009 and 2011, the years just before and after the energy efficiency improvement. We use a large control group to isolate any time-specific effects (such as changes in climatic conditions or general trends in the macro economy that may affect energy consumption). The control group consists of 4,593 owner-occupied dwellings, that were transacted in 2008 (with a label) and did not apply to any of the energy efficiency subsidy programs (e.g., tailored advice without premium, double glazing, solar panel subsidies, etc.) offered by the government during the period of the analysis.[19]

In Table 3.8, we report the summary statistics for the treatment and control groups. The treatment sample shows a slightly higher actual gas consumption and a lower level of energy efficiency (i.e., a higher energy index) compared to the control group. The subsidy applicants appear to be wealthier than the households in our control group. The change in average actual gas consumption for our control group between 2009 and 2011, which is around nine percent, is assumed to be due to other time variant factors (such as climate conditions). In order to isolate these time-specific effects in the non-parametric comparisons, we subtract this change from the percentage change in actual gas consumption between 2009 and 2011 that is documented for the treatment group. The simple calculation indicates that there is a reduction of about 15 percent in the actual gas consumption as a result of a 35 percent increase in the theoretical energy efficiency level of the dwellings in the treatment group. This points at an average rebound effect of 57 percent for the treated dwellings.

We estimate the rebound effect based on a regression analysis in order to control for other factors that might affect the savings in residential energy consumption. We use a first-difference estimator to identify the average rebound effect for the treated dwellings, isolating the exogenous variation in the energy efficiency of the dwellings in our treatment group, generated by the efficiency improvements:

$$\Delta ln(G_i) = \beta_0 + \beta_1 \Delta ln(EI_i) + \sum_{j=2}^{J} \beta_j \Delta Z_{ji} + \Delta\epsilon_i \tag{3.4.12}$$

where $\Delta ln(G_i)$ is the change in the logarithm of actual gas consumption from 2009 to 2011

[19]For both treatment and control groups, we exclude the dwellings in which the household composition changed from 2009 to 2011.

Table 3.8: Descriptive Statistics for Quasi-Experimental Analysis

	Treatment Group			Control Group		
Number of Observations	*605*			*4,593*		
Variables	2009	2011	%Change	2009	2011	%Change
Actual Gas Consumption (m^3)	2,318	1,766	-23.81	1,543	1,399	-9.33
	(822)	(680)		(731)	(634)	
Energy Index	2.34	1.52	-35.04	1.90	1.90	0.00
	(0.39)	(0.30)		(0.58)	(0.58)	
Size (m^2)	127.8	127.8		104.6	104.6	
	(35.4)	(35.4)		(33.2)	(33.2)	
Construction Year (Median)	1961	1961		1970	1970	
Number of Household Members	2.41	2.41		2.04	2.04	
	(1.08)	(1.08)		(1.11)	(1.11)	
Household Annual Net Income (1000 Euro)	40.1	39.8		33.9		
	(19.5)	(17.4)		(14.8)	(16.8)	
Household Wealth (1000 Euro)	285.8			80.3		
	(265.8)			(252.8)		

Notes:
Standard deviations are indicated in paranthesis.
Energy index of the dwellings in the control group is assumed to be constant between 2009 and 2011.
We report the infromation on household wealth for only 2009, as it is not available for 2011.

for dwelling i, and $\Delta ln(EI_i)$ is the change in logarithm of energy index for that dwelling.[20] For the dwellings in the control group, the change in energy index is assumed to be equal to zero. Thus, β_1 is the elasticity of the actual gas consumption with respect to energy efficiency. As there might be a random measurement error in the predicted energy index, which might cause a downward bias in the estimated β_1, we apply an IV approach by using the assignment to treatment as an instrument for the change in energy index. ΔZ_{ji} denotes the change in household characteristics, and $\Delta\epsilon_i$ is the change in error component which is assumed to be independent of the change in energy index. However, as the treatment and control groups are not randomly assigned, this assumption may not be valid, and the estimated β_1 might be biased. In order to reduce this potential selection bias, we apply a propensity score matching (PSM) method, where the probability of being treated is estimated by using a logit model including dwelling characteristics as regressors. This

[20]The Energy Index is calculated based on the predicted level of energy that is required for heating and lighting. We assume that the efficiency improvements only affect the energy used for heating, as the energy required for lighting is calculated based on the size of the dwelling and constitutes a negligible share of total energy demand.

probability is used as a balancing score between groups, as suggested by Rosenbaum and Rubin (1983). For the dwellings in treatment and control groups with the same balancing score, the distribution of the dwelling characteristics are the same. Thus, by applying PSM method, we rely on the assumption that conditional on the dwelling characteristics, the counterfactual change in actual gas consumption is independent of the assignment to treatment. In other words, we assume that assignment to treatment is not correlated with unobserved determinants of household's gas consumption, which might change during the period of analysis.

Table 3.9 reports the findings. The first-difference estimator leads to an elasticity parameter of about 41 percent. When we apply the IV approach, the elasticity of actual gas consumption with respect to efficiency is found to be 44.5 percent. The use of the PSM-IV method leads to a similar estimate (44.9 percent). These results indicate that the average rebound effect is around 55 percent for the dwellings in our treatment group. Accordingly, the estimated average rebound effect for the treatment group is larger compared to the average estimate that we documented for the full sample of owner-occupied dwellings (27 percent). This difference might be related to the heterogeneity of rebound effect based on the actual gas use intensity level, as the dwellings that benefited from the subsidy have higher actual gas consumption as compared to the other dwellings. As documented in Table 3.7, the estimated rebound effect highly depends on the actual gas use intensity level of the dwelling. The median actual gas consumption for the treatment group is 2,289 m^3, which corresponds to the 80th quantile of actual gas consumption distribution in the full sample. The estimated average rebound effect for our treatment group is close to the rebound effect estimated for 90th quantile in the full sample, which is around 52 percent.

Table 3.9: Difference-in-Differences and Propensity Score Matching Estimations

	(1) First-Diff.	(2) IV	(3) PSM-IV
Δ Log (Energy Index)	0.408***	0.445***	0.449***
	[0.031]	[0.032]	[0.036]
R^2	0.034	0.034	0.032
Number of households	5,198	5,198	5,198

Notes:
Dependent variable: Δ Log (Actual Gas Consumption)
Standard errors are indicated in paranthesis.
Years included in the analysis: 2009 and 2011
Income and working status of the household are included as control variables in all regressions.
For the IV and PSM estimations, we use assignment to treatment as an instrument for the change in energy index.
For the PSM estimation, we use dwelling characteristics (age, size, type, province) as determinants of assignment to treatment.
* $P<0.05$. ** $P<0.01$. *** $P<0.001$

3.5 Conclusions and Implications

In the current debate about the reduction of externalities from global carbon emissions, economists and policy makers increasingly focus on energy efficiency improvements as a means to affect energy consumption in the building stock. However, it has been asserted that technological improvements change household behavior, as the corresponding energy efficiency gains decrease the perceived cost of energy services, thus increasing demand (Brookes, 1990; Khazzoom, 1980, 1987; Wirl, 1997). This phenomenon has been termed the "rebound effect". The existence of the rebound effect is widely acknowledged, but the real debate lies in the identification and the size of the effect. This is of importance, as energy conservation policies should be designed to achieve actual energy savings, and not just to increase the engineering energy efficiency of buildings.

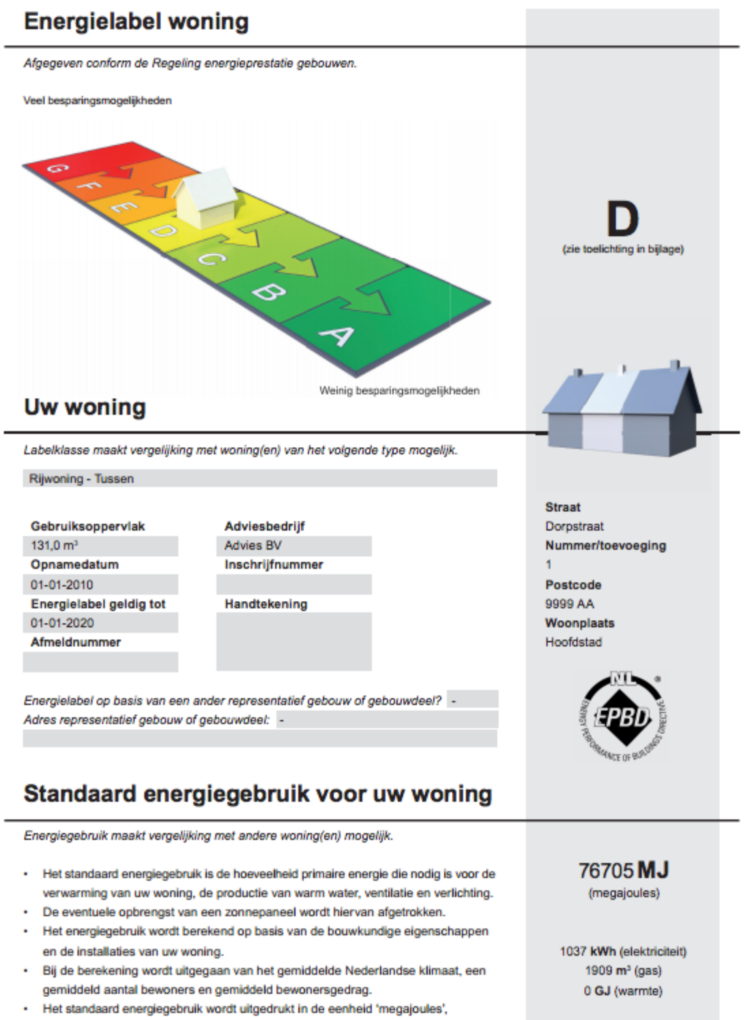
Due to the limited availability of energy efficiency data, empirical estimates of the rebound effect in the existing literature are mostly based upon households' response to variations in energy prices. However, there are significant drawbacks to this methodological approach, as it may lead to biased estimates (Sorrell et al., 2007). This is the first study to analyze the rebound effect based on a unique combination of information on the thermal efficiency of dwellings, their actual energy consumption, and characteristics of the occupants. Furthermore, the use of an IV approach and the panel structure of the dataset enable a more precise identification of a direct rebound effect in residential heating. We use a large sample of dwellings in the Netherlands to estimate the rebound effect for residential energy consumption. Examining the association between the engineering predictions on the energy consumption with the realized gas consumption of some 560,000 dwellings, we estimate the direct rebound effect. In order to account for random measurement error in the engineering predictions, we use an instrumental variable approach by including the dwelling age as an instrument. We document that the average rebound effect is about 41 percent for tenants and 27 percent for homeowners. According to these results, if the efficiency of an average dwelling is doubled, this will lead to a 59 percent energy reduction in rental dwellings and a 73 percent energy reduction in owner-occupied dwellings.

The comparison of OLS and IV estimation results indicates the importance of controlling for the measurement error in engineering predictions. Thus, studies neglecting this error have the potential of overestimating the rebound effect. We also estimate our model separately for different wealth cohorts, and document that there is significant heterogeneity in the estimated rebound effect. The results show that as households becomes wealthier, the rebound effect decreases. The rebound effect for the lowest wealth quantile is about 40 percent, while it is just 19 percent for the highest wealth quantile. We analyze separately the heterogeneity of the rebound effect among tenants with different income levels. For the lowest income quantile, the rebound effect is nearly 49 percent, while it is in the range of 38-40 percent for the upper quantiles. Additionally, using a quantile regression approach, we examine the heterogeneity of the rebound effect based on the actual gas use intensity level of the households. The results indicate that the rebound effect is more significant for the households that are consuming a larger amount of gas to heat their homes. We also confirm our findings by applying a quasi-experimental analysis. Using the data obtained from an energy efficiency subsidy program, we show that the efficiency improvements lead to a rebound effect of around 55 percent. The relative large size of the rebound effect as compared to the estimates found for the full sample supports the heterogeneity hypothesis, as the households that invest in the efficiency improvements are at the upper quantiles of the actual gas consumption distribution in the population.

Our findings stress the importance of considering the rebound effect in the design of efficiency improvement policies in residential sector. Policy makers have to incorporate this effect into the assessment of the effectiveness of energy efficiency improvement measures and programs, including subsidies and rebates. As confirmed by the quasi-experimental evidence, there is a significant potential for energy savings in residential sector through energy efficiency improvements, but the behavioral response of the households offsets part of the projected energy savings. The heterogeneity of the rebound effect also has some policy implications. The results in this paper indicate that the magnitude of the rebound effect varies by wealth, income and energy use level of the household. Thus, in order to increase the effectiveness of the energy efficiency policy measures, the characteristics of the target group should be incorporated in decision-making, as well as estimates of the predicted savings.

Appendix

3.A Cover Page of the EPC



Energielabel woning

Afgegeven conform de Regeling energieprestatie gebouwen.

Veel besparingsmogelijkheden

G F E D C B A

Weinig besparingsmogelijkheden

D

(zie toelichting in bijlage)

Uw woning

Labelklasse maakt vergelijking met woning(en) van het volgende type mogelijk.

Rijwoning - Tussen

Gebruiksoppervlak
131,0 m²
Opnamedatum
01-01-2010
Energielabel geldig tot
01-01-2020
Afmeldnummer

Adviesbedrijf
Advies BV
Inschrijfnummer

Handtekening

Straat
Dorpstraat
Nummer/toevoeging
1
Postcode
9999 AA
Woonplaats
Hoofdstad

Energielabel op basis van een ander representatief gebouw of gebouwdeel? -
Adres representatief gebouw of gebouwdeel: -

NL EPBD ENERGY PERFORMANCE OF BUILDINGS DIRECTIVE

Standaard energiegebruik voor uw woning

Energiegebruik maakt vergelijking met andere woning(en) mogelijk.

- Het standaard energiegebruik is de hoeveelheid primaire energie die nodig is voor de verwarming van uw woning, de productie van warm water, ventilatie en verlichting.
- De eventuele opbrengst van een zonnepaneel wordt hiervan afgetrokken.
- Het energiegebruik wordt berekend op basis van de bouwkundige eigenschappen en de installaties van uw woning.
- Bij de berekening wordt uitgegaan van het gemiddelde Nederlandse klimaat, een gemiddeld aantal bewoners en gemiddeld bewonersgedrag.
- Het standaard energiegebruik wordt uitgedrukt in de eenheid 'megajoules', dit wordt uitgesplitst naar elektriciteit (kWh), gas (m³) en warmte (GJ).

