The Rebound Effect in Residential Heating

Erdal Aydin
Tilburg University
Netherlands
e.aydin@uvt.nl

Dirk Brounen
Tilburg University
Netherlands
d.brounen@uvt.nl

Nils Kok
Maastricht University
Netherlands
n.kok@maastrichtuniversity.nl

August 30, 2013

Abstract

Over the years, various efficiency policies have been designed and implemented to reduce residential energy consumption. However, it is very common that the policy expectations that are based upon engineering calculations do not come true. The widely accepted explanation for the gap between expectation and the realization is the change of household behavior, as the energy efficiency gains change the perceived cost of energy services and thereby generate shifts in consumption patterns – the rebound effect. The real controversy about the rebound effect lies in the identification of its magnitude. In this paper, we estimate the rebound effect in residential energy consumption by comparing the actual gas consumption levels with the ex-ante predictions within a sample of well over 600,000 Dutch dwellings and households. We find a significant deviation between the engineering predictions and the households' actual energy consumption, a difference which varies by ownership, wealth, income and the actual gas use intensity. Our results show a rebound effect of 26.7 percent among home-owners, and 41.3 percent among tenants. Moreover, we find that these effects are greatest among the lower income-wealth groups, and among households that tend to use more gas than average.

JEL Codes: D12, Q51, R21

Keywords: energy efficiency, rebound effect, consumer behavior

The European Centre for Corporate Engagement (ECCE), the Dutch Ministry of Interior Affairs, and AgentschapNL provided financial support for this research. Kok is supported by a VENI grant from the Netherlands Organization for Scientific Research (NWO). We thank all participants at the 2013 AREUEA International Meeting in Jerusalem and 2013 ERES conference in Vienna for their comments.

1. Introduction

Residential energy consumption has returned on the top of agenda's in academia, business and policy. Around the world, new policy measures are being introduced to contend the outlook of depleting energy resources and the harmful effects of climate change that result from increasing carbon dioxide emissions. While stricter building codes have increased the thermal quality of newly constructed dwellings[1], many other residential energy conservation measures still struggle to meet their targets[2]. Irrespective of the effectiveness of these policies in increasing the thermal quality of the dwellings, a critical debate concerns how households respond to these efficiency improvements. Research showed that technological improvements leads to behavioral changes, as the corresponding energy efficiency gains decrease the perceived cost of energy services and thereby increases the demand – the rebound effect. Although the basic mechanism underlying the rebound effect is widely accepted, its magnitude remains a controversial issue. The studies that are analyzing the rebound effect in household heating provide estimates in the range 10-58 percent for the short-run direct rebound effect and 1.4-60 percent for the long-run effect (Sorrell et al., 2009). Inadequate definitions of the rebound effect, some methodological weaknesses and the small sample sizes are some of the reasons why these estimates differ too much. Methodological quality of most of these studies is relatively poor, with the majority using simple before-after comparisons, without use of a control group or accounting for measurement error in engineering predictions. Besides, many of them are prone to selection bias, since households choose to participate rather being randomly assigned. Another weakness is the small sample size which leads to imprecise estimates. The short monitoring periods make the identification of long term effects impossible.

In this paper, we empirically examine the rebound effect in residential heating. We exploit a large and detailed panel dataset that covers both the energy labels and utility bills of 670,000 addresses to investigate the misfit between engineering predictions and utility bills in the Dutch housing market. Using instrumental variable and fixed effects estimation methods, we compare the predicted energy use of the labels with actual energy consumption, while controlling for households composition and dwelling characteristics. The examination of the data reveals that the rebound effect is 41.3 percent for tenants and of 26.7 percent for the home-owners. Clearly, household energy behaviour does not align well with the predictions of engineers. Using the rich panel setting of our dataset, we also explore backgrounds that help to explain this behaviour. Here, we find that the rebound effect is strongest among the lower income groups since, as pointed out by Milne and Boarman (2000), these households are further from their satiation in consumption of many energy services. Finally, by using quantile regression approach, we

[1] See Grant D. Jacobsen and Matthew J. Kotchen, 2013
[2] See Frieden and Baker, 1983

examine whether the magnitude of the rebound effect depends upon the actual gas use intensity of the household. We find that the rebound effect is larger among the heavy energy consumers. It appears that income and usage patterns are key aspects to account for in the design of energy efficiency policies. The results and implications of this paper can be used by governments in other EU Member States, but also by countries outside the European Union, to increase the effectiveness of policies regarding energy efficiency measures.

The rest of this paper is organised as follows. The next section reviews the literature on rebound effect in residential energy use. Sections 3 describe the data and the calculation method used to predict residential energy use. In section 4, we present our methodology and the results, while section 5 concludes the paper.

2. Rebound Effects in Residential Energy Use

Over the years, various economists have focused on the question of how energy efficiency improvements affect energy consumption. From the outset, it became clear that energy consumption numbers are more than just a simple representation of the technical specification of the available hardware[3]. Technological improvements evoke behavioral responses, as the corresponding energy efficiency gains change the perceived cost of energy services and thereby trigger shifts in consumption patterns. In other words, as a response to the efficiency improvements, consumers often increase their total demand for the energy service, which partially offsets the initial efficiency gains[4]. The existence of this rebound effect is widely accepted, the real controversy lies in the identification of the size of the rebound (Greening et al., 2000). This is of great importance, as energy conservation policies are designed to reduce consumption levels, not consumption predictions.

The original paper by Khazzoom (1980) stimulated a series of empirical research on the rebound effect. The literature identifies three types of rebound effects that encompass the microeconomic and macroeconomic perspectives (Greening et al., 2000; Dimitropoulos and Sorrell, 2008): 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. This partly or fully offsets the expected reduction in energy 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. Economy-wide effects are the addition of direct and indirect effects.

[3] See Jevons (1865) for his early work on how the invention of more efficient steam engines, increased the use of coal.
[4] See Khazzoom (1980, 1987), Brookes (1990) and Wirl (1997) for a precise definition and discussion of the rebound effect.

In the literature, the transport and residential sectors are the two main areas where improvements in energy efficiency are of empirical relevance, as energy consumption levels are high in both, and technological innovations are abundant. For the residential sector, heating is one of the key interests, since there are many ways in which consumer behavior may influence the level of this energy demand, e.g. by means of choosing temperature levels, share of space heated and ventilation rates, setting thermostats and others. Yet, to derive efficient energy policies, it is necessary to know-at least roughly-the magnitude of the impact of consumer behavior changes which result from technical efficiency improvements. In the Netherlands, the market under investigation in this paper, the energy used for heating in the built environment makes up for almost 25 percent of total energy consumption. In recent years, the Dutch government has introduced several policy measures to stimulate the improvement of the energetic quality of dwellings[5]. For all of these policies, the policy makers assume that the expected energy savings equal to the expected efficiency gain. The available rebound effect literature, however, argues that these policy expectations are overshooting, as households are likely to respond to the efficiency improvements by increasing their demand for the particular energy service.

Measuring the rebound effect is not an easy task, as it involves an estimation of the elasticity of the demand for a particular energy services with respect to energy efficiency. Instead of using this original definition, the majority of available studies have estimated the rebound effect using price elasticity, since data on energy efficiency has always been limited. In principle, rational consumers should respond in the same way to a decrease in energy prices as they do to an improvement in energy efficiency. This assumption, however, does not always hold up, as energy efficiency itself may be affected by changes in energy prices[6].

