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

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Abstract

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 paper 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.

JEL Codes: D12, Q51, R21

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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 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 behaviour, 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 easily 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. In this model, households acquire utility from consuming energy services, rather than from consuming the energy itself. When energy efficiency of a particular service is improved, without leading to an offsetting change in the price of energy, household realizes 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 a rebound effect is widely acknowledged, the real debate lies in the identification and the size of it (Gillingham et al., 2013; Greening et al., 2000). So far, due to the uncertainty regarding its actual size, rebound effect has been disregarded in the ex-ante impact assessments of the energy conservation measures (e.g. building regulations and energy efficiency subsidy programs), leading to higher expectations about their role in saving

[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.

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. Besides, 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 also contribute to the development and targeting of the energy efficiency measures. Taking the heterogeneity into account, energy conservation policies can be designed in a way to target consumers that are less likely to change their consumption behavior. Due to these policy implications, there is a growing interest on the identification of the magnitude of the rebound effect.

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 the 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 the 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 (2014) documents that, for a sample of consumers who are enrolled to 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 the symmetry assumption is satisfied, many studies estimating price elasticity of energy demand fail to address the endogeneity concerns, as the adoption of energy-efficient technologies itself may be affected by changes in energy prices (Sorrell et al., 2009).[2]

In the literature, the transport sector and the residential sector are the two main areas

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

where improvements in energy efficiency have been studied previously, as energy consumption levels are high in both sectors, and technological innovations are fast-evolving.[3] However, due to the limited availability of data, the literature on the housing market has been limited thus far. For the housing market, residential heating is one of the key interests, 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.

A 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 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-section analysis may lead to a bias that might arise due to the unobserved heterogeneity. Finally, since a complete efficiency measure requires detailed information regarding the technical characteristics of the dwelling, 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 taken back (although not statistically significant) due to the change in internal temperature. Milne

[3]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.

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 - 100 percent less than the expected numbers. However, besides the problems associated to 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 the use of a control group. Since there might be other factors which may also have affected the observed outcome (thermostat setting), the use of simple before-after comparisons might lead to biased results (Meyer, 1995). Besides, they 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 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 with a continuous 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 (EPC), 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 also 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 higher 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 56 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.

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.[4] 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 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.[5]

In this study, we use predicted gas consumption, which is provided by EPC, as a measure of thermal efficiency. In Appendix B, we explain a simplified version of the engineering model that is used to predict the required amount of residential gas necessary to achieve a fixed level of thermal comfort.[6] As mentioned by Pérez-Lombard et al. (2009), these "asset rating" engineering models are based on standard usage patterns and climatic conditions that do not depend on occupant behavior, actual weather and indoor conditions, and are developed to rate the building and not the occupant. 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

[4]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.

[5]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.

[6]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.

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.[7]

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. 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 correlated with the degree of efficiency of a dwelling. Given the fact that the engineering models that are used in the calculation procedure are 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 in the engineering predictions of energy efficiency.

The other potential source of measurement error is the quality of the inspection. The maximum deviation from the real energy index that is acceptable is eight percent. The labels that deviate more than this value are considered as labels with a critical defect. In 2011, it was documented that 16.7 percent of the labeled dwellings exceeded this target.[8] Examination of

[7]In the engineering literature, there are studies which examine whether engineering predictions of energy consumption fit with the actual energy consumption. Comparing the predictions of three different engineering models with the utility bills, Edwards et al. (2013) report that engineering models over-predicts the households' actual gas consumption. The authors argue that the resulting gap is mostly associated to the assumptions regarding standard occupant behavior. As our aim in this study is to measure the gap between a percentage improvement in predicted energy consumption and the resulting percentage change in realized energy consumption, the over-prediction of energy consumption due to the assumptions regarding the standard occupant's behavior (which are same for all dwellings) do not affect our results.

[8]Ministry of Infrastructure and Environment (2011). Derde onderzoek naar de betrouwbaarheid van energielabels bij woningen.