76705 **MJ**
(megajoules)

1037 **kWh** (elektriciteit)
1909 **m³** (gas)
0 **GJ** (warmte)

Source: AgentschapNL

3.B Calculation of Theoretical Gas Consumption

The calculated gas use (G^p) is assumed to be a combination of gas used for space heating (G^h) and water heating (G^w).

$$G^p = G^h + G^w \tag{3.B.1}$$

The gas used for cooking is not included in the calculations, since it strongly depends on household behavior. However, we do not expect this to lead to biased estimations, since cooking typically represents just three percent of the total residential gas consumption. The gas used for space heating is calculated by the following formula:

$$G^h = [(G^d/\mu_d) - G^{sb}]/\mu_i + G^{pf} \tag{3.B.2}$$

where G^d is the heating demand of the dwelling. The parameters μ_d and μ_i denote the efficiency of the distribution and installation systems, respectively. Any potential gains from use of a solar boiler (G^{sb}) and the additional energy used for pilot flame (G^{pf}) are also accounted for in the prediction. As shown below, in order to calculate the demand for heating, the transmission (G^t) and ventilation (G^v) losses are summed up, and the internal (G^i) and solar (G^{sg}) heating gains are deducted from this aggregate.

$$G^d = G^t + G^v - G^i - G^{sg} \tag{3.B.3}$$

The transmission loss component in the equation above is calculated based on the following formula:

$$G^t = (\sum_{k=1}^{K} w_k A_k U_k)(T_i - T_o)t \tag{3.B.4}$$

where w_k is the weighting factor for surface k, which ranges from 0 to 1 depending on the position of the surface. A_k is the area of the surface and U_k is the U-value of that surface (an indication of its isolation quality). The heating season duration is denoted by t and it is assumed to be 212 days. The average indoor (T_i) and outdoor (T_o) temperatures are assumed to be 18 degrees Celsius and 5.64 degrees Celsius, respectively. The other component of equation (3.B.3) is the loss of energy through ventilation, which is calculated as follows:

$$G^v = [f_1 A_f + f_2 q_r (A_f / A_r)][\delta(T_i - T_o)t]\rho_a c_a \tag{3.B.5}$$

where f_1 and f_2 are the ventilation coefficients which depend on the type of ventilation and the infiltration rate. The usable floor area of the dwelling is denoted by A_f, and q_r, A_r are the ventilation loss and the floor area values of a reference house of same type. δ is the correction factor, ρ_a is the density of the air, c_a is the heat capacity of the air.

The second component of the residential gas consumption is the gas used for water heating, which is a combination of the gas used by the main boiler (G^{mb}) and the kitchen boiler (G^{kb}).

$$G^w = G^{mb} + G^{kb} \tag{3.B.6}$$

If there is a hot water system in the kitchen, then the energy consumed by the kitchen boiler is assumed to be equal to a fixed amount. The gas consumed by the main hot water installation is calculated as below:

$$G^{mb} = (\gamma Q / \mu_b) r_q + G^s + G^{sc}(A_f / 100)(1 - \tau_u) \tag{3.B.7}$$

$$Q = Q_k + Q_b + N(Q_p + Q_s F_s N_s + Q_{ba} N_b D_b) \tag{3.B.8}$$

where γ is the conversion factor, Q is the quantity of hot water consumed in a day, μ_b is the efficiency of the boiler, r_q is a correction factor for short piping, G^s is a fixed value assigned based on the type of boiler, G^{sc} is the circulation loss depending on the insulation level and τ_u is the used part of the circulation loss. The quantity of the hot water (Q) is a combination of hot water used in kitchen (Q_k), quantity used for basins (Q_b), quantity used for showering (Q_s) and quantity used for bath (Q_{ba}). N is the assumed number of people living in the house, which is assigned based on the dwelling size. F_s is the efficiency of the shower head and N_s is the assumed number of showering per person in a day. N_b is the assumed number of baths per person in a day and D_b is the indicator of existence of bath (1 or 0).

3.C Suplementary Tables

Table 3.C.1: Pooled OLS Estimations: Dwellings Constructed after 1999

	(1) Rental	(2) Owner-Occupied
Log (Predicted Gas Consumption)	0.492***	0.588***
	[0.015]	[0.028]
Number of Household Members	0.094***	0.157***
	[0.013]	[0.022]
Number of Household Members^2	-0.007***	-0.013***
	[0.002]	[0.004]
Number of Children (<18)	0.002	- 0.025
	[0.006]	[0.021]
Number of Elderly (Age>64)	0.002	0.009
	[0.004]	[0.016]
Number of Female	0.019***	0.030
	[0.004]	[0.017]
All Household Members Are Working (1=yes)	-0.057***	-0.044**
	[0.006]	[0.014]
Log (Household income)	0.007	0.032
	[0.007]	[0.017]
Receiving Rent Subsidy (1=yes)	-0.020*	
	[0.008]	
Province Dummy	Yes	Yes
Year Dummy	Yes	Yes
Constant	3.298***	2.336***
	[0.111]	[0.262]
R^2	0.161	0.285
Number of observations	68,112	4,214

Notes:
We restrict the sample to the dwellings which were constructed after 1999.
Dependent variable: Log (Actual Gas Consumption)
Years included in the analysis: 2008, 2009, 2010, and 2011
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by province and year.
* P<0.05. ** P<0.01. *** P<0.001

Table 3.C.2: Instrumental Variable Estimations: U-value Requirement for External Walls

	(1) Rental	(2) Owner-Occupied
Log (Predicted Gas Consumption)	0.567***	0.764***
	[0.014]	[0.022]
Number of Household Members	0.096***	0.101***
	[0.004]	[0.009]
Number of Household Members^2	-0.010***	-0.011***
	[0.001]	[0.001]
Number of Children (<18)	-0.005***	0.002
	[0.001]	[0.003]
Number of Elderly (Age>64)	0.034***	0.042***
	[0.002]	[0.004]
Number of Female	0.037***	0.015***
	[0.001]	[0.002]
All Household Members Are Working (1=yes)	-0.057***	-0.038***
	[0.002]	[0.004]
Log (Household income)	0.052***	0.048***
	[0.002]	[0.006]
Receiving Rent Subsidy (1=yes)	-0.034***	
	[0.002]	
Province Dummy	Yes	Yes
Year Dummy	Yes	Yes
Constant	2.416***	1.020***
	[0.091]	[0.164]
R^2	0.243	0.366
Number of observations	1,664,113	87,282
Number of dwellings	519,512	43,498

Notes:
Dependent variable: Log (Actual Gas Consumption)
Years included in the analysis: 2008, 2009, 2010, and 2011
“Predicted Gas Consumption” is instrumented by “Maximum U-value requirement for external walls at the time of construction”
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by province and year.
* P<0.05. ** P<0.01. *** P<0.001

Table 3.C.3: IV Estimations: Controling for House Size

	(1) Rental	(2) Owner-Occupied	(3) Rental	(4) Owner-Occupied
Log (Predicted Gas Consumption)	0.562***	0.711***	0.563***	0.710***
	[0.011]	[0.015]	[0.012]	[0.015]
Number of Household Members	0.088***	0.098***	0.088***	0.099***
	[0.003]	[0.007]	[0.003]	[0.007]
Number of Household Members^2	-0.009***	-0.010***	-0.009***	-0.011***
	[0.000]	[0.001]	[0.000]	[0.001]
Number of Children	-0.005***	-0.002	-0.004***	-0.002
	[0.001]	[0.003]	[0.001]	[0.003]
Number of Elderly (Age>64)	0.032***	0.038***	0.032***	0.038***
	[0.002]	[0.004]	[0.002]	[0.004]
Number of Female	0.033***	0.014***	0.033***	0.014***
	[0.001]	[0.002]	[0.002]	[0.002]
All Household Members Are Working (1=yes)	-0.051***	-0.036***	-0.052***	-0.036***
	[0.001]	[0.004]	[0.001]	[0.004]
Log (Household Income)	0.033***	0.035***	0.034***	0.034***
	[0.004]	[0.007]	[0.004]	[0.007]
Receiving Rent Subsidy (1=yes)	-0.032***		-0.032***	
	[0.002]		[0.002]	
Log (House Size)	0.111***	0.093***	- 0.433*	-0.132
	[0.012]	[0.018]	[0.195]	[0.203]
Log (House Size)^2			0.063***	0.025
			[0.021]	[0.022]
Province Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Constant	2.160***	1.114***	3.324***	1.638***
	[0.060]	[0.098]	[0.402]	[0.490]
R^2	0.247	0.383	0.247	0.383
Number of observations	1,664,113	87,282	1,664,113	87,282
Number of dwellings	519,512	43,498	519,512	43,498

Notes:
Dependent variable: Log (Actual Gas Consumption)
Years included in the analysis: 2008, 2009, 2010, and 2011
"Predicted Gas Consumption" is instrumented by "Year of Construction"
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by province and year.
* P<0.05. ** P<0.01. *** P<0.001

Table 3.C.4: Random-Effects (IV) Estimations

	Rental	Owner-occupied
Log (Predicted Gas Consumption)	0.582***	0.722***
	[0.002]	[0.009]
Number of Household Members	0.086***	0.094***
	[0.001]	[0.005]
Number of Household Members^2	-0.008***	-0.009***
	[0.000]	[0.001]
Number of Children (<18)	0.001	0.004
	[0.001]	[0.003]
Number of Elderly (Age>64)	0.026***	0.034***
	[0.001]	[0.003]
Number of Female	0.027***	0.011***
	[0.001]	[0.003]
All Household Members Are Working(1=yes)	-0.026***	-0.016***
	[0.001]	[0.003]
Log (Household income)	0.054***	0.075***
	[0.001]	[0.003]
Receiving Rent Subsidy (1=yes)	-0.013***	
	[0.001]	
Province Dummy	Yes	Yes
Year Dummy	Yes	Yes
Constant	2.705***	1.568***
	[0.019]	[0.067]
R^2	0.209	0.355
R^2 (within)	0.032	0.017
R^2 (between)	0.222	0.357
Number of observations	1,664,113	87,282
Number of households	519,512	43,498

Notes:
Dependent variable: Log (Actual Gas Consumption)
Years included in the analysis: 2008, 2009, 2010, and 2011
"Predicted Gas Consumption" is instrumented by "Year of Construction"
* $P<0.05$. ** $P<0.01$. *** $P<0.001$

Table 3.C.5: Quantile Regression (Non-IV) Estimations for Actual Gas Consumption Levels

Panel A: Sample of Owners

	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Log (Predicted Gas Consumption)	0.663***	0.609***	0.548***	0.463***	0.372***
	[0.007]	[0.004]	[0.004]	[0.004]	[0.004]

Panel B: Sample of Tenants

	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Log (Predicted Gas Consumption)	0.541***	0.323***	0.447***	0.393***	0.494***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]

Notes:
Dependent variable: Log (Actual Gas Consumption).Control variables are included in all regressions.
Years included in the analysis: 2008, 2009, 2010 and 2011.
Quantiles are chosen based on the actual gas use level of the households.
* P<0.05. ** P<0.01. *** P<0.001

Chapter 4

Capitalization of Energy Efficiency in the Housing Market

4.1 Introduction

In today's heated debate about climate change, and related, the carbon externality from energy consumption, energy efficiency seems the panacea that is globally embraced by policy makers. For example, the recent Clean Power Plan proposed by the United States Environmental Protection Agency (EPA) allows for investment in energy efficiency as a substitute for cutting carbon emissions from actual energy generation. Across the ocean, the EU aims for a 20 percent reduction in energy consumption, based solely on "cost effective" measures that are paid back from reduction in energy bills. And China has included energy efficiency as a cornerstone of its current five-year plan, with the ambition to retrofit four million square feet of non-residential space. But of course, the success of such programs depends on the willingness of homeowners, developers, and commercial real estate investors to invest in building upgrades.

Economists have long recognized that market failures can lead to what has been termed the "energy efficiency gap" – the difference between the optimal level of energy efficiency and the level actually realized (Allcott and Greenstone, 2012). Following on Akerlof (1970)'s classic "lemons" model, information asymmetry between seller and buyer is generally accepted as one of the main reasons leading to underinvestment in energy efficiency in the housing market. In the absence of information, buyers are not able to incorporate future energy costs of the home into their purchasing decisions, and therefore, sellers prefer not to invest in energy efficiency improvements. In recent years, energy labels have been proposed as a remedy to this potential market failure. In 2009, in order to provide information transparency in the relative energy consumption of buildings, EU member states were required to implement energy performance certification (EPC) schemes for residential dwellings. By providing information to market participants about energy performance of buildings, policy makers expect an increase in the demand for energy-efficient dwellings, which in return, may lead to higher investment in energy efficiency.

However, the effectiveness of this policy hinges on the extent to which buyers are willing to pay for increased energy efficiency. Furthermore, as upgrading a dwelling to improve its energy efficiency could involve a significant financial investment, the uncertainty regarding its financial return may be another reason for households not to undertake seemingly profitable investments in energy efficiency. Therefore, from both the policy maker's and investor's perspective, it is important to identify the market value of energy efficiency in the housing sector.

Previous literature provides some empirical evidence on the relationship between energy efficiency and home prices. Using a sample of dwellings with Energy Performance Certificates, Brounen and Kok (2011) document that consumers pay a four percent premium for green-labeled (labels A, B and C) houses in the Netherlands. Similarly, analyzing the property market in the Republic of Ireland, Hyland et al. (2013) find that the transaction price increases as the energy efficiency rating of the dwelling improves. Kahn and Kok (2014), using the transaction data from California housing market, find that houses labeled with a green label is sold at a small price premium compared to the non-labeled houses.

As energy labels are not necessarily available in other countries, researchers have also used other approaches to identify the market value of energy efficiency. Thorsnes and Bishop (2013) examine the capitalization of building standards that were introduced in New Zealand in 1978, and find a positive premium for the dwellings that were constructed after the legislation. Similarly, Koirala et al. (2014) estimate the value of energy efficiency building codes for American households, and find that building codes are capitalized into housing rents. Laquatra (1986) analyzes a sample of houses constructed through the Energy Efficient Housing Demonstration Program of the Minnesota Housing Finance Agency, and identifies the market values of energy efficiency investments based on a vector of thermal integrity factors. Zheng et al. (2012) document that "green" buildings, which are identified based on an index created using Google search, are sold at a price premium at the pre-sale stage. Comparable to these findings, Dastrup et al. (2012) find that solar panel installations are capitalized into house prices at around a 3.5 percent price premium in California.

While this body of literature is significant and growing, the most common methodological drawback of the evidence provided is the potential bias that may arise due to omission of unobserved dwelling characteristics that are correlated with measures of energy efficiency, as indicated by Zheng et al. (2012), Hyland et al. (2013) and Thorsnes and Bishop (2013). Klier and Linn (2012) also document the same problem while analyzing the capitalization of energy efficiency for the automobile sector. Typically, in order to minimize the omitted variable bias, the empirical strategy is to include detailed dwelling characteristics in hedonic model. However, this method does not rule out the presence of unobservable factors, and multicollinearity among the observed characteristics often leads to imprecise and implausible estimates of attribute prices. Atkinson and Halvorsen (1984) mention that the difficulties caused by multicollinearity are more apparent while analyzing energy efficiency, leading to insignificant and/or theoretically incorrect estimates for the coefficients of energy efficiency.