Regarding, the measurement of the rebound effect in residential heating, evidence is mostly derived from household survey data. Dubin et al.(1986) compare the actual energy used for heating to engineering estimates before and after the efficiency improvement. They document a rebound effect ranging from 52 to 81 percent. Hseuh and Gerner (1993) use data from 1,281 single family detached households in the U.S., dating back to 1981. Comparing the engineering calculations and the realized energy consumption, they find that the short-run direct rebound effect is 35 percent for electrically heated homes and 58 percent for gas heated homes. Klein (1987:1988) uses comparable data from more than 2,000 U.S. households, supplemented with an engineering model of thermal performance of buildings and data on the capital cost of equipment. Klein's model suggests a short-run direct rebound effect in the range 25 to

[5] These policies include subsidy grants for energetic improvements to existing homes, stricter building codes for new construction, price subsidies for double glazing, solar panels, and customized energy advice, and since 2008 a widespread introduction of energy labels.

[6] Sorrell, Steve. The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency. London: UK Energy Research Centre, 2007.

29 percent. Guertin et al. (2003) use detailed survey data from 440 single family Canadian households. Their model suggests a long-run mean rebound effect of 38 percent, varying from 29 percent for high income groups to 47 percent for low income groups. They also find that the rebound effect for water heating is in the range 34 to 38 percent. The rebound effect for German households, studied by Haas and Biermayr (2000), is 15 to 30 percent. Douthitt (1986), studying 370 Canadian households, suggests short-run effects in the range 10 to 17 percent and long-run effects in the range 25 to 60 percent. Although, these studies are more reliable compared to the studies based upon price elasticities, they also have some drawbacks. First, the measurement error in engineering calculations which potentially leads to a bias in the estimated rebound effect is not taken into account. Second, they all rely upon small samples which could lead to imprecise estimates. Besides that, many of them suffer from sampling bias resulting from selection techniques used for participants, and many other factors are not controlled for (Greening and Greene, 2000). Some of these studies take the changes in the thermostat set point as the true measure of the activity. However, the thermostat set is just one of the indicator measures of the service provided (Frey and Labay, 1988).

In our analysis, we use a large representative sample of dwellings and their occupants in the Netherlands to estimate the rebound effect for residential heating. Comparing the engineering estimates with the realized gas consumption, we are able to estimate the direct rebound effect. In order to account for the random measurement error in engineering estimates, we benefit from the instrumental variable approach by including the dwelling age as an instrument. Although we control for the observed household characteristics such as income, size, province, employment status, gender, and age, we also estimate a fixed effects model to control for potential unobserved household characteristics that might be correlated with the thermal quality of the dwelling. The estimated rebound effect is expected to be comparable to the cross-sectional estimate. Finally, since the rebound effect might be heterogeneous for different segments of the population, we estimate the model for the groups of people with different income-wealth levels and tenure, separately. Besides, in order to examine the heterogeneity based on actual gas use intensity level, which is expected to be highly correlated with the size of the house, we benefit from the quantile regression approach which enables us to estimate the rebound effect for different groups of people with different gas consumption levels.

3. Dutch Energy Label Predictions and Utility Bills

We exploit a large panel of 710,000 dwellings and their occupants, which adopted an Energy Performance Certificate (EPC) in the years 2011 and 2012. This dataset includes information on the dwelling characteristics, household characteristics and the household’s annual gas consumption from

2008 to 2011. AgencyNL, a government agency, provides information on the characteristics of the certificated dwellings as well as their predicted gas consumption. We merge the dwelling information with the annual occupant characteristics and their actual gas consumption, which are provided by Bureau of Statistics in the Netherlands (CBS). Since the predicted gas use is calculated based on a fixed heating degree days value (212 days with an average outside temperature equal to be 5.64°C), the actual gas use in each year is corrected for the annual heating degree days in that year. We exclude the years in which the occupants change their addresses, 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 zero gas-electricity use, and we exclude the outliers which are detected based on the sample distribution of the house size, actual and predicted energy use (electricity and gas) variables. The upper and lower boundaries for the outliers are selected as 99% and 1% percentiles. The final dataset includes an unbalanced panel of 670,000 dwellings. Additionally, in order to check whether there are significant differences between the characteristics of the dwellings with and without label, we also use a sample of 100,000 dwellings that are not labeled. These are the dwellings which were sold in years 2011 and 2012, and registered by the National Association of Realtors (NVM).

3.1 Energy labels and predictions

In the Netherlands, all transactions in the housing market need to be accompanied by an energy performance certificate. 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 home into one of the energy classes; an engineer visits a home and inspects the physical characteristics of the home (e.g., size, quality of insulation, type of windows, etc.). The collected information is used to predict the total energy consumption of the dwelling. 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 is reported to an official database. Once the information is verified, the certificate is registered and issued to the seller. Appendix A provides a stylized example of the EU energy label. 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. 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. In 2009, a revision of the Energy Performance Certification scheme started that led to improvements ranging from training and examination of assessors, to an updated methodology and software, to a new layout of the Energy Performance Certificate, and to a newly adopted quality assurance scheme.[7]

The predicted total energy consumption is a combination of predicted gas and electricity use. However, the electricity component does not include the electricity used by household appliances which expected to constitute nearly 40 percent of total residential electricity consumption (Majcen et al., 2013). Therefore, since the predicted electricity is not comparable with actual electricity use, we focus only on residential gas consumption. Below, we outline a simplified version of the calculation method of the residential gas use. 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).

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

The gas used for cooking is not included in the calculations, since it highly depends on household behavior. However, we do not expect this to cause important biases, since this cooking gas use constitutes only 3% of the total residential gas use. The gas used for space heating is calculated by using the following formula:

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

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 gain 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 sum.

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

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

$$G^t = \left(\textstyle\sum_{k=1}^{K} w_k A_k U_k\right)(T_i - T_o)t \tag{4}$$

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. 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

[7]See http://www.epbd-ca.org/Medias/Pdf/country_reports_14-04-2011/The_Netherlands.pdf for a description of the energy label in the Netherlands.

assumed to be 18°C and 5.64°C, respectively. The other component of equation (3) is the loss of energy through ventilation which is calculated as below:

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

where f_1 and f_1 are the ventilation coefficients which depend on the type of ventilation and the infiltration rate. The useful 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 use 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}).

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

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

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

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

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).

The above calculation method is based upon some assumptions which are expected to lead to a measurement error in theoretical gas use. Especially, for the older dwellings, the inspector has to make assumptions regarding the U-value of outer walls and the rates of ventilation and infiltration. Since these assumptions are made in the light of the empirical engineering findings, we assume that the measurement error is not systematic. The other potential source of the measurement error is the quality of the inspection. The maximum deviation from the real energy index that is acceptable is 8 percent. The labels which deviate more than this value are considered as labels with critical defect. It is found that, in 2011, 16.7 percent of the labeled dwellings exceed this target. However, the findings indicate that the inspection error is not systematic[8]. Another assumption made in the calculation is that the occupants heat the whole useful floor area of the dwelling. This assumption might seem unrealistic considering the case of older and large size dwellings, since the occupants might prefer to heat only some of the rooms because of the higher cost of heating the whole space. However, in our research context, this assumption is acceptable and even required since we want to estimate the response of the occupants to the changing cost of thermal comfort. So, if the occupant prefers to heat only one part of the dwelling, this can be interpreted as the rebound effect since this preference is a result of the higher cost of heating the whole space. Therefore, this assumption cannot be considered as a source of measurement error in engineering predictions.