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.[9]

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 dataset includes information on the dwelling characteristics, household characteristics and the households annual gas consumption from 2008 to 2011. 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), the actual gas consumption in each year is corrected for the annual heating degree days (HDD) in that year.[10]

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 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

[9]By using the data on 47 re-inspections, provided by Ministry of Infrastructure and Environment (2011), we found that there is no significant relationship between the true energy index and the inspection error. The estimated correlation coefficient is equal to 0.105 with a p-value 0.482.

[10]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 gap between engineering predictions and realized consumption in Table 1. Since we include year and location dummies in our model in order to control for varying climatic conditions, this correction is not needed in the analysis, and do not alter our results.

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 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. 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.

[Insert Table 1 here]

Figure 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.

[Insert Figure 1 here]

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 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.

[Insert Figure 2 here]

In Figure 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.

[Insert Figure 3 here]

4 Methodology and Results

The rebound effect can be described as the elasticity of demand for a particular energy service with respect to 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:

$$\tau_G = \partial ln(H)/\partial ln(\mu_H) \tag{1}$$

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:

$$\mu_H = H_r/G^* \tag{2}$$

In equation (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 a 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:

$$H = H_r(G^a/G^*) \tag{3}$$

where G^a denotes the actual gas consumption. By using Equations (2) and (3), the rebound effect (1) can be redefined as:

$$\tau_G = \partial ln[H_r(G^a/G^*)]/\partial ln[H_r/G^*] \tag{4}$$

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

$$\tau_G = 1 - \partial ln(G^a)/\partial ln(G^*) \tag{5}$$

which describes the relationship between actual and theoretical gas use.

A. 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:

$$ln(G^a_{it}) = \beta_0 + \beta_1 ln(G^p_{it}) + \sum_{j=2}^{j} \beta_j Z_{jit} + \alpha_i + \varepsilon_{it} \tag{6}$$

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 households 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:

$$\beta_1 = \partial ln(G^a)/\partial ln(G^p) \tag{7}$$

which is used to estimate the rebound effect formulated in Equation (5):

$$\tau_G = 1 - \beta_1 \tag{8}$$

We first estimate this model using pooled ordinary least squares (OLS), assuming that G^p_{it} is independent of $(\alpha_i + \varepsilon_{it})$. The results of these estimations are presented in Table 2. 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 actual energy consumption and engineering predictions. We interpret this as evidence on the influence of household behavior on residential energy consumption.

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.

[Insert Table 2 here]

B. Measurement Error in Engineering Predictions

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:

$$G^p = G^* e \tag{9}$$

As discussed in the data section, 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 average measurement error is zero and 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^*). Thus, the model specified in equation (6) can be rewritten as:

$$ln(G^a_{it}) = \beta_0 + \beta_1 \widehat{ln(G^p_{it})} + \sum_{j=2}^{j} \beta_j Z_{jit} + \alpha_i + \varepsilon_{it} \tag{10}$$

where

$$\widehat{ln(G^p_{it})} = \widehat{\theta}_0 + \sum_{q=1900}^{q=2012} \widehat{\theta}_q T_{qi} \tag{11}$$

T_q is the dummy variable indicating the construction year of the dwelling. $\widehat{\theta}_q$ are the OLS parameter estimates obtained from the estimation of this model (11). The IV model described in Equations (10) and (11) is estimated by using a 2SLS estimator. By testing the joint significance of $\widehat{\theta}_q$, we can examine the validity of the relevance assumption.

Table 3 reports the results of the IV-estimations. Compared to OLS-estimates in Table 2, we now document β_1 estimates of 0.587 and 0.733 for the rental and owner-occupied sample, respectively. 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 sample.

These results are in line with the estimates in the literature. 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 effect of wealth and income on the heterogeneity of the rebound effect.