In this study, using a large representative dataset from the Netherlands, we propose an instrumental variable approach in order to identify the capitalization of energy efficiency in the housing market. Our analysis benefits from a continuous measure of energy efficiency provided by Energy Performance Certificates, which enables us to estimate the elasticity of home prices with respect to its energy efficiency. As well as including detailed dwelling characteristics in the hedonic model, we use an instrumental variable approach to solve the issue of a potential omitted variable bias. We exploit the 1973-74 oil crisis, which created an exogenous discontinuity in the energy efficiency levels of the dwellings constructed before and after this date, and the evolution of building codes as instruments for energy efficiency.

Our results indicate that the OLS estimates are biased downwards: using an IV approach, we find that as the energy efficiency level increases by 50 percent, the market value of the dwelling increases by around 11 percent for an average dwelling in the Dutch housing market.

Furthermore, in order to investigate whether the value of energy efficiency increases when information transparency is higher through disclosure of an Energy Performance Certificate, we create a common energy efficiency measure for certified and non-certified dwellings, which is based on their actual energy consumption. We find that the market value of a percentage change in actual gas consumption is close to the value of the energy efficiency change that is estimated based on the energy efficiency indicator provided by Energy Performance Certificate. Our findings do not provide any evidence suggesting a higher capitalization rate for dwellings that are transacted with Energy Performance Certificate. We also use a regression discontinuity approach to test whether the label (classification) itself has a market value. Our results do not indicate a significant change in the transaction price at the threshold energy efficiency level that is used to assign the dwellings into different label classes. This implies that, after controlling for the continuous energy efficiency level, the labeling itself does not lead to a significant change in buyer's valuation of the dwelling.

Finally, in order to examine the over-time variation in the market value of energy efficiency, we estimate the hedonic model for each year separately from 2003 to 2011. We document that, although not statistically significant, the value of energy efficiency has doubled from 2003 to 2011, which might be partly related to the increase of energy prices, the relative decrease in house prices after 2008 and the general impact of policies and campaigns indicating the importance of energy efficiency.

Our findings suggest that, regardless of the provision of energy label, energy efficiency is significantly capitalized in the housing market. This implies that, in addition to the immediate financial benefits from lower energy expenses, energy efficiency improvements lead to higher transaction prices at the time of sale. Our results do not provide any significant evidence for intangible effects of energy labels on sale prices. For policy makers, the results of this paper may help in refining energy performance certification programs in a way that stresses the financial benefits of energy efficiency. Furthermore, as also mentioned by Allcott and Greenstone (2012), information campaigns might have a substantial role in the diffusion of energy efficiency investments. Therefore, the benefits that households and investors can derive (in terms of higher transaction prices) need to be highlighted in the public awareness campaigns.

The remainder of this paper is organized as follows. The next section describes the empirical specification and the data. In section 3, we present the methodology and the results. Section 4 provides a brief conclusion.

4.2 Empirical Specification and Data

Hedonic models are commonly used in the economics literature to estimate the value of individual attributes of a product (Rosen, 1974). When analyzing the property market, the size of the estimated coefficient on each variable represents the implicit value of that characteristic. Accordingly, our basic hedonic model takes the following form:

$$Log(Price_i) = \beta_0 + \beta_1 Log(E_i) + \beta_j X_i + \alpha_n + t_i + \varepsilon_i \tag{4.1}$$

where the dependent variable, $Price_i$, is the transaction price of dwelling i. E_i is the variable of interest which represents the energy efficiency level of the dwelling, and X_i is a vector of other dwelling characteristics. By using a log-log specification, we are able to estimate the elasticity of house price with respect to energy efficiency, which is denoted by β_1. To control for the unobserved location amenities, we include neighborhood fixed effects (α_n) in our model. t_i is a vector of transaction year dummies, which accounts for the macroeconomic factors that may influence house prices.

In order to estimate this model, we benefit from the transaction data provided by the National Association of Realtors (NVM) in the Netherlands. This data set contains detailed information on the characteristics of the dwellings transacted between 2003-2011, as well as their transaction price. To analyze the energy efficiency of dwellings, we match this data set with the Energy Performance Certificate (EPC) database managed by AgencyNL.

Following the EU directive 2002/91/EC on the energy performance of buildings, energy performance certification for transacted dwellings was introduced in the Netherlands in January 2008.[1] The energy performance certificate is issued by a professionally trained expert. The expert visits the dwelling and inspects its physical characteristics such as size, structure, quality of insulation, heating installation, ventilation, solar systems, and built-in lighting. The collected information is then used to predict the total energy consumption of the dwelling by using an engineering model, which is described in detail by Aydin et al. (2014). After scaling by the size and the heating loss area of the dwelling, the prediction is transformed into an Energy Performance Index (EPI), which is used to assign the dwelling to a certain label class ranging from "A++" for exceptionally energy-efficient dwellings, to "G" for highly inefficient dwellings. The EPC database includes detailed information on energy performance of dwellings, as well as information on some other characteristics (such as year of construction) of these dwellings.

As the certification program started in 2008, we limit our sample to the dwellings that were transacted between 2008-2011. We also exclude the dwellings that were constructed before 1900 or after 1999, as these dwellings are exempted from mandatory disclosure of an EPC label. For the sake of simplicity, we restrict our sample to single-family dwellings, which account for nearly 70 percent of the total transactions.[2] Finally, we eliminate outliers that are detected based on the sample distribution of house size, price, and energy performance index – the upper and lower boundaries for the outliers are set at the first and 99th percentile. This leads to a sample of 30,036 single-family dwellings that were transacted with an EPC between 2008-2011.

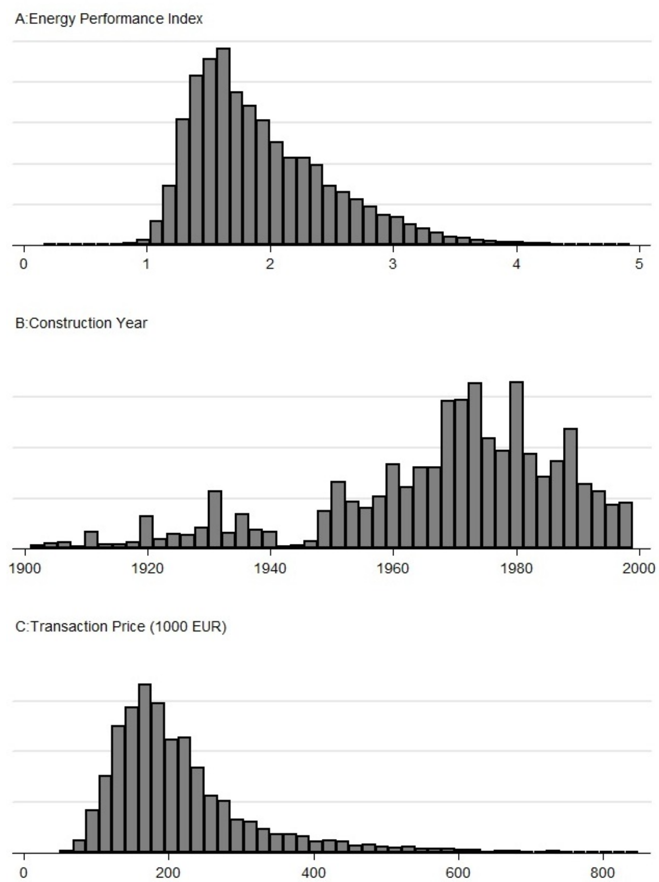
Figure 4.1 presents the distribution of transaction price, energy performance index and construction year of the dwellings in our sample. A higher energy performance index (EPI) indicates a lower energy efficiency level. According to this simple graph, most of the dwellings in the sample have an EPI value between 1-3, are constructed after 1950,

[1] Dwellings that have been constructed after 1999, or that are registered as monuments, are exempted from mandatory disclosure of the energy performance certificate. If the buyer of the dwelling signs a waiver, the seller is also exempt from providing the certificate.

[2] Bailey (1966) notes that, compared to single-family dwellings, apartment units may present special diffuculties of specification and measurement, and differences in the valuation of attributes between these two type of dwellings might exist. Similarly, Ridker and Henning (1967) and Kahn and Kok (2014) pay attention to single-family dwellings when analyzing the energy efficiency and house prices.

and sold at a price ranging from €100,000 to €300,000. Table 4.1 further documents the summary statistics for some of the main characteristics of the sample, distinguishing between "energy-efficient" (EPI<median) and "inefficient" (EPI>median) dwellings in our sample. According to these statistics, on average, efficient dwellings are sold at a higher price, have a larger size, and are more recently constructed as compared to the inefficient dwellings.

Figure 4.1: Distribution of Energy Performance Index, Construction Year and Transaction Price



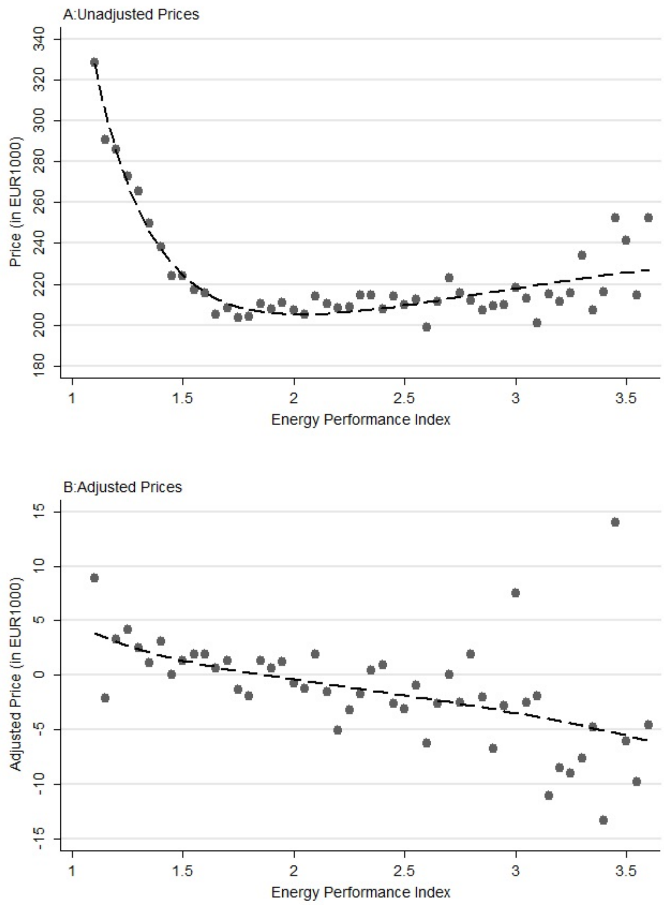
Source: AgentschapNL, National Association of Realtors (NVM)

Table 4.1: Descriptive Statistics for Energy Efficient and Inefficient Dwellings

	Energy-efficient dwellings *EPI≤1.8*		Energy-inefficient dwellings *EPI>1.8*	
Number of Observations	*15,170*		*14,866*	
Variables	Mean	Std.Dev.	Mean	Std.Dev.
Transaction Price (€1000)	229.3	(108.3)	210.8	(109.6)
Energy Performance Index (EPI)	1.507	(0.171)	2.342	(0.417)
Size (m^2)	122.9	(34.2)	116.3	(33.4)
Number of Rooms	4.822	(1.050)	4.835	(1.077)
Number of Floors	2.750	(0.545)	2.750	(0.592)
Year of Construction(Median)	1981		1965	
Type (fraction)				
Corner	0.249		0.257	
Semi-detached	0.103		0.139	
Between or Townhouse	0.552		0.508	
Detached	0.096		0.096	
Transaction Year (fraction)				
2008	0.435		0.425	
2009	0.206		0.218	
2010	0.172		0.176	
2011	0.187		0.181	

As a first analysis of the relationship between energy efficiency and house price, we plot the observed house price for varying levels of energy efficiency in Figure 4.2. In Panel A, using unadjusted prices, we obtain a U-shaped relationship between EPI and the value of the dwelling, which is not fully in line with expectations. This may be due to the omission of the other determinants of the house price, which are correlated with energy efficiency (such as dwelling type, location, construction year, etc.). In panel B, we plot the residuals estimated based on a hedonic model that includes all determinants of home price except the EPI. We observe a more distinct relationship in this graph, indicating that as the energy efficiency of a dwelling is lower, the transaction price decreases.

Figure 4.2: Transaction Prices and the Level of Energy Efficiency



Source: AgentschapNL, National Association of Realtors (NVM), authors' calculations

4.3 Methodology and Results

4.3.1 OLS Estimations

We first estimate the model in equation (4.1) using an ordinary least squares (OLS) estimation, assuming that the energy performance index (EPI_i), which is used as a measure of energy efficiency (E_i), is independent of the error term (ε_i). The results are presented in Table 4.2.[3] When we include the EPI as the sole regressor (column 1), the estimated impact of a 100 percent increase in the EPI is about 23 percent decrease in the value

[3]You can see detailed estimation results in Appendix Table 4.B.1

of the house. This impact decreases to 11 percent when we include the other dwelling characteristics. In column 3, we also include the construction year of the dwelling, as it is expected to be strongly correlated with the energy efficiency level. Controlling for all other factors, we document that a 100 percent increase in the energy performance index leads to a five percent decrease in the market value of the house.[4] This implies that if the energy requirements are halved, the market value of that dwelling increases by 2.5 percent, which corresponds to a price premium of €5,000 for the average dwelling in our sample. This result does not show a significant variation when we specify year of construction as dummy variables, instead of a continuous variable (column 4).

Table 4.2: OLS Estimation Results: House Prices and Energy Efficiency

	(1)	(2)	(3)	(4)
Log(Energy Performance Index)	-0.235***	-0.106***	-0.052***	-0.048***
	[0.019]	[0.007]	[0.007]	[0.007]
Dwelling Characteristics	No	Yes	Yes	Yes
Construction Year	No	No	Yes	Yes
R^2	0.106	0.836	0.843	0.846
Number of observations	30,036	30,036	30,036	30,036

Notes:
Dependent variable is logarithm of transaction price.
Dwelling characteristics are: dwelling size, dwelling type, quality, number of floors, number of rooms, type of parking place, location of the dwelling relative to center, road, park, water and forest.
Construction year is included as a third order polynomial in specification (3). In specification (4), we included dummy variables representing each construction year.
In all regressions, neighborhood and year of transaction dummies are included.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by neighborhood and transaction year.
* P<0.1. ** P<0.05. *** P<0.01

Although we use a large representative sample and control for the detailed dwelling characteristics in the OLS estimations, there is a potential bias in the estimated value of energy efficiency. The presence of unobserved determinants of the house price, which might be correlated with the energy efficiency level may influence the estimated coefficient.