3.2 Gas use across the housing market

According to the CBS statistics, in 2009, 58 percent of the housing stock consisted of owner-occupied dwellings. However, since the diffusion of EPC among the owner-occupied houses in the Netherlands is relatively slow, the share of owner-occupied dwellings in our sample is only around 7 percent, which is far below this population average. Therefore, the rental housing is overrepresented in our sample. Since this might cause a sampling bias in the estimation of average rebound effect, we analyze the owner-occupied and rental dwellings separately. In Table 1, we present the summary statistics for the dwelling and occupant characteristics. The sample statistics indicate that there are only few differences in the average characteristics of the two sub-samples (rental versus owner-occupied dwellings). The gas consumption in the owner market seems to exceed the consumption in the rental market, but once correcting for the variation in dwelling size, the difference disappear. For both the rental and owner-occupied homes in our sample we find that the gas consumption predictions that are issued by the labels are higher than the actual gas bills. This difference is 18 percent for the rental homes, and about 13 percent for the owner-occupied dwellings. Regarding the distribution of energy label categories, we find almost no differences between the sub samples. The other variables indicate that there is overrepresentation of apartments in our rental sample, that rental homes are slightly younger, are smaller and accommodate smaller 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 use and the occupant characteristics are very similar for both samples. However, the non-labeled sample contains more dwellings which are built after 2000. This can be expected as the label adoption is not mandatory for the dwellings constructed after 1999.

[8] See "Derde onderzoek naar de betrouwbaarheid van energielabels bij woningen, 2011" by Ministry of Infrastructure and Environment

[Table 1]

Furthermore, we visually show the descriptive statistics of actual versus predicted energy use across label categories. Figure 1 shows in grey that, on average, gas use predictions correspond with the label categorization. Obviously, this is a result by design, as these predictions determine the categorization. When comparing these results with black box-plots, representing realized gas consumption, we observe a similar trend, but also clear deviations in the tails. The predictions are lower than the realized gas use for efficient dwellings and the reverse is true for inefficient dwellings. This can be considered as a first indication of the rebound effect since we expect that the households living in inefficient dwellings decrease their heating demand because of the higher cost of heating. Moreover, we also observe that the variation in gas consumption is much larger than for the predictions. The higher variation in actual gas use can be explained by the behavioral factors, such as time spent at home, that are not included in the engineering predictions.

[Figure 1]

Before we explain factors econometrically, we also stratify our sample across house type, to assess whether these deviations are common or specific. When comparing the statistics plotted in Figure 2, we find very similar patterns. It seems that type of the dwelling is not a reason why real gas consumption is different from what could be expected from the label. For all four house types (apartments. between houses. corner houses and detached houses), we find underestimations of gas use for energy efficient dwellings, and overestimations for inefficient dwellings.

[Figure 2]

In Figure 3, we plot the relationship between the predicted gas use and the ratio of actual versus predicted gas use. Here, we can consider the “predicted gas use” as the cost of heating the whole area of the dwelling at a fixed temprature, 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 is in line with the rebound effect hypothesis. Moreover, the two shades of grey tell us that the deviations between predicted and realized gas volumes are larger for tenants. This difference can be partly explained by the income-wealth differences between the two subsamples, as we expect the households with lower income and wealth level to be more sensitive to the cost changes.

[Figure 3]

4. Econometric Analysis of the Rebound Effect

The rebound effect is the elasticity of the demand for a particular energy service with respect to efficiency. In our case, the demanded energy service can be named as 'residential heating' which is a combination of occupant's preferences regarding the temperature level, share of heated space, heating duration, showering, and bath. Thus, we can define the rebound effect for residential heating as:

$$\tau_G = \partial \ln(H)/\partial \ln(\mu_H) \tag{9}$$

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 reached by use of 1 m^3 of gas:

$$\mu_H = H_r/G^* \tag{10}$$

In the formula above 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°C for the whole space of the dwelling during the heating season (212 days), and a fixed amount of hot water per person in a day. Assuming that there is a perfect correlation between the actual gas use and the actual residential heating consumption, we can define the actual level of heating that is consumed by households as follows:

$$H = H_r(G^a/G^*) \tag{11}$$

where G^a denotes the actual gas use. By using Equations (10) and (11), the rebound effect in Equation (9) can be redefined as follows:

$$\tau_G = \partial \ln[H_r(G^a/G^*)]/\partial \ln[H_r/G^*] \tag{12}$$

Since H_r is fixed, the above equation is equal to:

$$\tau_G = 1 - \partial \ln(G^a)/\partial \ln(G^*) \tag{13}$$

which describes the gap between actual and theoretical gas use.

4.1 The empirical model

In order to identify the rebound effect in residential heating demand, we estimate the gap between actual and theoretical gas use by using different estimation approaches. The standard econometric model that is used to estimate this gap can be defined as:

$$\ln(G_{it}^{a}) = \beta_0 + \beta_1 \ln(G_{it}^{*}) + \sum_{j=2}^{j} \beta_j Z_{jit} + \alpha_i + \varepsilon_{it} \qquad (14)$$

where, i is the household identifier and t is year. Z_{jit} is a vector of observed control variables which are not included in the calculation of EPC, but affecting the household's actual gas use, such as household size and composition, province, year, income, employment status of the household members, ownership of the house. The composite error term is a combination of α_i which denotes the unobserved household effects and the independent and normally distributed error term; ε_{it} . The coefficient of interest is:

$$\beta_1 = \partial \ln(G^{a}) / \partial \ln(G^{*}) \qquad (15)$$

which is used to estimate the rebound effect formulated in Equation (13):

$$\tau_G = 1 - \beta_1 \qquad (15)$$

We first estimate this model using pooled ordinary least squares (OLS) estimator, assuming that G_{it}^{*} is independent of $(\alpha_i + \varepsilon_{it})$. The results of these estimations are presented in Table 2, and show only partial fits between predicted and actual gas consumption levels. Here, β_1 ranges between 0.441 and 0.589, depending on the model specifications and the ownership status. We observe that controlling for the household characteristics leads to a decrease in the estimated coefficient. The signs and magnitudes of the estimated effects of our control variables are in line with the intuition. We find that as the household size increases by one person there will be an increase in residential gas use by around 10 percent with a decreasing marginal effect in larger households. The number of elderly people and the number of female individuals in the household also has a positive effect on residential gas use. The presence of children in the household has a modest positive effect for the households who are living in rental dwellings. We also control for the employment status of the household members. By including the dummy variable which indicates whether all the 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, then the gas use of that household decreases by 6 percent in rental units and 4 percent in owner-occupied dwellings. The income elasticity of residential gas demand is found to be equal to 0.05 for tenants and 0.08 for the home-owners. This is comparable to the results provided by Meier and Rehdanz (2010). Analyzing the UK households, they find the income elasticity of residential heating 0.03 for tenants and 0.04 for home-owners. In line with this income effect, for the rental sample, we also find that receiving rent subsidy (which is only available for the lowest income groups) also coincides with lower gas usage. Finally, considering the explanatory power of our model, we see that the predicted gas use together with the province and year dummies, explains 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 when we include the household characteristics. In the OLS estimations, although we use a large representative sample and control for the household characteristics, there is a potential for bias in the estimated rebound effect, which originates from the measurement error in engineering predictions. In the next section, we present our methodological solution and its results, which take this measurement error into account.