[Insert Table 3 here]

C. 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 income 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 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 efficiency of the dwelling, keeping the characteristics of the household fixed. As described below, 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:

$$[ln(G^a_{it}) - \overline{ln(G^a_i)}] = \beta_0 + \beta_1[\widehat{ln(G^p_{it})} - \overline{\widehat{ln(G^p_i)}}] + \sum_{j=2}^{j} \beta_j [Z_{jit} - \overline{Z_{ji}}] + [\varepsilon_{it} - \overline{\varepsilon_i}] \tag{12}$$

where the variables are measured as the difference from the over-time mean value of the variable for the ith household. This model 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. Finally, 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 no 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 are independent of the theoretical gas consumption, we estimate a random-effects model, which provides the most efficient estimates compared to the pooled OLS and fixed-effects models. In Table 4, the results show that the RE estimates of the rebound effect are quite comparable to the pooled OLS results. However, in case of the presence of any correlation between the theoretical gas consumption 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 a fixed-effects model. According to the FE estimation results, in columns (3) and (4), the rebound effect for rental dwellings is nearly the same as the pooled OLS and RE estimates.[11] The rebound effect for homeowners is higher as compared to the OLS and RE estimations. However, the standard error of this point estimate is relatively large due to the limited number

[11] 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.

of homeowners who have changed their addresses. This leads to a larger confidence interval for the estimated rebound effect for homeowners.

We also test whether the differences between RE and FE estimates are significant. Based on Hausman test statistics, we conclude that there is no systematic difference between FE and RE estimates. Therefore, relying on the RE estimates, we conclude that the rebound effect for tenants is 41.8 percent and the rebound effect for homeowners is 27.8 percent. According to these results, 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, *ceteris paribus*.

[Insert Table 4 here]

D. 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 5, 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. (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.)

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 5 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. Wealth and income matter for the behavioral response of homeowners and tenants to the energy efficiency of a dwelling.

[Insert Table 5 here]

Another source of heterogeneity relates to the actual gas consumption level of the household. Using OLS and panel data 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 (10)-(11) as follows:

$$min_{\beta_j} \sum_{i=1}^{n} \sum_{t=1}^{t} |\alpha_i + \varepsilon_{it}| \tag{13}$$

which can be also written as:

$$min_{\beta_j} \sum_{i=1}^{n} \sum_{t=1}^{t} |ln(G_{it}^{a}) - [\beta_0 + \beta_1 \widehat{ln(G_{it}^{p})} + \sum_{j=2}^{j} \beta_j Z_{jit}]| \tag{14}$$

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 6, 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. 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.

[Insert Table 6 here]

E. 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.[12]

In Table 7, 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

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

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.

[Insert Table 7 here]

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:

$$\Delta ln(G_i) = \beta_0 + \beta_1 \Delta ln(EI_i) + \sum_{j=2}^{J} \beta_j \Delta Z_{ji} + \Delta\epsilon_i \tag{15}$$

where $\Delta ln(G_i)$ is the change in the logarithm of actual gas consumption from 2009 to 2011 for dwelling i, and $\Delta ln(EI_i)$ is the change in logarithm of energy index for that dwelling.[13] 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)

[13]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.

method, where the probability of being treated is estimated by using a logit model including dwelling characteristics as regressors. This 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.

[Insert Table 8 here]

Table 8 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 (44.1 percent). These results indicate that the average rebound effect is around 56 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 6, 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.

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.

This study uses 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 56 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.