[4]We also examine whether the unobserved determinants of label adoption is correlated with the error term in equation (4.1), which might lead to biased estimates. In order to test this, we first estimate a probit model to predict the individual probability of label adoption in our sample of labeled and non-labeled houses. Next, as proposed by Heckman (1979), we include the inverse Mills ratio in our model. The results indicate that there is not a significant correlation between the error term of model specified in equation (4.1) and the error term of the estimated probit model (p-value of the log-likelihood test is 0.176). Therefore, we conclude that there is not evidence for a sample selectivity bias.

Depending on the direction of the correlation between these unobserved factors and price, and between the unobserved factors and the energy efficiency level, this can either be a downward or upward bias. Furthermore, in case we control for the construction year in OLS estimates, the high level of multicollinearity between construction year and the energy performance index may increase the magnitude of a bias.[5]

Another econometric issue that may cause a biased estimate is the presence of measurement error in the engineering calculations. It could be the case that the engineering calculations include a measurement error, because of the assumptions made in the calculation method, and the potential mistakes made during the inspection.[6] We assume that the predicted energy efficiency (EPI) is a combination of the true value (EPI^*) and a random error component (e) that has a mean value equal to zero and that is not correlated with the true energy efficiency level. In this case, the OLS assumption that the EPI is independent of the error term may not be valid. The presence of this random measurement error leads to a downward bias in the OLS estimate of β_1.

In order to overcome the potential bias originating from unobserved factors and measurement error, a common approach is to use the instrumental variable (IV) method. Such an IV needs to be correlated with the true energy efficiency level (EPI^*), but has to be independent of both the measurement error (e) and the unobserved determinants of the dwelling price. In our case, an exogenous variation in energy efficiency can be considered as an instrument satisfying both of these conditions. Accordingly, we focus on the evolution of energy efficiency based on construction year of the dwelling.

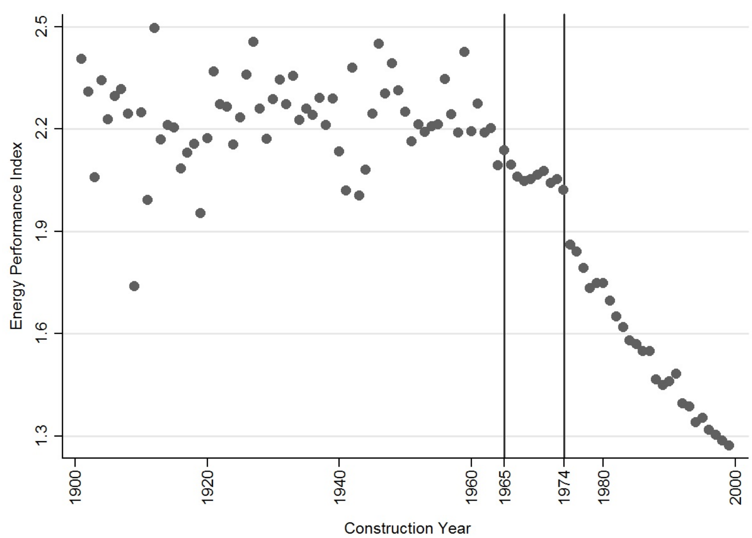
[5] See Mela and Kopalle (2002) for a theoretical explanation of the relationship between multicollinearity and the magnitude of bias.

[6] Especially for older dwellings, the engineer has to make assumptions regarding the U-value of outside walls and the rates of ventilation and infiltration. As the engineering models are examined through energy simulation tests and verified by pilot studies, we do not expect a significant systematic bias in the calculated energy efficiency level (Poel et al., 2007). Besides, a simple examination of the data on re-inspection of a sample of labeled dwellings indicates that the inspection error is not systematically and significantly correlated with the true value (Aydin et al., 2014).

4.3.2 Instrumental Variable Approach

Energy prices are one of the main drivers of the energy efficiency investments, as rising prices make thermal comfort more costly for households and decreases the payback period.[7] Appendix 4.A presents the development of oil prices from 1900 to 2000. The most remarkable increase in oil prices took place in 1974, when oil prices rose by 260 percent. Therefore, dwellings that were constructed just after the oil crisis may be more energy-efficient than the previously constructed dwellings. Indeed, as presented in Figure 4.3, there is a clear structural break and discontinuity in the average energy efficiency level of the dwellings constructed after this increase of energy prices.[8] The increased energy efficiency level can be considered as a combined result of the households' demand for more energy-efficient dwellings (and appliances), as well as the revision of building codes after the oil crisis.

Figure 4.3: Efficiency Level of the Dwellings by Year of Construction



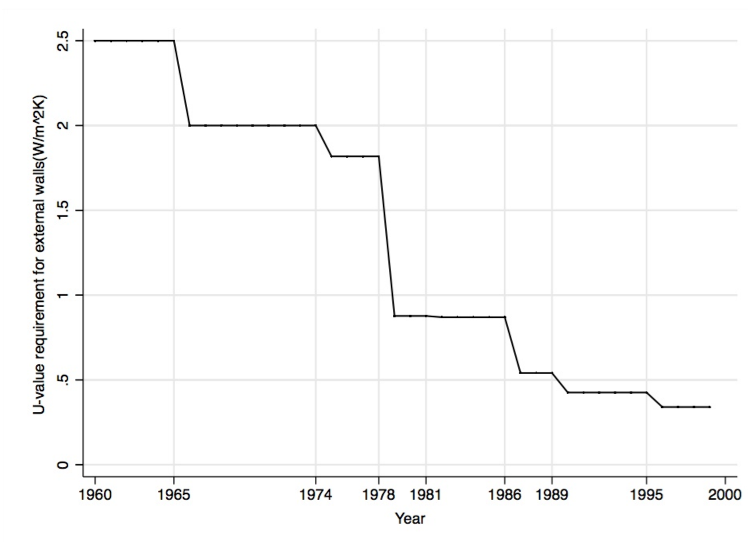
Source: AgentschapNL, authors' calculations

[7]See Knittel (2011), Li et al. (2009) and Klier and Linn (2010) for the analysis of how gasoline prices drive the fuel efficiency in the automobile sector.

[8]Haas and Schipper (1998) mention that after the decrease in residential energy demand following the 1973-74 oil crisis, energy demand did not rebound in times of declining energy prices (e.g., in 1985). They argue that irreversible efficiency improvements, which took place after the 1973-74 oil crisis, might be a reason for this observation.

Starting in 1965, the Dutch government introduced minimum legal requirements for the thermal efficiency level of new construction. This legislation set a maximum allowable U-value for each component (walls, windows, floor and roof) of the dwelling. The U-value is defined as the amount of heat loss through a single square meter of material, for every degree difference in temperature at either side of the material.[9] Figure 4.4 presents the over-time variation in the maximum allowable U-value requirements for the external walls of new constructions in the Netherlands. In order to reach the goal of zero energy buildings, these requirements have been strengthened over time. Figure 4.3 shows that the average efficiency level of constructed dwellings is quite stable until the 1960s, and starts increasing (decreasing EPI) at the time of the introduction of the first building code in 1965. After the substantial increase in energy costs in 1973-74, the increasing trend in energy efficiency accelerates, forced by stricter building codes.

Figure 4.4: Maximum Allowable U-value for External Walls of New Constructions in NL



Source: AgentschapNL

In order to identify the impact of energy efficiency on house prices, we first exploit the exogenous change in energy efficiency that took place in 1974 as an instrument, assuming

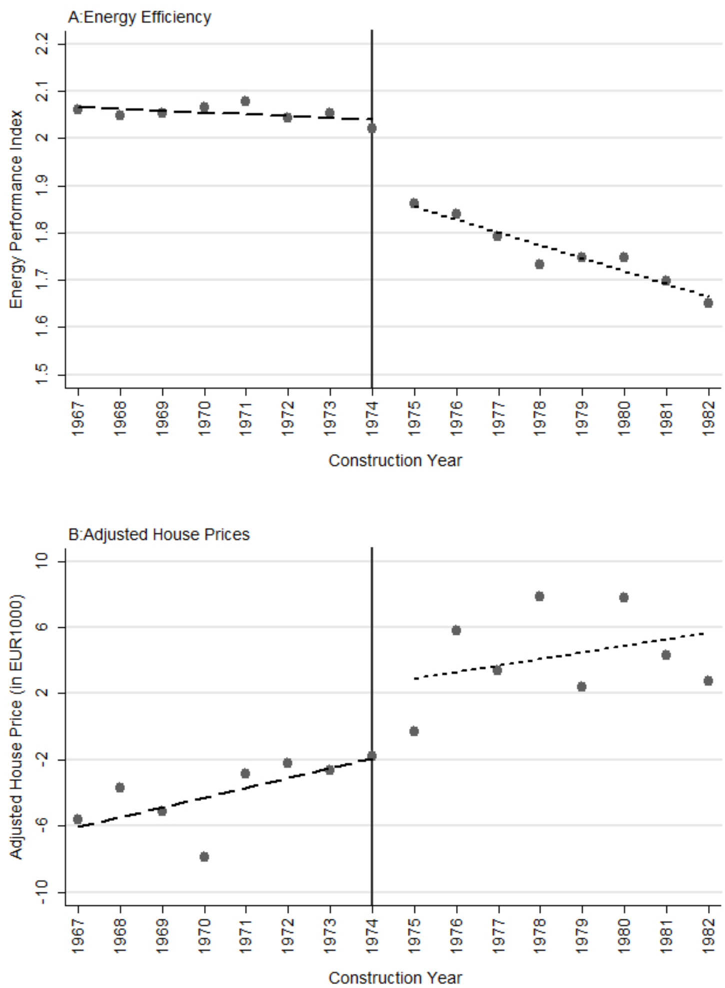
[9]For example, one square meter of a standard single glazed window transmits about 5.6 watts of energy for each degree difference at either side of the window, and thus has a U-Value of 5.6 W/m^2. On the other hand, a double glazed window has a U-value of 2.8 W/m^2.

that unobservable characteristics do not vary discontinuously in 1974. Based on the year of construction, we assign the dwellings which were constructed after 1974 as the dwellings which were exposed to significantly higher energy costs during their construction. Our main identifying assumption is that unobserved characteristics vary continuously with the year of construction. Thus, any discontinuity of the conditional distribution of the energy efficiency as a function of the year of construction in 1974 can be considered as the evidence of a causal effect of the oil crisis.[10]

To obtain more accurate estimates of the trends in energy efficiency before and after the exogenous shock, and to be able to compare dwellings having similar characteristics, we limit our sample of dwellings to those that were constructed between 1967-1982. This enables us to identify the discontinuity in energy efficiency by isolating the trend effect that might be correlated with the over-time change in unobserved characteristics of the constructed dwellings (such as time-variant luxury attributes in homes). Figure 4.5 (Panel A) presents the discontinuity in energy efficiency of dwellings in 1974. We benefit from this exogenous change as an instrument for the energy efficiency in our hedonic model. As can be observed in Panel B of Figure 4.5, there is a clear jump in house prices for the dwellings that were constructed after 1974.

[10]Vollaard and Van Ours (2011) use a similar approach when analyzing the impact of stricter built-in security standards on burglary rate.

Figure 4.5: Energy Efficiency and Price of the Dwellings Constructed Before and After 1974



Source: AgentschapNL, National Association of Realtors (NVM), authors' calculations

Using the discontinuity in energy efficiency as an instrument for the energy performance index (EPI), we are able to disentangle the true (and exogenous) variation in energy efficiency. Thus, the first and second stage regression models of the IV estimation can be written as:

$$Log(EPI_i) = \alpha_0 + \alpha_1 D_i^{1974} + \alpha_2 T_i + \alpha_3 D_i^{1974} T_i + \alpha_j X_i + \tau_i + \eta_n + \epsilon_i \tag{4.2}$$

$$Log(Price_i) = \delta_0 + \delta_1 \widehat{Log(EPI_i)} + \delta_2 T_i + \delta_3 D_i^{1974} T_i + \delta_j X_i + t_i + \alpha_n + \varepsilon_i \tag{4.3}$$

where T indicates the construction year of the dwelling and D^{1974} is a dummy variable which is equal to one for the dwellings that were constructed after 1974 and zero otherwise. By specifying time trends separately before and after 1974, we are able to capture the exogenous variation in energy efficiency.

Table 4.3 reports the results of the IV estimations that are based on different sample specifications. Results of the first stage regression model imply that average energy requirement of the dwellings that were constructed after 1974 oil crisis is about 6-8 percent lower than previously constructed dwellings.[11] The results in column (1), which are based on the sample of dwellings constructed between 1967-1982, indicate that a 100 percent increase in energy performance index will lead to a decrease in the market value of the dwelling by around 22 percent. The estimated coefficient does not vary significantly as we extend our sample further by including the dwellings that were constructed long before and after the oil shock (columns 2 and 3). Thus, assuming that the change in energy efficiency in 1974 is exogenous, the IV results provide evidence that the value of energy efficiency is underestimated in the OLS regressions.

[11] You can see the detailed first-stage and second stage estimation results in Appendix Table 4.B.2 and Table 4.B.3, respectively

Table 4.3: IV Estimation Results (Discontinuity in 1974): House Prices and Energy Efficiency

Construction Period	(1967-1982)	(1959-1990)	(1950-1999)
Log(Energy Performance Index)	-0.227***	-0.185**	-0.198***
	[0.090]	[0.085]	[0.064]
Dwelling Characteristics	Yes	Yes	Yes
Construction Year	Yes	Yes	Yes
R^2	0.852	0.852	0.854
First Stage			
D^{1974}	-0.080***	-0.060***	-0.073***
	[0.009]	[0.007]	[0.006]
F statistic for excluded instrument	74.03	73.20	134.85
Number of observations	12,513	20,270	25,311

Notes:
Dependent variable is logarithm of transaction price.
Energy Index is instrumented by D^{1974}
In all regressions, we include dwelling characteristics, linear construction year variable (before and after 1974), neighborhood and year of transaction dummies as control variables.
Dwelling characteristics are: dwelling size, dwelling type, quality, number of floors, number of rooms, type of parking place, location of the dwelling relative to center, road, park, water and forest.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by neighborhood and transaction year.
* P<0.1. ** P<0.05. *** P<0.01

The identifying assumption of using a discontinuity in energy efficiency as an instrument is that the timing of the oil shock does not coincide with a discontinuity in unobserved dwelling characteristics that might also affect the price of the house. Although this assumption cannot be tested directly, we examine the validity of our findings by using an alternative instrument that is specifically targeted at energy efficiency of new buildings and that exhibits more variation (compared to a one-time energy price shock). We use the over-time variation in the stringency of building codes as an alternative instrument for the energy performance index (EPI). We use the maximum allowable U-value requirement for outside walls as a proxy for the stringency of the building codes (see Figure 4.4).

