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

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Abstract

This paper investigates the rebound effect in residential heating, using a sample of 563,000 households in the Netherlands. Using instrumental variable and fixed-effects approaches, we address potential endogeneity concerns. The results show a rebound effect of 26.7 percent among homeowners, and 41.3 percent among tenants. We corroborate the findings through a quasi-experimental analysis, using a large retrofit subsidy program. We also document significant heterogeneity in the rebound effect, determined by household wealth and income, and the actual energy use intensity. The findings in this paper confirm 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, in part, from the carbon externality of energy consumption in buildings. Evidence on the effect of stricter building codes on the energy consumption of newly constructed dwellings is inconclusive (Jacobsen and Kotchen, 2013; Levinson, 2016), and codes as a policy instrument alone may thus be insufficient to meet broader energy reduction targets for the built environment (Majcen et al., 2013). Irrespective of the effectiveness of policies that aim to increase the thermal quality of the building stock, a critical debate focuses on how households respond to improvements in the energy efficiency of their homes.

Indeed, research has shown that as a consequence of the associated changes in consumer behavior, technological improvements may lead to lower energy savings than expected (Jevons, 1906; Khazzoom, 1980; Wirl, 1997). The mechanism underlying this behavioral change relates to neoclassical economic theory: when the energy efficiency of a particular energy service is improved, households realize a reduction in the effective price of that service. Consequently, improved energy efficiency leads to an increase in the demand of energy service. This implicit price mechanism generates a so-called "rebound effect," as it partially offsets the initial efficiency gains.

Although the existence of the rebound effect is widely acknowledged, the real debate lies in the identification and the size of the effect (Gillingham et al., 2013; Greening et al., 2000). The discussion on the extent of the rebound effect has led to different views on the role of energy efficiency policies in addressing climate change (Borenstein, 2015). Thus far, due to the uncertainty regarding its actual size, the rebound effect has been disregarded in ex-ante impact assessments of energy conservation measures (e.g. building regulations and energy efficiency subsidy programs), leading to perhaps misguided expectations about the role of these measures in saving energy (Jacobsen and Kotchen, 2013; Fowlie et al., 2015). This is of importance, as realized savings ultimately determine the success of energy efficiency policies in reducing energy consumption and carbon emissions. Incorporating the rebound effect into policy evaluations can thus help to develop cost-effective energy conservation policies.[1]

In this study, we address some of the limitations in the current literature that focuses on the identification of the rebound effect. This is the first study that is based on a large, representative sample of dwellings, using a continuous energy efficiency measure. We analyze a detailed panel dataset that covers both the individual engineering predictions and the actual energy consumption of 560,000 households in the Dutch housing market. Exploiting the widespread diffusion of home energy performance certificates (EPCs), which are mandatory in all Member states of the European Union, we investigate the *elasticity* of actual energy consumption relative to the engineering predictions of energy performance. In addition to the use of an extensive data set, we benefit from different identification strategies to identify the magnitude of the rebound effect and its heterogeneity among households.

First, we address the issue of potential random measurement error in the engineering predictions of energy efficiency, as it might lead to a downward bias in OLS estimates. It is possible that the engineering predictions of energy efficiency include a random measurement error, because of assumptions made in the calculation procedure and potential mistakes made during the inspection. In order to eliminate the effect of this type of error, we apply an instrumental variable (IV) approach. Our identifying assumption is that engineering models do not include a non-random measurement error. Although we discuss the plausibility of our identifying assumption in detail in the following sections, we should note that our parameter estimate will be sensitive to any systematic mistake in engineering models. Using the year of construction and the stringency of building codes at the time of construction as instruments, we document that, on average, the rebound effect for residential heating is 41.3 percent for tenants and 26.7 percent for homeowners.

Another concern about the identification of a rebound effect relates to the potential endogeneity problem originating from unobserved household heterogeneity. Although

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

we control for a large set of observed household characteristics such as income, size, employment status, gender and age, unobserved household characteristics correlated with the energy efficiency of the dwelling and the household's energy demand may still exist. Exploiting the panel structure of our dataset, we estimate a fixed-effects model by tracking the movements from one address to another address for the same households over time. The address change generates variation in the energy efficiency level of the home, while keeping the characteristics of the household fixed. Using this approach, we document that fixed effects (FE) results are comparable to the cross-sectional IV estimates.

Third, we corroborate our findings through a quasi-experimental analysis. Although a fixed-effects estimator controls for the potential differences in unobserved household characteristics, it is not able to eliminate the influence of unobserved home characteristics that might also lead to a bias in the estimated rebound parameter. We estimate the rebound effect based on a subsample of dwellings that benefited from an energy efficiency subsidy program initiated by the Dutch government. Using this quasi-experimental setting enables examining the rebound effect, while controlling for unobserved home and household characteristics at the same time. For the households that participated in the energy efficiency subsidy program, we show that the efficiency improvements in their homes led to a rebound effect of around 55 percent.