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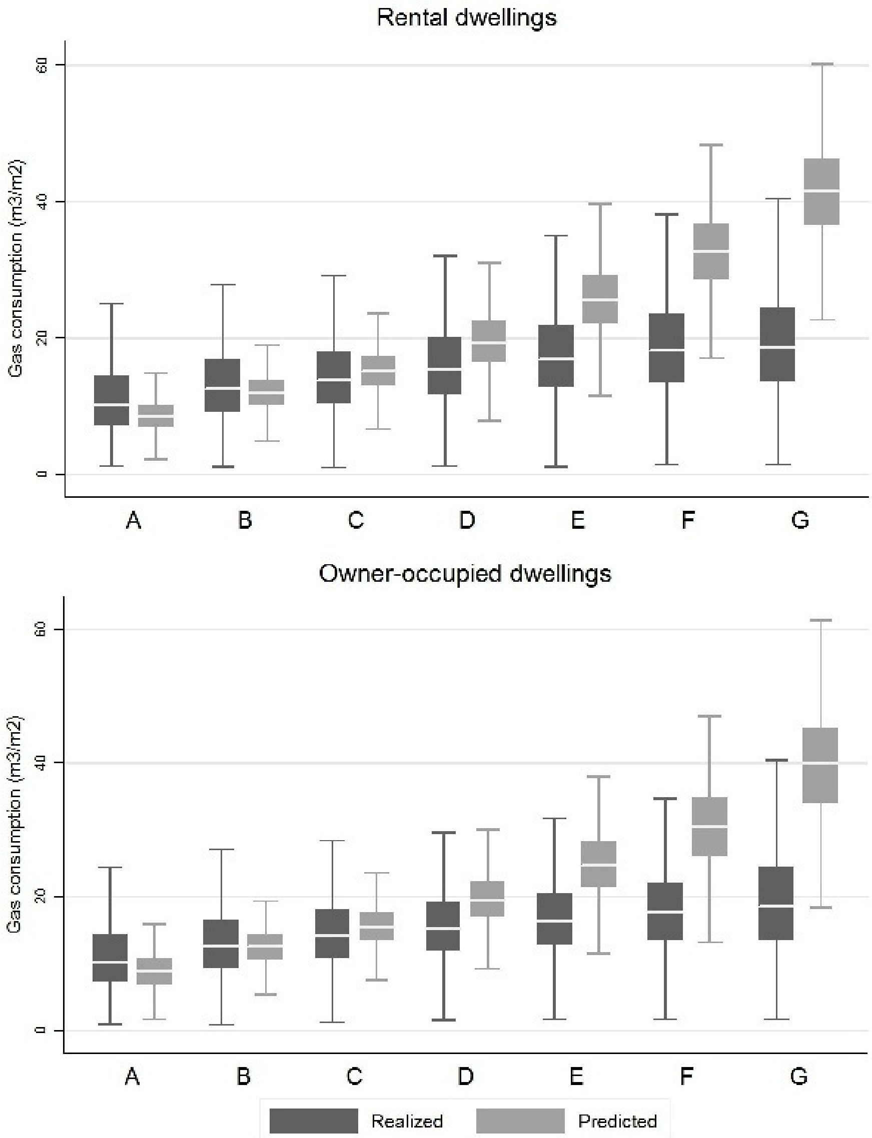
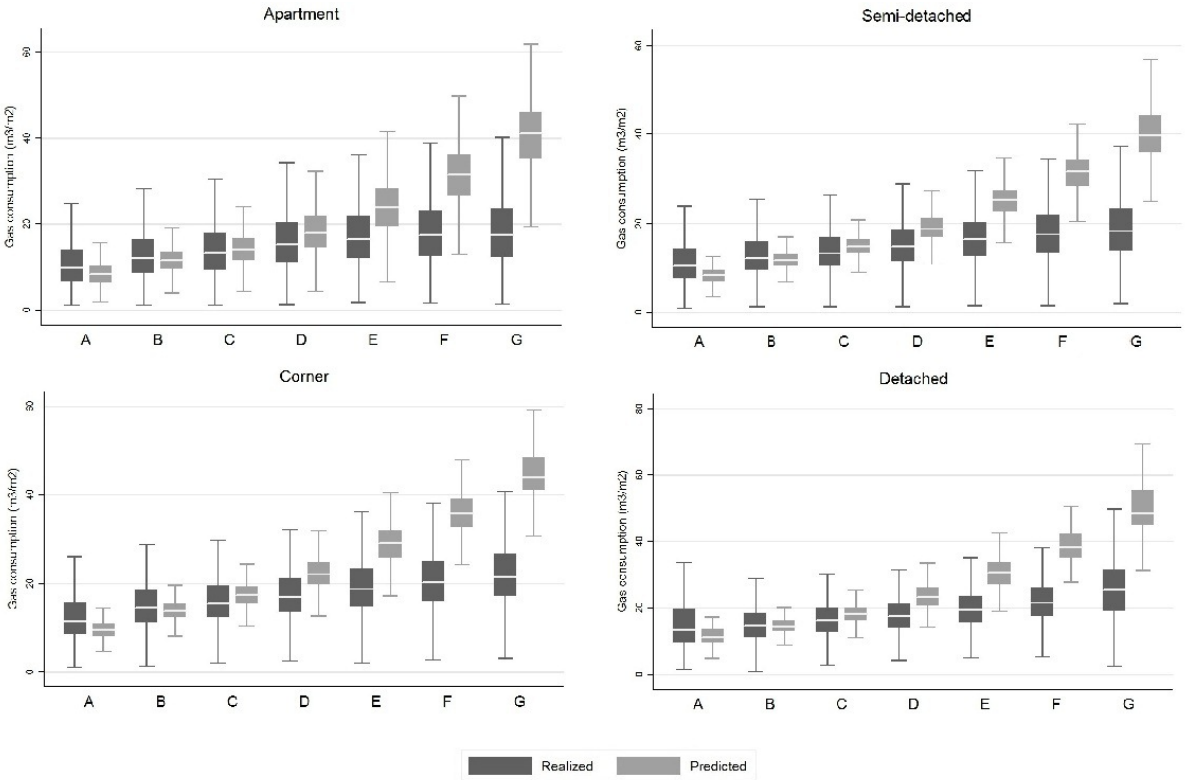
Figure 1: Predicted versus Actual Gas consumption