Table 4.4 documents the IV estimation results that are based on the evolution of U-value requirements for external walls of newly constructed homes.[12] The first stage regression

[12]You can see the detailed first-stage and second stage estimation results in Appendix Table 4.B.4 and Table 4.B.5, respectively

results indicate that the U-value requirement is significantly associated with the energy efficiency level of the dwellings that were constructed under that requirement, which is in line with the findings of Jacobsen and Kotchen (2013). According to the estimated coefficient on energy performance index (EPI), as the predicted energy requirement of an average dwelling doubles, the market value of that dwelling decreases by around 21 percent, which is close the results of the discontinuity approach.[13] These findings imply that if the energy requirement of a dwelling is reduced by half, its market value increases by around 11 percent, which corresponds to about €23,000 for the average dwelling in our sample.

Table 4.4: IV Estimation Results (Building Codes): House Prices and Energy Efficiency

Log(Energy Performance Index)	-0.214***
	[0.074]
Dwelling Characteristics	Yes
Construction Year	Yes
R^2	0.837
First Stage Results	
U-value	0.071***
	[0.006]
F statistic for excluded instrument	138.00
Number of observations	30,036

Notes:
Dependent variable is logarithm of transaction price.
We include dwelling characteristics, construction year variable, neighborhood and year of transaction dummies as control variables in the regression.
Dwelling characteristics are: dwelling size, dwelling type, quality, number of floors, number of rooms, type of parking place, location of the dwelling relative to center, road, park, water and forest.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by neighborhood and transaction year.
* P<0.1. ** P<0.05. *** P<0.01

[13] According to the results provided by Brounen and Kok (2011), green labeled (A, B, C) houses are sold with a 3.6 percent price premium compared to the non-green (D, E, F, G) houses. Our sample statistics indicate that the average energy performance index of green houses are 40 percent less than the non-green houses. Thus, assuming linearity, we can conclude that their results imply an elastcity around nine percent which is lower than our estimate. On the other side, Thorsnes and Bishop (2013) document that the building code legislation that was introduced in 2002 in New Zealand (leading to a 39 percent increase in energy efficiency) has led to a 14 percent increase in the market value of dwellings that were constructed after the legislation. Again assuming linearity, this result implies an elasticity around 35 percent which is larger compared to our estimate. However, it should be noted that the calculated elasticity parameters in both studies fall within our estimate of 95 percent confidence interval.

From the homeowner's perspective, the question of interest is, of course, what our findings suggest about the value of energy efficiency relative to its cost. According to the statistics provided by MilieuCentraal (Center for Environment) – a government agency, in order to decrease the energy requirement of the average dwelling in our sample by 50 percent, the required saving measures cost around €15,000.[14] This implies that, for homeowners, more than the invested amount is paid back in the resale stage. In addition to this price premium, households realize lower energy bills as a result of the improved energy efficiency. Given that in 2011 the gas consumption of an average house in our sample was 1,650 m^3 and the price of gas was 0.65 cent per m^3, households realize an estimated €535 annual saving as a result of a 50 percent decrease in the required level of energy.[15]

4.3.3 The Impact of Information Provision

Information asymmetry is generally accepted as one of the main reasons why households underinvest in profitable energy efficiency investment projects (Gillingham et al., 2009).

[14] According to the information provided by MilieuCentraal, the estimated unit costs of insulating the components of a dwelling are; €40/m^2 for floors, €100/m^2 for outside walls, €60/m^2 for the roof, €160/m^2 for windows and €2,900 for a boiler (see "http://www.milieucentraal.nl/" for detailed information). Given that the average dwelling in our sample has a 59 m^2 of floor area, 82 m^2 of roof area, 65 m^2 of external wall area and 25 m^2 of window area, if all the saving measures are implemented for the average dwelling in our sample, this leads to a 70 percent reduction in the expected energy use. The total cost of this reurbishment is €20,680. Assuming linearity, a 50 percent reduction in the required energy costs around €15,000. However, it should be noted the effectiveness of different saving measures might vary based on their simplicity. Our calculation is based on the saving measures that are necessary in order to decrease the energy requirement of an average dwelling by 70 percent.

[15] Energy efficiency investments at the time of construction might be even more profitable. According to a study published by Energy Research center of the Netherlands (Menkveld, Leidelmeijer, Tigchelaar, Vethman, Cozijnsen, Heemskerk, and Schulenberg, Menkveld et al.), the material cost of a dwelling that is constructed with an energy performance index (EPI) value of 0.8 is €3,500 higher relative to a dwelling with an EPI value of 1.0. Assuming that the difference between the expected energy requirements of these dwellings is 20 percent ((1.0-0.8)/1.0=0.2), and the relationship between energy efficiency and its cost is linear, a 50 percent reduction in energy requirement of a dwelling (with an EPI value of 1.0) costs around €8,750 at the time of its construction. Comparing this estimated cost with the estimated value of energy efficiency in the housing market (€23,000), we can conclude that there is a significant financial return for the energy efficiency investments made during construction. However, it should be noted that this comparison needs to be interpreted carefully as the estimated value of energy efficiency represents the average dwelling in our sample with an EPI value of 1.8 and, on the other side, the estimated cost represents a dwelling with an EPI value of 1.0. We might expect diminishing returns to investing in energy efficiency. If so, the the market value of energy efficiency for a dwelling with an EPI value of 1.0 will be lower than the average dwelling and thus, the financial return of investment might be lower.

The underlying mechanism is that, if energy efficiency information is not available, consumers are not able to incorporate the operating costs into their purchasing decisions, which in return leads to lower investments in energy efficiency. So far, in order to enhance the transparency of energy efficiency in the real estate market, energy performance certificates have been used as the main policy instrument in many of the EU countries. This provision of information is expected to enable households and investors to take energy efficiency into account in their purchasing and investment decisions, thus leading to a higher capitalization rate of energy efficiency. Given that our results show that energy efficiency is capitalized in a sample of the certified dwellings, the question that remains is how the provision of an energy label affects the capitalization rate of energy efficiency in the market for single-family dwellings.

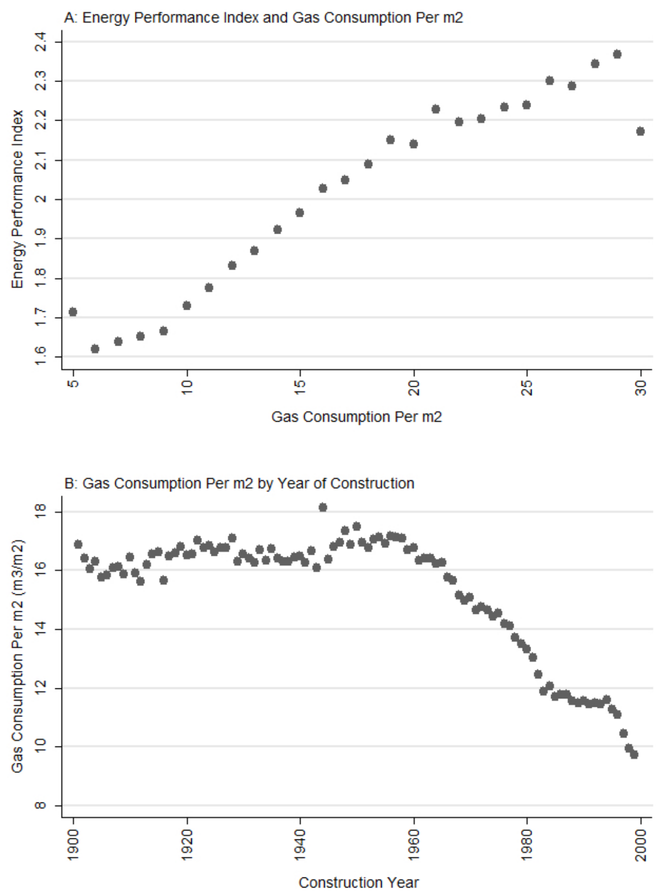
In order to test whether the capitalization of energy efficiency varies with the disclosure of an EPC, we create a common energy efficiency measure for certified and non-certified dwellings. Since the energy performance index is not available for non-certified dwellings, we benefit from the variation in actual energy consumption to estimate the model in equation (4.1). We match our data set with annual gas consumption data provided by Central Bureau of Statistics (CBS) for the years between 2004-2011.[16] We calculate the average annual gas consumption (per m^2) level for each dwelling, and use this as a proxy for the energy efficiency level of that dwelling (See Figure 4.6, Panel A for the relationship between gas consumption per m^2 and the EPI).[17] CBS also provides information on the household characteristics, including household composition and their income level. We calculate the average characteristics of the households that reside in each dwelling between 2004-2011. We include these average household characteristics in the model as control variables, as they might be correlated with gas consumption (Brounen et al., 2012). In order to obtain information on the exact year of construction of the non-certified dwellings, we merge our

[16]Since residential electricity consumption in the Netherlands highly depends on the use of household appliances instead of the characteristics of the dwelling, we do not include household's electricity consumption as a measure of home's energy efficiency in our analysis. According to the statistics provided by Odyssee database, in 2011, nearly 85 percent of residential electricity consumption is used for household appliances in the Netherlands, and the share of electricity used for air cooling is about 0.3 percent.

[17]The gas consumption data is not available for the years 2005 and 2007. While calculating the dwelling's average gas consumption level, we correct for annual heating degree days and exclude the years of transaction.

data set with the housing data provided by CBS. Finally, we exclude the outliers detected based on the sample distribution of gas consumption per m^2, transaction price, house size and household income level (the upper and lower boundaries for the outliers are set at the first and 99th percentile). The complete sample includes 103,834 dwellings that transacted, without EPC, between 2008-2011.

Figure 4.6: Gas Consumption per m^2, Energy Performance Index and Year of Construction



Source: AgentschapNL, Central Bureau of Statistics (CBS), authors' calculations

In Table 4.5, we report some of the descriptive statistics for certified and non-certified dwellings separately. The transaction price for non-certified dwellings is significantly larger compared to certified dwellings. This might be due to the larger fraction of detached and semi-detached houses in the sample of non-certified dwellings. The efficiency indicator, which is proxied by gas consumption per m^2, is not statistically different for certified and non-certified dwellings. The average dwelling in our sample is occupied by two people who have an average annual income around €35,000 (€31,000 for certified dwellings). The average annual gas consumption is 1,800 m^3 for non-certified dwellings and 1,650 m^3 for certified dwellings. According to these statistics, given that the consumer price of gas was 65 cents per m^3 in 2011, the annual gas expenditure of the average consumer corresponds to nearly four percent of the income of the average household in our sample – a sizable expenditure.

Table 4.5: Descriptive Statistics for Non-certified and Certified Dwellings

Number of Observations	Non-certified Dwellings *103,834*		Certified Dwellings *23,187*	
Variables	Mean	Std.Dev.	Mean	Std.Dev.
Transaction Price (€1000)	257.0	(113.3)	214.5	(100.1)
Gas Consumption (m^3)	1,795	(646)	1,647	(581)
Size (m^2)	126.9	(31.1)	117.5	(29.8)
Gas Consumption Intensity(m^3/m^2)	14.44	(4.82)	14.35	(4.67)
Number of Rooms	4.976	(1.073)	4.807	(1.032)
Number of Floors	2.790	(0.556)	2.756	(0.560)
Year of Construction(Median)	1965		1968	
Type (fraction)				
Corner	0.205		0.258	
Semi-detached	0.164		0.121	
Between or Townhouse	0.490		0.537	
Detached	0.141		0.084	
Transaction Year (fraction)				
2008	0.277		0.434	
2009	0.230		0.205	
2010	0.257		0.173	
2011	0.236		0.188	
Household Characteristics				
Number of Household Members	2.405	(1.011)	2.270	(0.934)
Number of Elderly (Age>65)	0.343	(0.547)	0.332	(0.513)
Number of Children (Age<18)	0.597	(0.774)	0.529	(0.696)
Number of Female Household Members	1.209	(0.625)	1.158	(0.585)
Household Income (€1000)	35.34	(14.74)	31.21	(13.32)

First, we use OLS to estimate the market value of energy efficiency for non-certified dwellings. The gas consumption per m^2 is used as a proxy for the energy efficiency level of the dwelling. In column (1) of Table 4.6, we report the results of the estimation of the model without including control variables.[18] According to the estimated coefficient, if the actual gas consumption per m^2 is doubled, the value of the house decreases by around seven percent. However, when we include control variables, the sign of the estimated coefficient becomes significantly positive, which is contrary to expectations. According to the results reported in column (4), keeping the dwelling and household characteristics fixed, if the gas expenditure is doubled, the value of the dwelling increases by around ten percent for non-certified dwellings. The estimated coefficient is nearly the same when we estimate the model for the certified dwellings (column 5).[19]

Table 4.6: OLS Estimation Results for Non-certified and Certified Dwellings

	(1)	(2)	(3)	(4)	(5)
Log(Actual Gas Cons. per m^2)	-0.071***	0.049***	0.112***	0.105***	0.086***
	[0.008]	[0.004]	[0.003]	[0.003]	[0.005]
Dwelling Characteristics	No	Yes	Yes	Yes	Yes
Construction Year	No	No	Yes	Yes	Yes
Household Characteristics	No	No	No	Yes	Yes
R^2	0.010	0.756	0.774	0.794	0.855
Number of observations	103,834	103,834	103,834	103,834	23,187

Notes:
Dependent variable is logarithm of transaction price.
Dwelling characteristics are: dwelling size, dwelling type, quality, number of floors, number of rooms, type of parking place, location of the dwelling relative to center, road, park, water and forest.
Household characteristics are: number of household members, number of children (age<18), number of elderly (age>65), number of females and household net income
Construction year is included as a third order polynomial.
In column (5), we estimate the same model for the sample of certified dwellings.
In all regressions, neighborhood and year of transaction dummies are included.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by neighborhood and transaction year.
* P<0.1. ** P<0.05. *** P<0.01

A potential explanation for these findings is that, due to the omission of unobserved factors and the presence of multicollinearity between actual gas consumption and other dwelling characteristics, the OLS estimation leads to a biased result (Atkinson and Halvorsen, 1984; Mela and Kopalle, 2002). Therefore, we again use an IV approach in order to isolate the exogenous variation in actual gas consumption resulting from stricter building codes (See Figure 4.6, Panel B for the over-time variation in gas consumption per

[18] You can see the detailed estimation results in Appendix Table 4.B.6

[19] Using a similar approach, Cerin et al. (2014) also reports a positive price premium for decreased level of energy efficiency for the average dwelling in Sweden.

m^2 of new dwellings). We estimate the same model using the evolution of building codes as an instrument for actual gas consumption per m^2. Table 4.7 documents the results of the IV estimation using the maximum U-value requirement for external walls at the time of construction as an instrument for actual gas consumption per m^2.[20] The results show that, keeping the other dwelling and household characteristics constant, as the actual gas consumption is doubled, the market value of the dwelling decreases by around 24 percent for non-certified dwellings and 20 percent for certified dwellings, which is in line with our previous findings. The estimated coefficient is not statistically different for certified and non-certified dwellings, which provides some indication that there is limited evidence to argue that the salience of energy efficiency increases with the adoption of an EPC.[21]

[20]You can see the detailed first-stage and second stage estimation results in Appendix Table 4.B.7 and Table 4.B.8, respectively

[21]It is important to note that, as documented by Aydin et al. (2014), the actual energy consumption does not represent the exact efficiency level due to the existence of rebound effect. Therefore, the estimated market value of a decrease in the level of actual gas consumption is expected to be larger than the value of a decrease in the energy performance index (EPI), as it also captures the increased level of thermal comfort. The first stage results also support the rebound effect hypothesis, as the increased U-value has less impact on the actual gas consumption then it has on energy performance index, although not statistically significant (Columns 2 and 3). This might also explain the larger coefficient we find by using actual gas consumption compared to using the EPI.