[Table 2]

4.2 Dealing with measurement error

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

$$G^p = G^* e^v \tag{16}$$

The multiplicative error term assumption is more plausible when a variable (i.e. theoretical gas use) is bounded from below by zero than that of the additive term assumption. Besides, as we already discussed in the data section, the allowable inspection error is described by percentage values (8%) by the engineers, which means that the inspection error is expected to be multiplicative. We also assume that the average measurement error is zero and e^v is not a systematic engineering mistake that is correlated with the theoretical gas use level.

$$E\,[e^v] = 0 \tag{17}$$

$$Cov\,[G^*,\ e^v] = 0 \tag{18}$$

Econometric theory suggests that 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 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^v). In our case, the age of the dwelling can be considered as an instrument satisfying both of these conditions as formulated below:

$$Cov\,[G^p,\ Age] \neq 0 \tag{19}$$

$$Cov\,[e^v,\ Age] = 0 \tag{20}$$

If the above assumptions are satisfied, we are able to disentangle the true variation in theoretical gas use (G^*). Thus, the econometric model specified in equation (14) can be rewritten as:

$$\ln(G^a_{it}) = \beta_0 + \beta_1 * \widehat{\ln(G^p_{it})} + \sum_{j=2}^{j} \beta_j Z_{jit} + \alpha_i + \varepsilon_{it} \tag{21}$$

where

$$\widehat{\ln(G^p_{it})} = \emptyset_0 + \sum_{q=1900}^{q=2012} \emptyset_q Age_{qi} + \widehat{\omega}_{it} \tag{22}$$

and Age_q is the dummy variable indicating the construction year (age) of the dwelling. $\hat{\theta}_q$ are the OLS parameter estimates obtained from the estimation of this model. The IV model described in Equations (21) and (22) is estimated by use of 2SLS estimator. By testing the joint significance of $\emptyset_q$, we can simply examine the validity of the relevance assumption specified in Equation (19). Table 3 reports the results of the IV-estimations.

[Table 3]

Compared to the previous OLS-estimates, we now find β_1 estimates of 0.587 and 0.733 for the rental and owner market, respectively. So, while the control variables all remained in place and of similar importance, we find that the use of IV-estimators has greatly reduced our rebound effect estimates to 41.3 percent and 26.7 percent. These results are much in line with the estimates of the available literature (Madlener and Hauertmann (2011), Hseuh and Gerner (1993), Klein (1987:1988), Guertin et al. (2003), Douthitt (1986), Haas and Biermayer (2000)). The difference between the estimated rebound effects for rental and owner-occupied dwellings is in line with the intuition that wealthier households are less sensitive to the cost changes. Madlener and Hauertmann (2011), analyzing the price elasticity of the residential heating for tenants and home-owners, also find a similar result for the German households. In the following sections, we further analyze the effect of wealth on the rebound effect. Considering the validity of our instrumental variable, it can be seen that the R-square of the first stage model which links the predicted gas use to the age of the dwelling is very high (25%). This indicates that our instrumental variable satisfies the relevance assumption which is a necessary condition for a valid instrument. On the other hand, since we have only one instrumental variable, we are not able to test the exogeneity assumption that is specified in Equation (20). However, we think that there is not an obvious reason to believe that the measurement error is correlated with the age of the dwelling. Overall, these IV estimation results indicate the importance of controlling for the measurement error in engineering calculations. Thus, any study which neglects this error has a potential of over-estimating the rebound effect.

4.3 Dealing with endogeneity

Another econometrical issue that may cause a biased estimate is the potential presence of household specific factors that affect both the actual gas use and thermal quality of the house. One reason for this potential correlation might be that the energy-conservative households select the energy-efficient dwellings. This selection may lead to overestimation of β_1, and so underestimation of the rebound effect. On the other hand, because of having low income, the cost-sensitive households might be accommodating in inefficient dwellings. In this case, there will be a downward bias in the estimation of β_1. Thus, our estimate will be biased if there exists any correlation between the theoretical gas use and unobserved household-specific factors:

$$Cov[G^*, \alpha_i] \neq 0 \tag{23}$$

In order to account for this correlation, we use the fixed effects (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 use due to the change of the characteristics of the dwelling in which the household lives. So, we can observe the change in the efficiency of the dwelling, keeping the corresponding household fixed. As described below, by using the fixed effect estimator, we are able to eliminate any unobserved household specific effects (α_i) that are correlated with the thermal quality of the house:

$$\Delta \ln(G_{it}^{a}) = \beta_0 + \beta_1 * \Delta \widehat{\ln(G_{it}^{p})} + \sum_{j=2}^{j} \beta_j \Delta Z_{jit} + \Delta \varepsilon_{it} \tag{24}$$

In the above equation Δ indicates the difference from the over-time mean value of the variable for the i th household. Independent of the validity of condition (23), the FE estimate of β_1 is consistent. Finally, in order to examine the condition (23), we test whether there is a significant difference between the random effect (RE-IV) and fixed effect (FE-IV) estimates of β_1. If there is not a significant difference between two estimates, then we can rely on the RE-IV results since it provides more efficient estimates.

First, assuming that the household specific effects are randomly distributed and independent of the theoretical gas use, we estimate the random effect model which provides efficient estimates compared to the polled OLS and fixed effects models. In Table 4, we see that the RE estimates of the rebound effect are very close to the pooled OLS results. However, in case of the presence of any correlation between the theoretical gas use and household specific unobserved factors, both pooled OLS and RE models lead to biased estimates. Therefore, as a next step in the analysis, we estimate the fixed effects model. According to the FE results, the rebound effect for rental dwellings is nearly same as the pooled OLS and RE estimates. However, the rebound effect for home-owners is higher compared to its OLS and RE counterparts. However, the standard error of this point estimate is relatively larger due to the limited number of home-owners who have changed their addresses. This leads to a larger confidence interval for the estimated rebound effect for home-owners. Next, we test whether the differences between RE and FE estimates are significant. Based on the t-test results, we conclude that there is not a systematic difference between FE and RE estimates. Therefore, relying on the RE estimates, we can conclude that the rebound effect for tenants is 41.8 percent and the rebound effect for home-owners is 27.8 percent. According to these results, on average, if the efficiency of an average dwelling is increased by 100 percent, this will lead to a 58 percent energy saving in rental dwellings and 72 percent energy saving in owner-occupied dwellings.

[Table 4]

4.4. Heterogeneous Effects

A final concern regarding the identification of the rebound effect relates to the potential heterogeneity of this effect among population. As we have seen from the results, the rebound effect differs by tenure. This leads us to further analyze the wealth effects on the magnitude of the rebound effect. The literature on price elasticity of energy indicates that the price elasticity parameter depends on the socio-economic characteristics of the consumers. Accordingly, since we expect that wealthier households are less sensitive to the cost changes, the rebound effect may be relatively lower for these households. Besides, it can be expected that these households already fully enjoy the residential heating, or come close to it. So, the utility that can be gained from heating the home above a comfortable room temperature will be lower. In order to test the impact of wealth on the rebound effect, we estimate our model separately for different wealth groups, and check whether there is any significant difference between the estimated rebound effects. In Table 5, we provide the results for different wealth groups among the home-owners. We divide the sample into five categories based on their position in the wealth distribution. The results show that as the household becomes richer the estimated rebound effect decreases. The rebound effect for the lowest

20th quantile is nearly 40 percent, while it is 19 percent for the upper 20th quantile. It should be noted that the average rebound effect for the home-owners in the lowest 20th quantile is nearly same as the estimated rebound effect for the average household living in a rental dwelling. Further, we analyze the heterogeneity of the rebound effect among tenants with different income levels. This time, we classify the households according to their income level since most of the tenants don't have any wealth. The results provided in Table 6 indicate that the rebound effect is heterogeneous among different income groups. For the lowest 20th quantile, the rebound effect is nearly 49 percent, while it is in the range of 38-40 percent for the upper quantiles.