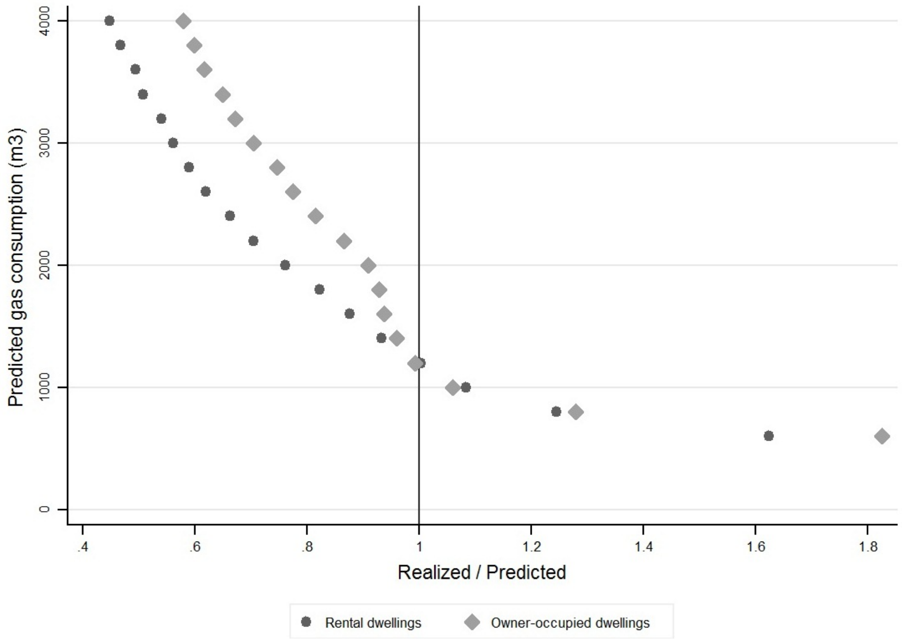
Source: Bureau of Statistics in the Netherlands (CBS), AgentschapNL, authors' calculations

Figure 2: Predicted versus Realized Gas consumption by Dwelling Type



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

Figure 3: Realized/Predicted Gas Consumption



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

Table 1: Descriptive Statistics

	Rental (With Label)		Owner-Occupied (With Label)		Owner-Occupied (Without Label)	
Number of Observations	*519,512*		*43,498*		*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.