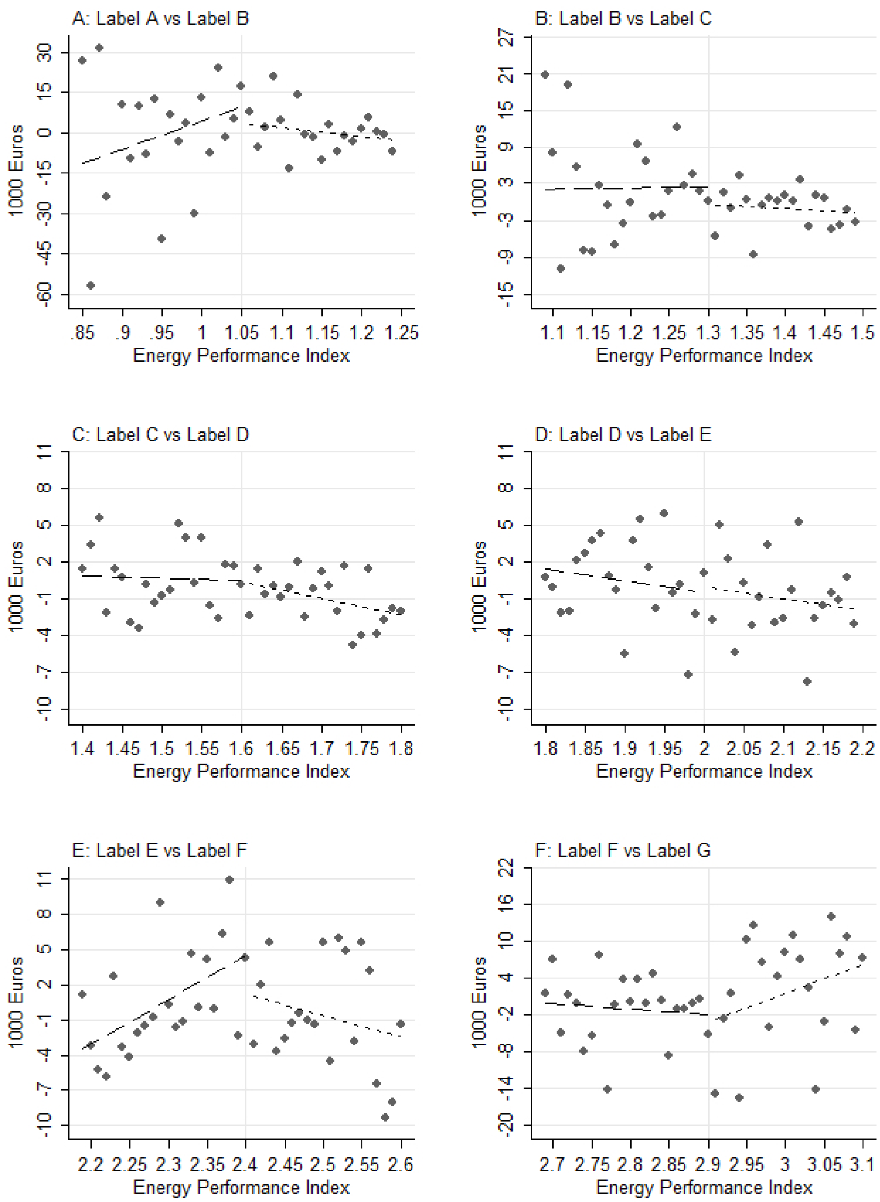
Table 4.7: IV Estimation Results for Non-certified and Certified Dwellings

	(Non-certified)	(Certified)	(Certified)
Log(Actual Gas Cons. per m^2)	-0.239***	-0.195**	
	[0.052]	[0.090]	
Log(Energy Performance Index)			-0.185***
			[0.080]
Dwelling Characteristics	Yes	Yes	Yes
Construction Year	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes
R^2	0.740	0.818	0.844
First Stage Results			
U-value	0.068***	0.065***	0.069***
	[0.004]	[0.009]	[0.006]
F statistic for excluded instrument	307.10	50.07	113.37
Number of observations	103,834	23,187	23,187

Notes:
Dependent variable is logarithm of transaction price.
In all regressions, we include household characteristics, dwelling characteristics, construction year variable, neighborhood and year of transaction dummies as control variables.
Dwelling characteristics are: dwelling size, dwelling type, quality, number of floors, number of rooms, type of parking place, location of the dwelling relative to center, road, park, water and forest.
Household characteristics are: number of household members, number of children (age<18), number of elderly (age>65), number of females and household net income.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by neighborhood and transaction year.
* P<0.1. ** P<0.05. *** P<0.01

We also examine directly whether the energy label itself has an additional impact on the transaction price. We apply a regression discontinuity (RD) approach based on the rule that is used to assign dwellings in energy efficiency classes. The basic idea behind this approach is that assignment to treatment is determined by the value of an observed characteristic being on either side of a cutoff value (Imbens and Lemieux, 2008). The main identifying assumption is that unobserved characteristics vary continuously with the observable characteristic that is used in the assignment rule (Jacob and Lefgren, 2004). We test whether there exists discontinuity in the transaction price of the dwelling around the threshold values of EPI for different label categories. We focus on a narrow bandwidth ($\pm$0.2 EPI) around the threshold values. In Figure 4.7, comparing the subsequent label categories, we plot the variation in the adjusted transaction price based on the energy performance index around the cutoff points. We do not observe a clear discontinuity in transaction price at the threshold points that are used to assign dwellings in different label categories.

Figure 4.7: Transaction Price (adjusted) by Label Category and Energy Performance Index



Source: AgentschapNL, National Association of Realtors (NVM), authors' calculations

In order to formally test the potential labeling effect, we estimate the following model for each threshold level:

$$Log(Price_i) = \phi_0 + \phi_1 Log(EPI) + \phi_2 D_i^{L.label} Log(EPI) + \phi_3 D_i^{L.label} + \phi_j X_i + \varepsilon_i \quad (4.4)$$

where $D^{L.label}$ is a dummy variable which is equal to one for the dwellings that were assigned to the label indicating lower energy efficiency level, and zero otherwise. X_i is a vector of dwelling characteristics. $Log(EPI)$ and $D_i^{L.label} Log(EPI)$ control for the continuous effect of the EPI on transaction price within each label category, and thus ϕ_3 represents the impact of label itself on transaction price, which is our parameter of interest. Table 4.8 reports the estimates of ϕ_3 for each threshold value that is used in the assignment to different label categories. For all cutoff points, the estimated change in transaction price that results from the assignment to a lower energy efficiency class is negative but not statistically significant. Thus, there is not enough evidence to argue that the labeling itself has a significant impact on the transaction price.

Table 4.8: Regression Discontinuity Estimation Results for Label Effect

	(A-B)	(B-C)	(C-D)	(D-E)	(E-F)	(F-G)
$D^{L.label}$=1	-0.013	-0.012	-0.002	-0.000	- 0.007	-0.015
	[0.029]	[0.008]	[0.007]	[0.008]	[0.011]	[0.018]
Log(EPI)	0.171	-0.011	-0.019	-0.052	0.300**	-0.055
	[0.262]	[0.085]	[0.059]	[0.089]	[0.136]	[0.270]
Log(EPI)*$D^{L.label}$	-0.433	-0.060	-0.088	-0.037	-0.494**	0.530
	[0.312]	[0.107]	[0.093]	[0.152]	[0.224]	[0.464]
Dwelling Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Construction Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.841	0.863	0.848	0.841	0.843	0.825
Number of obs.	1,461	6,879	11,009	6,899	4,606	2,146

Notes:
Dependent variable is logarithm of transaction price.
We include dwelling characteristics, construction year variable, neighborhood and year of transaction dummies as control variables in the regression.
Dwelling characteristics are: dwelling size, dwelling type, quality, number of floors, number of rooms, type of parking place, location of the dwelling relative to center, road, park, water and forest.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by neighborhood and transaction year.
* P<0.1. ** P<0.05. *** P<0.01

Finally, we examine whether the estimated value of energy efficiency varies over time. By using actual gas consumption per m^2 as a proxy for energy efficiency, we are able to estimate the market value of residential energy efficiency for each year from 2003 to 2011. As reported in Table 4.9, we find that the estimated coefficient increases from 2003 to 2011, although the difference is not statistically significant. This can be partly explained by the decreasing house prices after 2008 and the relative increase in energy costs (see Figure 4.8).[22] Besides, the introduction of EPC in 2008 might also have a general influence on the capitalization of energy efficiency (for both certified and non-certified dwellings), as it may change the households' perception of importance of energy efficiency.

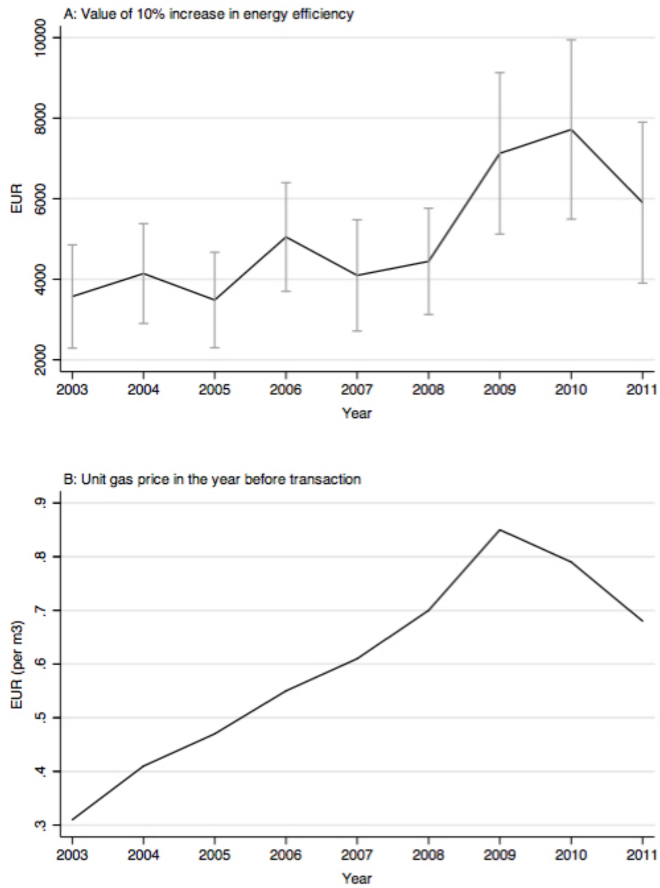
[22]See Kahn (1986), Allcott and Wozny (2014), Busse et al. (2013) for the anlysis of how the market value of fuel economy in the automobile sector is associated to the changes in gasoline prices.

Table 4.9: Market Value of Energy Efficiency Over Time

Year	Log(Gas Cons. per m^2)	N
2003	-0.156*** [0.056]	42,346
2004	-0.177*** [0.053]	42,847
2005	-0.144*** [0.049]	48,702
2006	-0.202*** [0.054]	48,632
2007	-0.160*** [0.054]	47,976
2008	-0.175*** [0.052]	39,030
2009	-0.302*** [0.085]	28,742
2010	-0.319*** [0.092]	30,768
2011	-0.248*** [0.084]	28,936

Notes:
Dependent variable is logarithm of transaction price.
In all regressions, we include household characteristics, dwelling characteristics, construction year variable, and neighborhood dummies as control variables.
Dwelling characteristics are: dwelling size, dwelling type, quality, number of floors, number of rooms, type of parking place, location of the dwelling relative to center, road, park, water and forest.
Household characteristics are: number of household members, number of children (age<18), number of elderly (age>65), number of females and household net income.
We include both certified and non-certified dwellings in the analysis.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are clustered by neighborhood.
* P<0.1. ** P<0.05. *** P<0.01

Figure 4.8: Value of Energy Efficiency and Gas Prices



Source: Central Bureau of Statistics (CBS), International Energy Agency, National Association of Realtors (NVM), authors' calculations

4.4 Conclusion

Enhancing residential energy efficiency has been a key element of debate among policy makers, investors, and academics. Notwithstanding promising engineering estimates, large-scale diffusion of energy efficiency enhancements in the single-family housing market has been far from easy. One of the causes of such slow uptake is that the associated returns to efficiency upgrades have not been identified convincingly. Requiring households to make upfront investment for an uncertain return has been complicated further during the recent period of financial liquidity constraints.

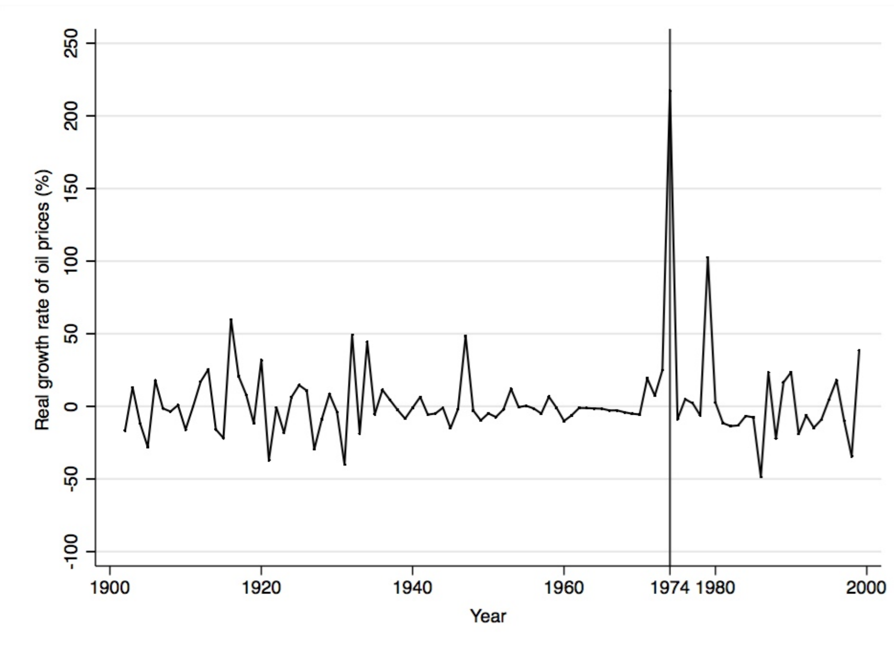
In this paper, we investigate how consumers capitalize energy efficiency in the housing market, and how the provision of an energy performance certificate affects this capitalization rate. Although this is not the first paper to address this capitalization process, most of the available evidence suffers from a common methodological drawback – the potential bias that may arise due to omission of unobserved dwelling characteristics that are correlated with measures of energy efficiency. This paper contributes to this literature by proposing an instrumental variable approach to estimate the capitalization of energy efficiency in the residential sector. We also contribute to the literature by examining the impact of information provision, in the form of energy labels, on consumers' valuation of energy efficiency.