[Table 5]

[Table 6]

Another source of heterogeneity relates to the actual gas use intensity of the household. So far, by use of OLS and panel data estimators we obtained conditional mean of β_1, which leads to estimation of an 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 can expect that the households who have to use relatively more gas because of the lower efficiency levels (including house size) are more sensitive to the efficiency changes. Therefore, the rebound effect might be larger for these households. In order to capture this heterogeneity, we benefit from the quantile regression approach. By doing so, we are able to estimate 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 (21)-(22) as follows:

$$min_{\beta_j} \sum_{i=1}^{n} \sum_{t=1}^{t} |\alpha_i + \varepsilon_{it}| \tag{25}$$

which can be also written as below:

$$min_{\beta_j} \sum_{i=1}^{n} \sum_{t=1}^{t} \left| \ln(G_{it}^{a}) - \left[\beta_0 + \beta_1 \widehat{\ln(G_{it}^{p})} + \sum_{j=2}^{j} \beta_j Z_{jit} \right] \right| \tag{26}$$

Another advantage of the quantile regression approach is its robustness to 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 use.

In table 7, we estimate the rebound effect for different quantiles of the actual gas use distribution. The 50th quantile (median) estimates of the rebound effect are nearly same as the conditional mean estimates. So, we can conclude that the outliers do not affect our results significantly. Considering the other quantiles of the distribution, we observe that as the actual gas use intensity of the household increases the rebound effect becomes more prominent. It increases from 30 percent to 50 percent for the rental dwellings and from 8 percent to 51 percent for the owner-occupied dwellings as we go from 10^{th} quantile to 90^{th} quantile of the actual gas use distribution.

5. Conclusions and Implications

Over the recent years, economists and policy makers have focused on the question of how energy efficiency improvements affect energy consumption. From the outset, it became clear that technological improvements change household behavior, as the corresponding energy efficiency gains decrease the perceived cost of energy services and so increase the demand. This phenomenon is termed as rebound effect. Since the existence of the rebound effect is widely accepted by the economist, the real controversy lies in the identification of the size of the rebound. This is of great importance, as energy conservation policies are mainly designed to increase the energy savings, not the energy efficiency.

In this study, we use a large representative sample of dwellings and their occupants in the Netherlands to estimate the rebound effect for residential heating. Comparing the engineering predictions with the realized gas consumption, we estimate the direct rebound effect. In order to account for the random measurement error in engineering predictions, we benefit from the instrumental variable approach by including the dwelling age as an instrument. We find that the rebound effect is 41 percent for tenants and 27 percent for home-owners. According to these results, on average, if the efficiency of an average dwelling is increased by 100 percent, this will lead to a 59 percent energy reduction in rental dwellings and 73 percent energy reduction in owner-occupied dwellings. The comparison of OLS and IV estimation results indicate the importance of controlling for the measurement error in engineering predictions. Thus, any study which neglects this error has a potential of over-estimating the rebound effect. Although we control for the observed household characteristics such as income, size, province, employment status, gender, and age, we also estimate a fixed effects model to control for potential unobserved household characteristics that might be correlated with the thermal quality of the dwelling. Using the t-test results, we conclude that there is not a systematic difference between FE, RE and OLS estimates. We also estimate our model separately for different wealth groups, and check whether there is any significant difference between the estimated rebound effects. The results show that as the household becomes richer the rebound effect decreases. The rebound effect for the lowest 20^{th} quantile is around 40 percent, while it is nearly 19 percent for the upper 20^{th} quantile. Moreover, we analyze the heterogeneity of the rebound effect among tenants with different income levels. For the lowest 20^{th} quantile, the rebound effect is nearly 49 percent, while it is in the range of 38-40 percent for the upper quantiles. Another source of heterogeneity relates to the gas use intensity of the household. In order to capture this heterogeneity, we benefit from the quantile regression approach. We observe that as the actual gas use intensity of the household increases, the rebound effect becomes more prominent. It increases from 30 percent to 50 percent for the rental dwellings and from 8 percent to 51 percent for the owner-occupied dwellings as we go from 10^{th} quantile to 90^{th} quantile of the actual gas use distribution.

This study is the first study analyzing the rebound effect based on a large data set including high-variation efficiency data. The use of IV approach and the panel structure of the dataset enable us to identify the rebound effect in residential heating. It appears that income and usage patterns are key aspects to account for in the design of energy efficiency policies. The results and implications of this paper can be used by governments in other EU Member States, but also by countries outside the European Union, to increase the effectiveness of policies regarding energy efficiency measures.

References

A. Greening, L., Greene, D. L., & Difiglio, C. (2000). Energy efficiency and consumption — the rebound effect — a survey.*Energy Policy*, *28*(6–7), 389–401.

Alcott, B. (2005). Jevons' paradox. *Ecological Economics*, *54*(1), 9–21.

Berkhout, P. H. G., Muskens, J. C., & W. Velthuijsen, J. (2000). Defining the rebound effect. *Energy Policy*, *28*(6–7), 425–432.

Binswanger, M. (2001). Technological progress and sustainable development: what about the rebound effect? *Ecological Economics*, *36*(1), 119–132.

Brookes, L. (1990). The greenhouse effect: the fallacies in the energy efficiency solution. *Energy Policy*, *18*(2), 199–201.

Dolthitt, R. A. (1986). The Demand for Residential Space and Water Heating Fuel by Energy Conserving Households. *Journal of Consumer Affairs*, *20*(2), 231–248.

Dubin, J. A., Miedema, A. K., & Chandran, R. V. (1986). Price Effects of Energy-Efficient Technologies: A Study of Residential Demand for Heating and Cooling. *RAND Journal of Economics*, *17*(3), 310–325.

Freire González, J. (2010). Empirical evidence of direct rebound effect in Catalonia. *Energy Policy*,*38*(5), 2309–2314.

Frey, C. J. (Liberty D. C., & Labay, D. G. (College of M. S. (1988). An examination of energy take-back.*Energy Systems and Policy; (USA)*, *12:3*.

Frieden, B. J., & Baker, K. (1983). The market needs help: The disappointing record of home energy conservation. *Journal of Policy Analysis and Management*, *2*(3), 432–448.

Guertin, C., Kumbhakar, S.C.&Duraiappah,A.K. (2003) Determining demand for energy services: investigating income-driven behaviors. International Institute for Sustainable Development.

Haas, R., & Biermayr, P. (2000). The rebound effect for space heating Empirical evidence from Austria. *Energy Policy*,*28*(6–7), 403–410.

Haas, R., & Schipper, L. (1998). Residential energy demand in OECD-countries and the role of irreversible efficiency improvements.*Energy Economics*, *20*(4), 421–442.