Table 2: 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***
	[0.001]	[0.003]	[0.001]	[0.003]
Number of Household Members			0.118***	0.132***
			[0.001]	[0.005]
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***
			[0.001]	[0.003]
Number of Female			0.037***	0.016***
			[0.001]	[0.003]
All Household Members Are Working (1=yes)			-0.060***	-0.042***
			[0.001]	[0.003]
Log (Household Income)			0.054***	0.075***
			[0.001]	[0.003]
Receiving Rent Subsidy (1=yes)			-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^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
* P<0.05. ** P<0.01. *** P<0.001

Table 3: Pooled OLS-Instrumental Variable Estimations

	(1) Rental	(2) Owner-Occupied
Log (Predicted Gas Consumption)	0.587***	0.733***
	[0.001]	[0.007]
Number of Household Members	0.093***	0.105***
	[0.001]	[0.005]
Number of Household Members^2	-0.010***	-0.011***
	[0.000]	[0.001]
Number of Children (<18)	-0.004***	0.001
	[0.001]	[0.003]
Number of Elderly (Age>64)	0.031***	0.049***
	[0.001]	[0.003]
Number of Female	0.034***	0.043***
	[0.001]	[0.003]
All Household Members Are Working (1=yes)	-0.056***	-0.038***
	[0.001]	[0.004]
Log (Household income)	0.052***	0.051***
	[0.001]	[0.004]
Receiving Rent Subsidy (1=yes)	-0.034***	
	[0.001]	
Province Dummy	Yes	Yes
Year Dummy	Yes	Yes
Constant	2.276***	1.208***
	[0.015]	[0.054]
R^2	0.239	0.375
R^2 (First stage regression)	0.225	0.256
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"
* P<0.05. ** P<0.01. *** P<0.001

Table 4: Random-Effects (IV) and Fixed-Effects (IV) Estimations

	Random-Effects Model		Fixed-Effects Model	
	(1) Rental	(2) Owner-occupied	(3) Rental	(4) Owner-occupied
Log (Predicted Gas Consumption)	0.582***	0.722***	0.584***	0.663***
	[0.002]	[0.009]	[0.011]	[0.051]
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***	0.000	0.004
	[0.001]	[0.003]	[0.001]	[0.006]
Log (Household income)	0.054***	0.075***	0.001	0.008
	[0.001]	[0.003]	[0.002]	[0.007]
Receiving Rent Subsidy (1=yes)	-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^2	0.209	0.355	0.165	0.243
R^2 (within)	0.032	0.017	0.024	0.021
R^2 (between)	0.222	0.357	0.176	0.249
Number of observations	1,664,113	87,282	994,804	44,876
Number of households	519,512	43,498	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"
For the fixed-effects analysis, we exclude the households that had a change in their composition between 2008 and 2011.
* $P<0.05$. ** $P<0.01$. *** $P<0.001$

Table 5: Pooled OLS-IV Estimations for Wealth and Income Cohorts

Panel A: Wealth Cohorts (Owners)

	(1) 0-20%	(2) 20-40%	(3) 40-60%	(4) 60-80%	(5) 80-100%
Log (Predicted Gas Consumption)	0.602*** [0.021]	0.676*** [0.021]	0.724*** [0.018]	0.811*** [0.017]	0.811*** [0.019]
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)

	(1) 0-20%	(2) 20-40%	(3) 40-60%	(4) 60-80%	(5) 80-100%
Log (Predicted Gas Consumption)	0.515*** [0.004]	0.597*** [0.003]	0.599*** [0.003]	0.625*** [0.003]	0.598*** [0.003]
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).
* P<0.05. ** P<0.01. *** P<0.001

Table 6: Quantile Regression-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)	0.922***	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}
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.
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

Table 7: 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.

Table 8: Difference-in-Differences and Propensity Score Matching Estimations

	(1) First-Diff.	(2) IV	(3) PSM-IV
Δ Log (Energy Index)	0.408*** [0.031]	0.445*** [0.032]	0.449*** [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

Appendix A Cover Page of the EPC

Energielabel woning

Afgegeven conform de Regeling energieprestatie gebouwen.

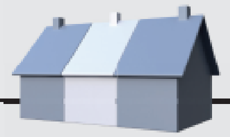
Veel besparingsmogelijkheden

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

Appendix 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).

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

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:

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

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.

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

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

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

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 (B.3) is the loss of energy through ventilation, which is calculated as follows:

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

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}).

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

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:

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

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

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).