We examine a large representative dataset from the Netherlands, exploiting the discontinuity in the energy efficiency levels of the newly constructed homes during the 1973-74 oil crisis, and the stringency of building codes at the time of construction as instruments for energy efficiency. Our results indicate that the use of OLS leads to biased estimates of the market value of energy efficiency. Using an IV approach, we find that if the energy requirement of a dwelling is reduced by half, the market price of the dwelling increases by around 11 percent for an average dwelling in the Dutch housing market. In order to examine whether the capitalization of energy efficiency varies with the disclosure of an EPC, we estimate the same model by using actual energy consumption as a proxy for a common energy efficiency measure for certified and non-certified homes. Our findings do not provide a significant evidence suggesting a higher capitalization rate for dwellings that transacted with an energy performance certificate. We also use a regression discontinuity approach to test whether labeling itself has a market value. The results show that there is not a significant change in the transaction price at the threshold energy efficiency level that is used to assign the dwellings into different label classes, which implies that the labeling itself does not lead to a significant change in buyer's valuation of the dwelling. Finally, we examine the over-time change in the market value of energy efficiency, and document that the value of energy efficiency has doubled from 2003 to 2011, which might be a result of the increase in energy prices, the relative decrease in house prices after 2008 and the general influence of policies and information campaigns stressing the importance of energy efficiency.

Our findings imply that, beyond the direct financial benefits from lower energy expenses, residential energy efficiency improvements lead to higher transaction prices, regardless of the provision of an energy label. From a policy perspective, the results of this paper may be used to enhance the public awareness regarding the financial benefits of energy efficiency investments. In order to facilitate the uptake of energy efficiency measures, the financial benefits that homeowners can derive from energy efficiency improvements need to be emphasized in the public information campaigns, and can also be incorporated into the energy performance certification programs. In relation to "energy efficiency gap" literature, our results also raise the question why energy efficiency investments in the housing sector are far below the optimal level, given that the market value of, for example, insulation is so much higher than its cost. The additional costs (such as the nuisance during the retrofit work and the information costs), the risk of undervaluation of the energy efficiency improvement in the market, liquidity constraints and the future discounting behavior might be some of the reasons that lead to this sub-optimal outcome. Thus, more research needs to be done to understand homeowners' investment decisions, and accordingly cost-effective policies need to be designed in a way to deal with these underlying reasons.

Appendix

4.A Development of Oil Prices



Source: International Energy Agency

4.B Supplementary Tables

Table 4.B.1: OLS Estimation Results: House Prices and Energy Efficiency

	(1)	(2)	(3)	(4)
Log (Energy performance index)	-0.235***	-0.106***	-0.052***	-0.048***
	(0.019)	(0.007)	(0.007)	(0.007)
Log (House size)		0.673***	0.671***	0.676***
		(0.012)	(0.013)	(0.013)
Number of rooms		0.015***	0.019***	0.019***
		(0.002)	(0.002)	(0.002)
Number of floors		-0.013***	-0.017***	- 0.018***
		(0.004)	(0.003)	(0.003)
House type=Semi-detached		0.129***	0.112***	0.109***
		(0.005)	(0.005)	(0.005)
House type=Between or Townhouse		-0.031***	-0.033***	0.033***
		(0.002)	(0.002)	(0.002)
House type=Detached house		0.318***	0.296***	0.292***
		(0.006)	(0.007)	(0.007)
Parking place		0.055***	0.049***	0.045***
		(0.006)	(0.006)	(0.006)
Only carport		0.072***	0.075***	0.074***
		(0.008)	(0.007)	(0.007)
Only garage		0.147***	0.146***	0.143***
		(0.004)	(0.004)	(0.004)
Garage and carport		0.175***	0.172***	0.171***
		(0.009)	(0.009)	(0.009)
Garage for multiple cars		0.188***	0.192***	0.190***
		(0.009)	(0.009)	(0.009)
Location relative to the center (unspecified)		-0.154***	-0.142***	-0.144***
		(0.016)	(0.016)	(0.016)
Location relative to the center (residential area)		-0.175***	-0.160***	-0.160***
		(0.016)	(0.016)	(0.016)
Location relative to the center (center)		-0.127***	-0.130***	-0.133***
		(0.017)	(0.017)	(0.017)
Near forest		0.116***	0.127***	0.126***
		(0.010)	(0.010)	(0.010)
Near waterside		0.087***	0.078***	0.076***
		(0.006)	(0.006)	(0.006)
Near park		0.043***	0.044***	0.041***
		(0.006)	(0.006)	(0.006)
Clear view		0.027***	0.028***	0.028***
		(0.004)	(0.003)	(0.003)
Location relative to the road (unspecified)		-0.012***	-0.012***	-0.012***
		(0.003)	(0.003)	(0.002)
Location relative to the road (near a busy road)		-0.033***	-0.041***	-0.042***
		(0.009)	(0.009)	(0.009)
Quality==0		-0.058**	-0.055**	-0.046*
		(0.028)	(0.027)	(0.026)
Quality==1		-0.062***	-0.056***	-0.051***
		(0.020)	(0.018)	(0.018)
Quality==2		0.458***	0.450***	0.443***
		(0.097)	(0.097)	(0.103)
Construction-year			0.002***	
			(0.000)	
Construction-year^2			0.000***	
			(0.000)	
Construction-year^3			0.000***	
			(0.000)	
Constant	5.580***	1.851***	1.779***	1.899***
	(0.017)	(0.070)	(0.074)	(0.099)
Observations	30,036	30,036	30,036	30,036
R-squared	0.106	0.836	0.843	0.846

Notes:
Dependent variable is logarithm of transaction price.
The omitted categories are: for ”house type” variable it is ”Corner house”, for ”parking type” variable it is ”no parking place”, for ”location relative to the center” variable it is ”outside the urban area”, for ”view type” variable it is ”not specified”, for ”location relative to the road” variable it is ”near a quite road”, and for ”quality” variable it is ”not specified”.

Table 4.B.2: IV First-stage Estimation Results: Discontinuity in 1974

Construction Period	(1950-1999)	(1959-1990)	(1967-1982)
D^{1974}	-0.073***	-0.060***	-0.080***
	(0.006)	(0.007)	(0.009)
Construction-year (until1974)	-0.004***	-0.006***	-0.001
	(0.001)	(0.001)	(0.002)
Construction-year (after 1974)	-0.012***	-0.011***	-0.013***
	(0.001)	(0.001)	(0.002)
Log of house size(m^2)	-0.064***	-0.064***	-0.066***
	(0.010)	(0.012)	(0.015)
Number of rooms	-0.002	-0.003	-0.002
	(0.002)	(0.002)	(0.003)
Number of floors	0.009**	0.011***	0.014**
	(0.004)	(0.004)	(0.005)
House type=Semi-detached	0.013**	0.007	0.005
	(0.005)	(0.006)	(0.009)
House type=Between or Townhouse	-0.014***	-0.013***	-0.020***
	(0.003)	(0.003)	(0.004)
House type=Detached house	-0.005	0.002	0.020
	(0.008)	(0.009)	(0.013)
Parking place	-0.004	-0.010	-0.015
	(0.006)	(0.007)	(0.010)
Only carport	-0.004	-0.006	-0.006
	(0.007)	(0.008)	(0.010)
Only garage	0.004	0.007	0.005
	(0.004)	(0.005)	(0.006)
Garage and carport	-0.020**	-0.017	-0.027*
	(0.010)	(0.012)	(0.016)
Garage for multiple cars	-0.007	0.002	-0.001
	(0.011)	(0.013)	(0.017)
Location relative to the center (unspecified)	-0.011	0.012	-0.012
	(0.022)	(0.024)	(0.032)
Location relative to the center (residential area)	-0.021	0.004	-0.014
	(0.022)	(0.024)	(0.032)
Location relative to the center (center)	-0.007	0.025	0.017
	(0.024)	(0.027)	(0.035)
Near forest	0.013	0.018	0.014
	(0.012)	(0.014)	(0.017)
Near waterside	-0.004	-0.002	-0.002
	(0.006)	(0.007)	(0.010)
Near park	-0.000	-0.009	-0.009
	(0.007)	(0.008)	(0.010)
Clear view	-0.003	-0.006	-0.016***
	(0.004)	(0.005)	(0.006)
Location relative to the road (unspecified)	-0.001	-0.002	-0.001
	(0.003)	(0.003)	(0.004)
Location relative to the road (near a busy road)	0.008	0.013	0.003
	(0.012)	(0.013)	(0.016)
Quality==0	-0.061**	-0.055**	-0.072**
	(0.026)	(0.026)	(0.032)
Quality==1	-0.006	-0.017	-0.028
	(0.018)	(0.015)	(0.022)
Quality==2	-0.094	-0.105*	-0.093
	(0.065)	(0.060)	(0.100)
Constant	0.988***	0.947***	0.885***
	(0.062)	(0.069)	(0.124)
Observations	25,311	20,270	12,513
R-squared	0.445	0.362	0.258

Notes:
Dependent variable is logarithm of energy performance index.
The omitted categories are: for ”house type” variable it is ”Corner house”, for ”parking type” variable it is ”no parking place”, for ”location relative to the center” variable it is ”outside the urban area”, for ”view type” variable it is ”not specified”, for ”location relative to the road” variable it is ”near a quite road”, and for ”quality” variable it is ”not specified”.

Table 4.B.3: IV Second-stage Estimation Results: Discontinuity in 1974

Construction Period	(1950-1999)	(1959-1990)	(1967-1982)
Log (Energy performance index)	-0.198***	-0.185**	-0.227**
	(0.064)	(0.085)	(0.090)
Log of house size(m^2)	0.613***	0.597***	0.595***
	(0.012)	(0.012)	(0.015)
Number of rooms	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.003)
Number of floors	-0.026***	-0.030***	-0.037***
	(0.004)	(0.004)	(0.005)
House type=Semi-detached	0.110***	0.120***	0.137***
	(0.005)	(0.006)	(0.008)
House type=Between or Townhouse	-0.037***	-0.035***	- 0.039***
	(0.002)	(0.003)	(0.003)
House type=Detached house	0.324***	0.342***	0.365***
	(0.007)	(0.008)	(0.011)
Parking place	0.044***	0.039***	0.039***
	(0.006)	(0.006)	(0.009)
Only carport	0.076***	0.070***	0.059***
	(0.007)	(0.007)	(0.008)
Only garage	0.155***	0.154***	0.145***
	(0.004)	(0.004)	(0.005)
Garage and carport	0.172***	0.171***	0.161***
	(0.009)	(0.010)	(0.014)
Garage for multiple cars	0.209***	0.218***	0.223***
	(0.010)	(0.011)	(0.014)
Location relative to the center (unspecified)	-0.176***	-0.153***	-0.144***
	(0.021)	(0.023)	(0.028)
Location relative to the center (residential area)	-0.192***	-0.168***	-0.160***
	(0.020)	(0.023)	(0.028)
Location relative to the center (center)	-0.150***	-0.128***	-0.130***
	(0.022)	(0.025)	(0.032)
Near forest	0.130***	0.133***	0.113***
	(0.010)	(0.011)	(0.013)
Near waterside	0.077***	0.076***	0.067***
	(0.006)	(0.007)	(0.010)
Near park	0.037***	0.038***	0.040***
	(0.006)	(0.006)	(0.008)
Clear view	0.027***	0.023***	0.016***
	(0.003)	(0.004)	(0.005)
Location relative to the road (unspecified)	-0.011***	-0.011***	-0.010***
	(0.002)	(0.003)	(0.003)
Location relative to the road (near a busy road)	-0.026***	-0.028**	-0.035***
	(0.010)	(0.011)	(0.013)
Quality==0	-0.113***	-0.120***	-0.162***
	(0.026)	(0.026)	(0.032)
Quality==1	-0.097***	-0.099***	-0.132***
	(0.018)	(0.020)	(0.028)
Quality==2	0.355**	0.350**	0.464***
	(0.158)	(0.165)	(0.176)
Construction-year (until 1974)	-0.002***	-0.001*	0.005***
	(0.001)	(0.001)	(0.001)
Construction-year (after 1974)	0.006***	0.005***	-0.006**
	(0.001)	(0.001)	(0.002)
Constant	2.295***	2.344***	2.400***
	(0.082)	(0.095)	(0.106)
Observations	25,311	20,270	12,513
R-squared	0.854	0.852	0.852

Notes:
Dependent variable is logarithm of transaction price.
The omitted categories are: for ”house type” variable it is ”Corner house”, for ”parking type” variable it is ”no parking place”, for ”location relative to the center” variable it is ”outside the urban area”, for ”view type” variable it is ”not specified”, for ”location relative to the road” variable it is ”near a quite road”, and for ”quality” variable it is ”not specified”.

Table 4.B.4: IV First-stage Estimation Results: U-value Requirements for Walls

U-value requirement for external walls	0.071***
	(0.006)
House type=Semi-detached	0.004
	(0.005)
House type=Between or Townhouse	-0.016***
	(0.003)
House type=Detached house	-0.014**
	(0.007)
Log of house size(m^2)	-0.059***
	(0.010)
Number of rooms	-0.000
	(0.002)
Number of floors	0.010***
	(0.004)
Parking place	-0.013**
	(0.007)
Only carport	-0.008
	(0.007)
Only garage	0.005
	(0.004)
Garage and carport	-0.020**
	(0.010)
Garage for multiple cars	-0.020*
	(0.010)
Location relative to the center (unspecified)	0.008
	(0.016)
Location relative to the center (residential area)	0.001
	(0.016)
Location relative to the center (center)	0.014
	(0.018)
Near forest	0.003
	(0.012)
Near waterside	-0.005
	(0.006)
Near park	-0.002
	(0.007)
Clear view	0.001
	(0.004)
Location relative to the road (unspecified)	-0.001
	(0.003)
Location relative to the road (near a busy road)	0.018*
	(0.010)
Quality==0	-0.061**
	(0.025)
Quality==1	-0.004
	(0.015)
Quality==2	-0.128***
	(0.044)
Construction-year	-0.008***
	(0.000)
Construction-year^2	-0.000***
	(0.000)
Construction-year^3	-0.000***
	(0.000)
Constant	0.768***
	(0.054)
Observations	30,036
R-squared	0.414

Notes:
Dependent variable is logarithm of energy performance index.
The omitted categories are: for ”house type” variable it is ”Corner house”, for ”parking type” variable it is ”no parking place”, for ”location relative to the center” variable it is ”outside the urban area”, for ”view type” variable it is ”not specified”, for ”location relative to the road” variable it is ”near a quite road”, and for ”quality” variable it is ”not specified”.