Hsueh, L.-M., & Gerner, J. L. (1993). Effect of Thermal Improvements in Housing on Residential Energy Demand. *Journal of Consumer Affairs*, *27*(1), 87–105.

Jacobsen, G. D., & Kotchen, M. J. (2011). Are Building Codes Effective at Saving Energy? Evidence from Residential Billing Data in Florida. *Review of Economics and Statistics*,*95*(1), 34–49.

Jevons, W.S., (1865) The Coal Question: Can Britain Survive? First puplished in 1865, re-published by Macmillan, London, UK, 1906.

Jin, S.-H. (2007). The effectiveness of energy efficiency improvement in a developing country: Rebound effect of residential electricity use in South Korea. *Energy Policy*, *35*(11), 5622–5629.

Kaza, N. (2010). Understanding the spectrum of residential energy consumption: A quantile regression approach. *Energy Policy*,*38*(11), 6574–6585.

Khazzoom, J. D. (1980). Economic Implications of Mandated Efficiency in Standards for Household Appliances. *The Energy Journal*, *Volume 1*(Number 4), 21–40.

Khazzoom, J. D. (1987). Energy Saving Resulting from the Adoption of More Efficient Appliances. *The Energy Journal*, *Volume 8*(Number 4), 85–89.

Klein, Yehuda L. (1988). An Econometric Model of the Joint Production and Consumption of Residential Space Heat. *Southern Economic Journal*, *55*(2), 351.

Klein, Yehuda Levi. (1987). Residential energy conservation choices of poor households during a period of rising fuel prices.*Resources and Energy*,*9*(4), 363–378.

Majcen, D., Itard, L., & Visscher, H. (2013). Actual and theoretical gas consumption in Dutch dwellings: What causes the differences? *Energy Policy*,*61*, 460–471.

Milne, G., & Boardman, B. (2000). Making cold homes warmer: the effect of energy efficiency improvements in low-income homes A report to the Energy Action Grants Agency Charitable Trust.*Energy Policy*, *28*(6–7), 411–424.

Mizobuchi, K. (2008). An empirical study on the rebound effect considering capital costs. *Energy Economics*, *30*(5), 2486–2516.

Sorrell, S., & Dimitropoulos, J. (2008). The rebound effect: Microeconomic definitions, limitations and extensions. *Ecological Economics*, *65*(3), 636–649.

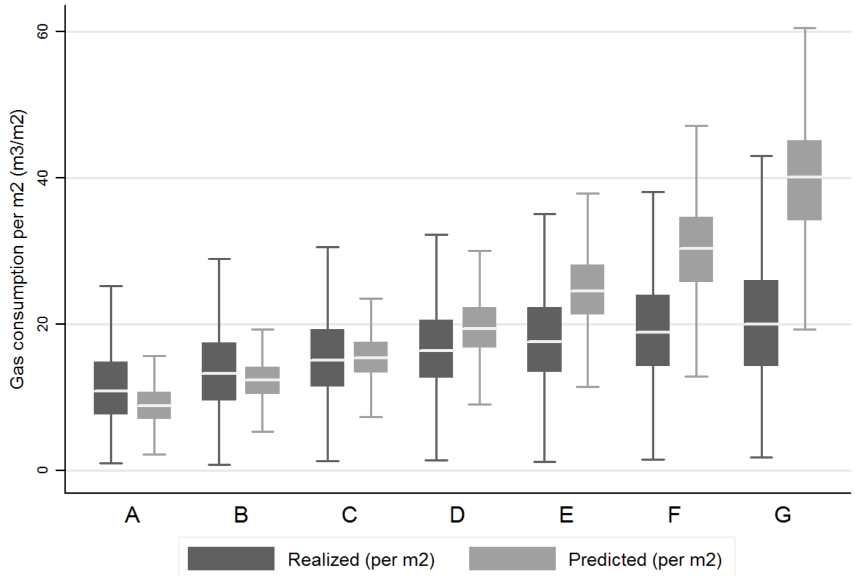
Sorrell, S., Dimitropoulos, J., & Sommerville, M. (2009). Empirical estimates of the direct rebound effect: A review. *Energy Policy*,*37*(4), 1356–1371.

The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency. (n.d.).

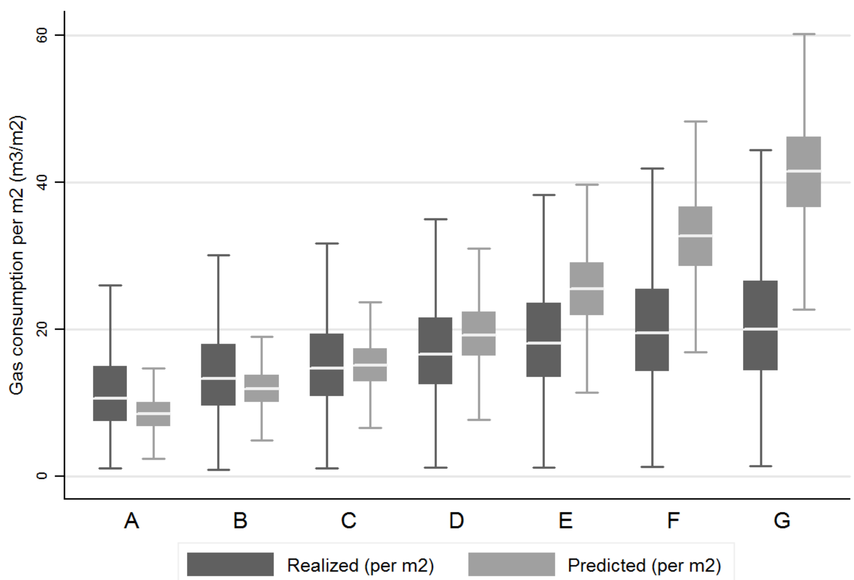
Wirl, F. (1997). The Economics of Conservation Programs. Springer.