Table 4.B.5: IV Second-stage Estimation Results: U-value Requirements for Walls

Log (Energy performance index)	-0.214***
	(0.074)
House type=Detached house	0.112***
	(0.005)
House type=Between or Townhouse	-0.035***
	(0.003)
House type=Detached house	0.294***
	(0.007)
Log of house size(m^2)	0.662***
	(0.014)
Number of rooms	0.019***
	(0.002)
Number of floors	-0.015***
	(0.004)
Parking place	0.047***
	(0.006)
Only carport	0.074***
	(0.007)
Only garage	0.147***
	(0.004)
Garage and carport	0.169***
	(0.009)
Garage for multiple cars	0.188***
	(0.009)
Location relative to the center (unspecified)	-0.140***
	(0.017)
Location relative to the center (residential area)	-0.159***
	(0.016)
Location relative to the center (center)	-0.128***
	(0.018)
Near forest	0.127***
	(0.011)
Near waterside	0.077***
	(0.006)
Near park	0.043***
	(0.006)
Clear view	0.028***
	(0.003)
Location relative to the road (unspecified)	-0.013***
	(0.003)
Location relative to the road (near a busy road)	-0.038***
	(0.009)
Quality==0	-0.065**
	(0.028)
Quality==1	-0.057***
	(0.018)
Quality==2	0.430***
	(0.099)
Construction-year	0 .000
	(0.001)
Construction-year^2	0.000***
	(0.000)
Construction-year^3	0.000***
	(0.000)
Constant	1.920***
	(0.095)
Observations	30,036
R-squared	0.837

Notes:
Dependent variable is logarithm of transaction price.
The omitted categories are: for ”house type” variable it is ”Corner house”, for ”parking type” variable it is ”no parking place”, for ”location relative to the center” variable it is ”outside the urban area”, for ”view type” variable it is ”not specified”, for ”location relative to the road” variable it is ”near a quite road”, and for ”quality” variable it is ”not specified”.

Table 4.B.6: OLS Estimation Results based on Gas Consumption per m^2

	(1)	(2)	(3)	(4)	(5)
Log (Gas consumption per m^2)	-0.071***	0.049***	0.112***	0.105***	0.086***
	(0.008)	(0.004)	(0.003)	(0.003)	(0.005)
Log of house size(m^2)		0.813***	0.802***	0.720***	0.632***
		(0.009)	(0.009)	(0.008)	(0.013)
Number of rooms		0.012***	0.016***	0.013***	0.014***
		(0.001)	(0.001)	(0.001)	(0.002)
Number of floors		-0.016***	-0.017***	-0.020***	- 0.014***
		(0.002)	(0.002)	(0.002)	(0.004)
House type=Detached house		0.103***	0.090***	0.085***	0.101***
		(0.003)	(0.003)	(0.003)	(0.005)
House type=Between or Townhouse		-0.028***	-0.024***	-0.025***	- 0.022***
		(0.002)	(0.002)	(0.002)	(0.002)
House type=Detached house		0.259***	0.240***	0.239***	0.267***
		(0.004)	(0.004)	(0.004)	(0.007)
Parking place		0.055***	0.044***	0.038***	0.041***
		(0.004)	(0.003)	(0.003)	(0.006)
Only carport		0.070***	0.070***	0.062***	0.063***
		(0.004)	(0.004)	(0.004)	(0.007)
Only garage		0.111***	0.110***	0.104***	0.127***
		(0.002)	(0.002)	(0.002)	(0.004)
Garage and carport		0.142***	0.133***	0.124***	0.149***
		(0.005)	(0.004)	(0.004)	(0.009)
Garage for multiple cars		0.140***	0.146***	0.143***	0.178***
		(0.004)	(0.004)	(0.004)	(0.010)
Location relative to the center (unspecified)		-0.133***	-0.140***	-0.145***	-0.186***
		(0.007)	(0.007)	(0.007)	(0.018)
Location relative to the center (residential area)		-0.149***	-0.163***	-0.171***	-0.205***
		(0.007)	(0.008)	(0.008)	(0.018)
Location relative to the center (center)		-0.149***	-0.158***	-0.161***	-0.176***
		(0.008)	(0.008)	(0.008)	(0.019)
Near forest		0.120***	0.121***	0.112***	0.100***
		(0.006)	(0.006)	(0.006)	(0.011)
Near waterside		0.085***	0.069***	0.066***	0.072***
		(0.004)	(0.004)	(0.004)	(0.007)
Near park		0.034***	0.035***	0.029***	0.035***
		(0.003)	(0.003)	(0.003)	(0.006)
Clear view		0.025***	0.025***	0.025***	0.025***
		(0.002)	(0.002)	(0.002)	(0.004)
Location relative to the road (unspecified)					
		(0.002)	(0.002)	(0.002)	(0.003)
Location relative to the road (near a busy road)		-0.066***	-0.068***	-0.057***	-0.037***
		(0.005)	(0.005)	(0.005)	(0.009)
Quality==0		-0.246***	-0.248***	-0.217***	-0.066**
		(0.054)	(0.053)	(0.049)	(0.028)
Quality==1		-0.041**	-0.042**	-0.046**	-0.056***
		(0.020)	(0.019)	(0.018)	(0.020)
Quality==2		0.098	0.082	0.070	0.182**
		(0.081)	(0.080)	(0.072)	(0.081)
Construction-year			0.003***	0.003***	0.003***
			(0.000)	(0.000)	(0.000)
Construction-year^2			0.000***	0.000***	0.000***
			(0.000)	(0.000)	(0.000)
Construction-year^3			0.000***	0.000***	0.000***
			(0.000)	(0.000)	(0.000)
Number of household members				-0.040***	-0.044***
				(0.002)	(0.004)
Number of children (age<18)				0.026***	0.030***
				(0.002)	(0.004)
Number of elderly (age>64)				0.007***	0.014***
				(0.002)	(0.003)
Number of female				0.017***	0.015***
				(0.001)	(0.003)
Log (income)				0.174***	0.158***
				(0.003)	(0.006)
Constant	5.701***	1.049***	0.887***	-0.403***	0.211**
	(0.021)	(0.053)	(0.053)	(0.066)	(0.103)
Observations	103,834	103,834	103,834	103,834	23,187
R-squared	0.010	0.756	0.774	0.794	0.855

Notes:
Dependent variable is logarithm of transaction price.
The omitted categories are: for "house type" variable it is "Corner house", for "parking type" variable it is "no parking place", for "location relative to the center" variable it is "outside the urban area", for "view type" variable it is "not specified", for "location relative to the road" variable it is "near a quite road", and for "quality" variable it is "not specified".

Table 4.B.7: IV Estimation First-stage Results for Non-EPC Sample

	(1)	(2)	(3)
U-value requirement for external walls	0.068***	0.065***	0.069***
	(0.004)	(0.009)	(0.006)
Construction-year	-0.005***	-0.004***	-0.008***
	(0.000)	(0.001)	(0.000)
Construction-year^2	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Construction-year^3	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Log of house size(m^2)	-0.444***	-0.477***	-0.031***
	(0.006)	(0.013)	(0.012)
Number of rooms	0.012***	0.009***	0.005**
	(0.001)	(0.002)	(0.002)
Number of floors	-0.023***	-0.013***	0.014***
	(0.002)	(0.004)	(0.004)
House type=Detached house	0.018***	0.015**	0.007
	(0.003)	(0.007)	(0.006)
House type=Between or Townhouse	-0.123***	-0.118***	- 0.017***
	(0.002)	(0.004)	(0.003)
House type=Detached house	0.093***	0.107***	- 0.023***
	(0.004)	(0.008)	(0.008)
Parking place	0.025***	0.024**	-0.012
	(0.004)	(0.011)	(0.008)
Only carport	0.016***	0.024**	-0.008
	(0.004)	(0.012)	(0.009)
Only garage	0.053***	0.057***	0.007
	(0.002)	(0.005)	(0.005)
Garage and carport	0.046***	0.049***	-0.023**
	(0.005)	(0.015)	(0.012)
Garage for multiple cars	0.036***	0.052***	-0.015
	(0.005)	(0.012)	(0.013)
Location relative to the center (unspecified)	0.054***	-0.008	0.035*
	(0.007)	(0.021)	(0.020)
Location relative to the center (residential area)	0.048***	-0.014	0.032
	(0.007)	(0.021)	(0.020)
Location relative to the center (center)	0.059***	0.016	0.037*
	(0.008)	(0.023)	(0.022)
Near forest	0.030***	0.064***	0.004
	(0.006)	(0.014)	(0.013)
Near waterside	0.013***	0.011	-0.007
	(0.004)	(0.010)	(0.007)
Near park	0.016***	0.015	-0.005
	(0.004)	(0.010)	(0.008)
Clear view	0.002	-0.001	0.003
	(0.002)	(0.006)	(0.005)
Location relative to the road (unspecified)	-0.002	0.000	-0.001
	(0.002)	(0.004)	(0.003)
Location relative to the road (near a busy road)	0.020***	0.031***	0.017
	(0.006)	(0.012)	(0.012)
Quality==0	-0.082**	-0.023	-0.061*
	(0.037)	(0.049)	(0.031)
Quality==1	-0.075***	-0.071**	0.021
	(0.020)	(0.032)	(0.017)
Quality==2	-0.126**	-0.332	-0.073**
	(0.058)	(0.238)	(0.030)
Number of household members	0.013***	0.024***	-0.019***
	(0.002)	(0.005)	(0.004)
Number of children (age<18)	0.003	0.005	0.010**
	(0.003)	(0.006)	(0.004)
Number of elderly (age>64)	0.072***	0.051***	0.023***
	(0.002)	(0.004)	(0.003)
Number of female	0.019***	0.014***	-0.003
	(0.002)	(0.005)	(0.003)
Log (income)	0.036***	0.045***	-0.022***
	(0.003)	(0.007)	(0.005)
Constant	4.179***	4.367***	0.825***
	(0.036)	(0.079)	(0.075)
Observations	103,834	23,187	23,187
R-squared	0.392	0.375	0.417

Notes:
Dependent variable is logarithm of gas consumption per m^2.
The omitted categories are: for "house type" variable it is "Corner house", for "parking type" variable it is "no parking place", for "location relative to the center" variable it is "outside the urban area", for "view type" variable it is "not specified", for "location relative to the road" variable it is "near a quite road", and for "quality" variable it is "not specified".

Table 4.B.8: IV Estimation Second-stage Results for Non-EPC Sample

	(1)	(2)	(3)
Log (Gas consumption per m^2)	-0.239***	-0.195**	
	(0.052)	(0.090)	
Log (Energy performance index)			-0.185**
			(0.080)
Log of house size(m^2)	0.569***	0.500***	0.587***
	(0.022)	(0.044)	(0.013)
Number of rooms	0.018***	0.016***	0.015***
	(0.001)	(0.002)	(0.002)
Number of floors	-0.028***	-0.018***	-0.013***
	(0.002)	(0.004)	(0.004)
House type=Detached house	0.091***	0.105***	0.104***
	(0.003)	(0.005)	(0.005)
House type=Between or Townhouse	-0.067***	-0.054***	- 0.035***
	(0.007)	(0.011)	(0.003)
House type=Detached house	0.271***	0.297***	0.272***
	(0.006)	(0.012)	(0.008)
Parking place	0.046***	0.047***	0.040***
	(0.004)	(0.007)	(0.006)
Only carport	0.067***	0.070***	0.064***
	(0.004)	(0.008)	(0.007)
Only garage	0.123***	0.144***	0.134***
	(0.004)	(0.007)	(0.004)
Garage and carport	0.140***	0.163***	0.149***
	(0.005)	(0.011)	(0.010)
Garage for multiple cars	0.155***	0.193***	0.180***
	(0.005)	(0.011)	(0.010)
Location relative to the center (unspecified)	-0.126***	-0.187***	-0.179***
	(0.008)	(0.018)	(0.018)
Location relative to the center (residential area)	-0.154***	-0.208***	-0.199***
	(0.009)	(0.018)	(0.018)
Location relative to the center (center)	-0.140***	-0.171***	-0.168***
	(0.009)	(0.020)	(0.019)
Near forest	0.122***	0.118***	0.106***
	(0.006)	(0.013)	(0.011)
Near waterside	0.070***	0.075***	0.071***
	(0.004)	(0.007)	(0.007)
Near park	0.034***	0.039***	0.035***
	(0.004)	(0.007)	(0.006)
Clear view	0.026***	0.025***	0.026***
	(0.002)	(0.004)	(0.004)
Location relative to the road (unspecified)	-0.012***	-0.009***	-0.009***
	(0.002)	(0.003)	(0.003)
Location relative to the road (near a busy road)	-0.051***	-0.029***	-0.032***
	(0.005)	(0.010)	(0.009)
Quality==0	-0.246***	-0.074**	-0.080***
	(0.051)	(0.033)	(0.031)
Quality==1	-0.073***	-0.077***	-0.059***
	(0.018)	(0.018)	(0.018)
Quality==2	0.026	0.091**	0.142**
	(0.066)	(0.043)	(0.061)
Construction-year	-0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)
Construction-year^2	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Construction-year^{3}Construction-year	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Number of household members	-0.036***	-0.037***	-0.045***
	(0.002)	(0.004)	(0.004)
Number of children (age<18)	0.028***	0.031***	0.032***
	(0.002)	(0.004)	(0.004)
Number of elderly (age>64)	0.033***	0.029***	0.023***
	(0.004)	(0.006)	(0.003)
Number of female	0.024***	0.019***	0.015***
	(0.002)	(0.003)	(0.003)
Log (income)	0.187***	0.170***	0.158***
	(0.004)	(0.007)	(0.006)
Constant	1.073***	1.464***	0.767***
	(0.218)	(0.418)	(0.122)
Observations	103,834	23,187	23,187
R-squared	0.741	0.822	0.848

Notes:
Dependent variable is logarithm of transaction price.
The omitted categories are: for ”house type” variable it is ”Corner house”, for ”parking type” variable it is ”no parking place”, for ”location relative to the center” variable it is ”outside the urban area”, for ”view type” variable it is ”not specified”, for ”location relative to the road” variable it is ”near a quite road”, and for ”quality” variable it is ”not specified”.

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