Figure 1: Predicted versus Actual Gas consumption

a) Rental

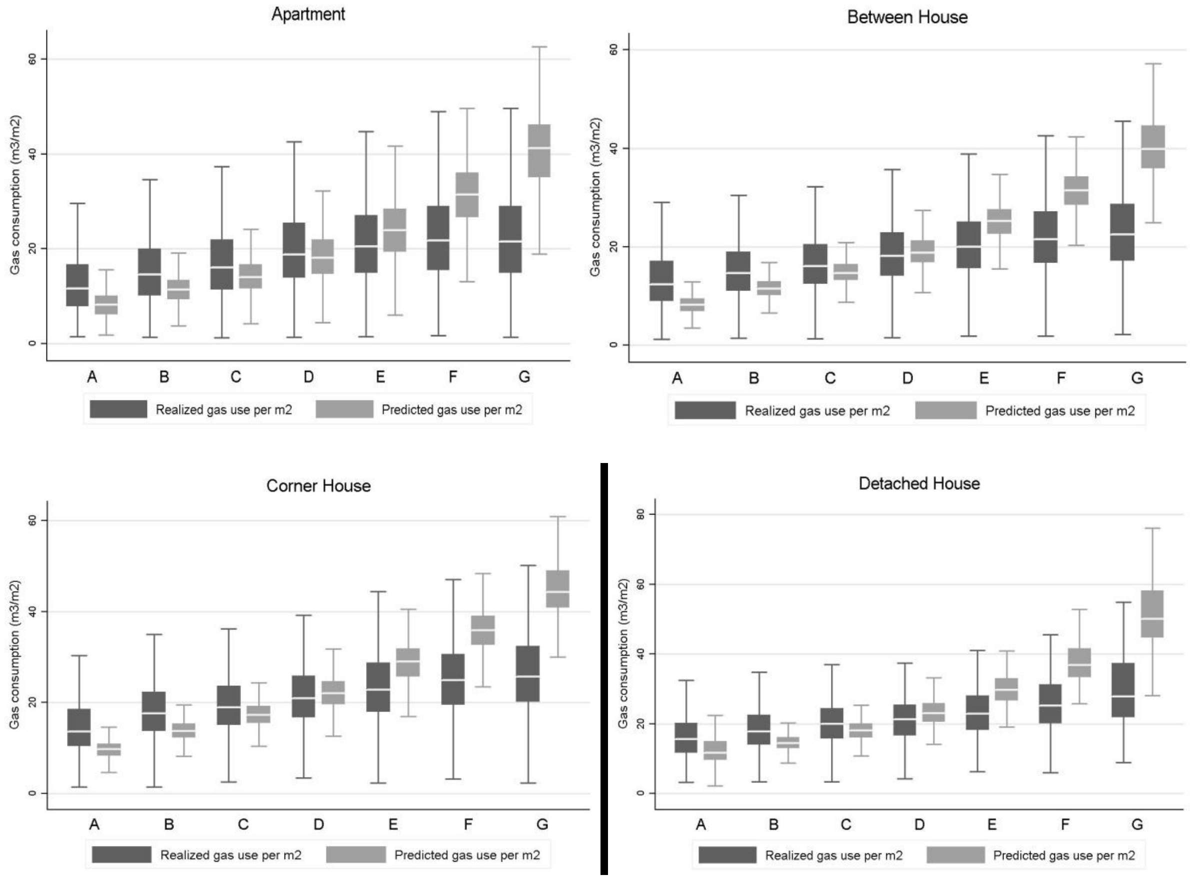


b) Owner-occupied



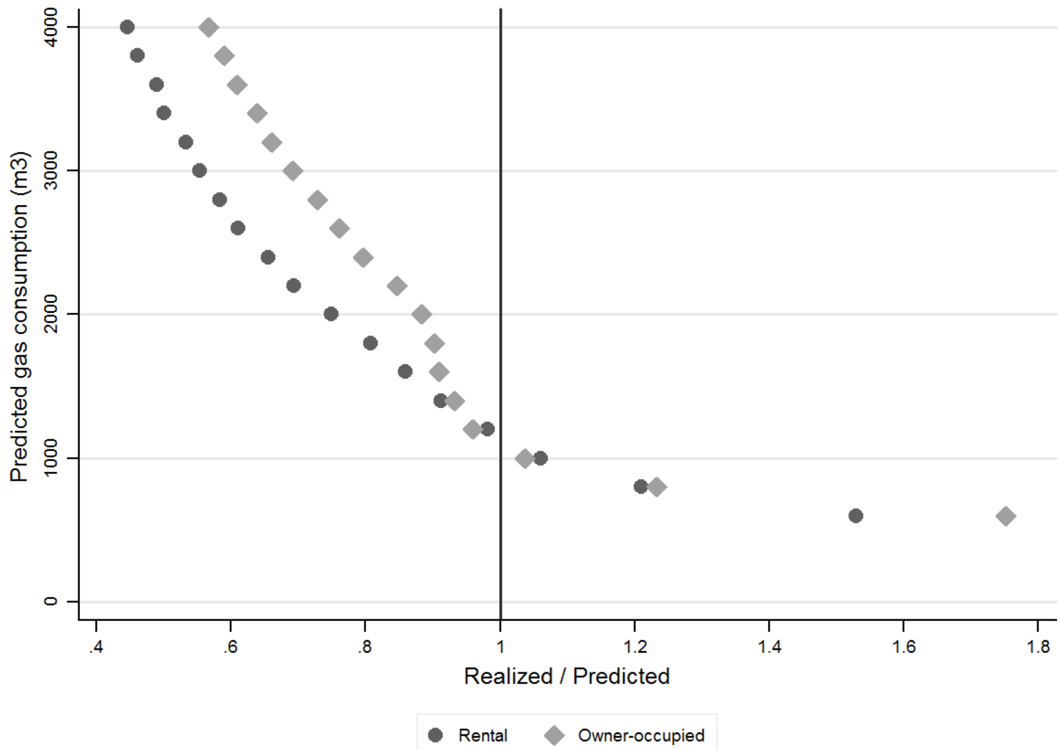
Source: Bureau of Statistics in the Netherlands (CBS) and AgentschapNL

Figure 2: Predicted versus Realized Gas consumption by House Type



Source: Bureau of Statistics in the Netherlands (CBS) and AgentschapNL

Figure 3: Realized/Predicted Gas Use



Source: Bureau of Statistics in the Netherlands (CBS) and AgentschapNL

Table 1: Descriptive Statistics

	Rental (With Label)		Owner occupied (With Label)		Owner occupied (Without Label)	
Variables	Mean	Std	Mean	Std	Mean	Std
Actual Gas Consumption (m^3)	1,218	[606]	1,536	[657]	1,532	[626]
Predicted Gas Consumption (m^3)	1,407	[651]	1,864	[759]		
Actual Gas Consumption (m^3/m^2)	16.8	[7.7]	16.3	[6.9]		
Predicted Gas Consumption (m^3/m^2)	18.7	[8.1]	18.1	[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			
House Type						
Apartment	0.49		0.27		0.21	
Between	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	0.2		0.19		0.15	
1970-1979	0.19		0.25		0.17	
1980-1989	0.2		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	1.89	[1.11]	2.35	[1.21]	2.26	[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 Female	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 (Euro)	24,496	[12,514]	39,210	[23,013]	39,297	[26,185]
Household Wealth (Euro)	23,198	[91,572]	208,238	[393,767]	219,910	[539,534]
Share of households receiving rent subsidy	0.41					
Number of Observations	623,868		44,741		92,843	

Since the label categories A+ and A++ have a small share in the full sample, we merged these categories with the label A. "Apartment"' category is a combination of 4 different apartment types which are reported in the AgentschapNL data.

Table 2: Pooled OLS Estimation Results

	Rental	Owner	Rental	Owner
Predicted Gas Use	0.485***	0.589***	0.441***	0.528***
	[0.001]	[0.003]	[0.001]	[0.003]
N. Household Members			0.118***	0.132***
			[0.001]	[0.005]
N. Household Members^2			-0.012***	-0.014***
			[0.000]	[0.001]
N. Children(<18)			-0.009***	0.001
			[0.001]	[0.003]
N. Elderly (Age>64)			0.031***	0.049***
			[0.001]	[0.003]
N. Female			0.037***	0.016***
			[0.001]	[0.003]
All Household members are working			-0.060***	-0.042***
			[0.001]	[0.003]
Log of household income			0.054***	0.075***
			[0.001]	[0.003]
Rent subsidy			-0.032***	
			[0.001]	
Province Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Constant	3.725***	3.038***	3.295***	2.481***
	[0.006]	[0.026]	[0.012]	[0.039]
R-Squared	0.210	0.361	0.255	0.402
N	1,664,113	87,282	1,664,113	87,282
N-groups	623,868	44,741	623,868	44,741

* P<0.05. ** P<0.01. *** P<0.001

Table 3: Pooled OLS-Instrumental Variable Estimation Results

	Rental	Owner
Predicted Gas Use	0.587***	0.733***
	[0.001]	[0.007]
N. Household Members	0.093***	0.105***
	[0.001]	[0.005]
N. Household Members^2	-0.010***	-0.011***
	[0.000]	[0.001]
N. Children(<18)	-0.004***	0.001
	[0.001]	[0.003]
N. Elderly (Age>64)	0.031***	0.049***
	[0.001]	[0.003]
N. Female	0.034***	0.043***
	[0.001]	[0.003]
All Household members are working	-0.056***	-0.038***
	[0.001]	[0.004]
Log of household income	0.052***	0.051***
	[0.001]	[0.004]
Rent subsidy	-0.034***	
	[0.001]	
Province Dummy	Yes	Yes
Year Dummy	Yes	Yes
Constant	2.276***	1.208***
	[0.015]	[0.054]
R-Squared	0.239	0.375
R-Squared (First stage regression)	0.225	0.256
N	1,664,113	87,282
N-groups	623,868	44,741

* P<0.05. ** P<0.01. *** P<0.001

"Predicted gas use" is instrumented by "Year of Construction"

Table 4: Random Effects and Fixed Effects-Instrumental Variable Estimation Results

	Random Effect Model		Fixed Effect Model	
	Rental	Owner	Rental	Owner
Predicted Gas Use	0.582***	0.722***	0.584***	0.663***
	[0.002]	[0.009]	[0.011]	[0.051]
N. Household Members	0.086***	0.094***		
	[0.001]	[0.005]		
N. Household Members^2	-0.008***	-0.009***		
	[0.000]	[0.001]		
N. Children(<18)	0.001	0.004		
	[0.001]	[0.003]		
N. Elderly (Age>64)	0.026***	0.034***		
	[0.001]	[0.003]		
N. Female	0.027***	0.011***		
	[0.001]	[0.003]		
All Household members are working	-0.026***	-0.016***	0.000	0.004
	[0.001]	[0.003]	[0.001]	[0.006]
Log of household income	0.054***	0.075***	0.001	0.008
	[0.001]	[0.003]	[0.002]	[0.007]
Rent subsidy	-0.013***		0.001	
	[0.001]		[0.001]	
Province Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Constant	2.705***	1.568***	3.961***	2.138***
	[0.019]	[0.067]	[0.110]	[0.423]
R-Squared	0.209	0.355	0.165	0.243
R-Squared (within)	0.032	0.017	0.024	0.021
R-Squared (between)	0.222	0.357	0.176	0.249
N	1,664,113	87,282	994,804	44,876
N-groups	623,868	44,741	351,462	21,595

* P<0.05. ** P<0.01. *** P<0.001

"Predicted gas use" is instrumented by "Year of Construction"

Fixed Effect results are based on the sample of households with constant household composition over-time.

Table 5: Pooled OLS-IV Estimation Results for Different Wealth Percentiles

	0-20%	20-40%	40-60%	60-80%	80-100%
Predicted Gas Use	0.602***	0.676***	0.724***	0.811***	0.811***
	[0.021]	[0.021]	[0.018]	[0.017]	[0.019]
N. Household Members	0.170***	0.182***	0.102***	0.047***	0.012
	[0.015]	[0.015]	[0.014]	[0.014]	[0.018]
N. Household Members^2	-0.019***	-0.017***	-0.014***	-0.002	0.001
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]
N. Children(<18)	0.015	-0.008	0.019*	-0.019*	-0.006
	[0.010]	[0.010]	[0.009]	[0.009]	[0.012]
N. Elderly (Age>64)	0.054***	0.023*	0.012	0.034***	0.027***
	[0.013]	[0.011]	[0.007]	[0.006]	[0.007]
N. Female	0.008	0.002	0.021**	0.017*	0.017
	[0.008]	[0.007]	[0.007]	[0.008]	[0.0010]
All Household members are working	0.006	0.006	0.029**	0.065***	0.043***
	[0.010]	[0.011]	[0.010]	[0.010]	[0.012]
Log of household income	0.042***	0.017	0.063***	0.052***	0.021
	[0.010]	[0.011]	[0.010]	[0.010]	[0.013]
Province Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Constant	2.189***	1.858***	1.168***	0.689***	1.037***
	[0.170]	[0.177]	[0.159]	[0.147]	[0.174]
R-Squared	0.300	0.330	0.352	0.335	0.339
N	11,342	11,342	11,342	11,342	11,342

* P<0.05. ** P<0.01. *** P<0.001

"Predicted gas use" is instrumented by "Year of Construction"

We only use the sample of owner-occupied houses, and we exclude year 2011 from the analysis since the wealth information is not available for this year

Households are assigned to the groups based on their wealth levels (percentiles)

Table 6: Pooled OLS-IV Estimation Results for Different Income Percentiles

	0-20%	20-40%	40-60%	60-80%	80-100%
Predicted Gas Use	0.515***	0.597***	0.599***	0.625***	0.598***
	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]
N. Household Members	0.140***	0.052***	0.066***	0.102***	0.134***
	[0.005]	[0.004]	[0.003]	[0.003]	[0.002]
N. Household Members^2	-0.017***	-0.005***	-0.010***	-0.011***	0.013***
	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
N. Children(<18)	0.015***	0.030***	0.023***	-0.009***	-0.013***
	[0.004]	[0.003]	[0.002]	[0.002]	[0.001]
N. Elderly (Age>64)	0.107***	0.056***	0.022***	0.019***	0.030***
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
N. Female	0.062***	0.026***	0.027**	0.027***	0.017***
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
All Household members are working	-0.029***	-0.082***	-0.097***	-0.052***	-0.026***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Log of household income	0.031***	0.008	-0.008	0.109***	0.053***
	[0.005]	[0.013]	[0.012]	[0.009]	[0.003]
Rent subsidy	-0.017***	-0.038***	-0.036***	-0.042***	-0.042***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Province Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
Constant	2.915***	2.688***	2.836 ***	1.410***	2.122***
	[0.052]	[0.126]	[0.121]	[0.093]	[0.041]
R-Squared	0.169	0.213	0.245	0.243	0.243
N	332,299	332,225	332,275	332,284	332,305

* P<0.05. ** P<0.01. *** P<0.001

“Predicted gas use” is instrumented by “Year of Construction”

We only use the sample of rental houses.

Households are assigned to the groups based on their income levels (percentiles)

Table 7: Quantile Regression-IV Estimation Results for Different Actual Gas Consumption Levels

	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Rental	0.699***	0.647***	0.599***	0.553***	0.494***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
Owner-occupied	0.922***	0.826***	0.750***	0.644***	0.492***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]

* P<0.05. ** P<0.01. *** P<0.001

"Predicted gas use" is instrumented by "Year of Construction"

Quantiles are chosen based on the actual gas use level of the households

Appendix A| Cover Page of the EPC

Energielabel woning

Afgegeven conform de Regeling energieprestatie gebouwen.

Veel besparingsmogelijkheden

Weinig besparingsmogelijkheden

D

(zie toelichting in bijlage)

Uw woning

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

Rijwoning - Tussen

Gebruiksoppervlak	**Adviesbedrijf**
131,0 m²	Advies BV
Opnamedatum	**Inschrijfnummer**
01-01-2010	
Energielabel geldig tot	**Handtekening**
01-01-2020	
Afmeldnummer	

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: -

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