We then explore the heterogeneity of the rebound effect, which may help to better understand our findings. The identification of heterogeneity in the rebound effect may also contribute to better assessment of potential outcomes from energy efficiency policies. As discussed by Borenstein (2015), the size of the rebound effect might differ across households that are targeted by energy efficiency regulations. For instance, low-income households, which are more likely to reside in poorly insulated homes, might be more responsive to efficiency improvements as these households are expected to be more cost-sensitive (having higher price elasticity). In that case, efficiency policies that are specifically targeting inefficient dwellings will result in a rebound effect that is higher than average.

We separately estimate the models for cohorts of households with different income and/or wealth levels. We document that the rebound effect is strongest among lower income groups – these households are likely to be further from their satiation in consumption of energy services, including thermal comfort (Milne and Boardman, 2000). This result can also provide guidance regarding policy expectations for different regions of the world (or within countries) with different income levels.

Another source of heterogeneity might be the variation in the energy use intensity of households. As the cost of heating is higher for households that are more energy dependent, these households may display a stronger response to energy efficiency changes. Identification of this heterogeneity may also help to predict how the size of the rebound effect may vary for other residential energy services that require different amounts of energy input. Using a quantile regression approach, we examine whether the magnitude of the rebound effect depends upon the actual energy use intensity of households. We find that the rebound effect is larger among consumers with relatively high energy consumption. This result implies that the magnitude of the rebound effect is also determined by the energy requirement of the demanded energy service, which can partially explain the variation in the rebound effect documented for different energy-using products (such as automobiles, air conditioners, lighting, etc.).

The results of this article 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 at 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. Although 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 employ. Using these adjusted, more realistic models may increase the effectiveness of policies targeting 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 aimed at improving energy efficiency, with the recently adopted energy policies in California as an example.

The remainder of this article is organized as follows: the next section discusses the related literature. In Section 3, we provide an overview of the engineering models used to predict residential energy efficiency, and we discuss the potential methodological issues that might effect our results. Section 4 describes the data, and provides some descriptive statistics. In section 5, we present the methodology and the results. Section 6 provides a brief conclusion.

2 Related Literature

The mechanism underlying the "rebound effect" can be derived from 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 space heating and cooking. Households obtain utility from consuming energy services, rather than from consuming energy itself. When the energy efficiency of a particular service is improved, without leading to an offsetting change in the price of energy, households realize a reduction in the effective price of that service due to the decrease in the amount of energy that is required for its production. Therefore, under the condition that the demand for the energy service is price-elastic, improved energy efficiency leads to an increase in its demand. This implicit price mechanism causes the so-called "rebound effect," as it partially cancels out the expected energy savings from efficiency improvements.[2] Although the existence of the rebound effect is widely accepted, there is an ongoing discussion about the identification and the size of the effect (Gillingham et al., 2013; Greening et al., 2000).

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.

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

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

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

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

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

levels, share of space heated, ventilation rates, etc.

One strand of literature on the topic is based on cross-sectional analysis of household survey data. 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 variations in energy price and energy efficiency indicators, the authors report a price elasticity of heating demand ranging from 52 to 81 percent. Using a cross-sectional database of about 500 Austrian households, Haas and Biermayr (2000) estimate a rebound effect of about 30 percent, based on the variation in the thermal characteristics of the dwellings.

Although these studies provide more reliable estimates of the rebound effect compared to the evidence that is based on price elasticities only, it also has some drawbacks, especially with regard to the data and methodology used in the estimations. The studies are based on small samples, which leads to imprecise (or even statistically insignificant) estimates of the rebound effect. In addition, given the lack of detailed information on dwelling and household characteristics, the use of cross-sectional analysis may lead to a bias arising from unobserved heterogeneity. Finally, since an accurate measure of energy efficiency requires detailed information regarding the technical characteristics of dwellings, which are hard to measure through 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. For example, Hirst et al. (1985) compare the internal temperature settings before and after efficiency improvements for 79 U.S. households that received subsidies. The authors document that 11 percent of the potential savings are not achieved due to the change in temperature settings. Milne and Boardman (2000) examine the average change in home 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. However, in addition to problems associated with limited sample size, there are also some concerns regarding the methodological quality of these studies. The results are based upon simple before-after comparisons, without use of a control group. As there are other factors that may also affect the observed outcome (e.g. weather, income), the use of simple before-after comparisons may lead to biased results. These studies also 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 heating demand, as it does not take other determinants of thermal comfort into account.

In a recent study, Fowlie et al. (2015) document a significant gap between expected and actual energy savings, comparing the actual and predicted energy consumption after energy efficiency improvements in a sample of Michigan homes. The findings are comparable to the results in this article, but the interpretation of the findings is different from our interpretation. As the authors do not find a significant difference in indoor temperature of the surveyed homes with improved energy efficiency compared to a control sample, they argue that there is no evidence for a rebound effect. However, as discussed above, changing the temperature setting in the living room is only one of the potential channels that households may use as a response to efficiency improvements. For instance, Healy and Clinch (2002) report that the thermal comfort differences between fuel-poor households and other households are more distinct in other areas of homes (such as bedrooms and bathrooms). These are the areas where households may not heat properly when they realize higher energy costs. Therefore, in the case of efficiency improvements, we can expect that household responses will be better observable in these less-used areas of the home. The thermostat setting in the living room might thus not be the best proxy for total household heating demand, as it does not capture other factors related to thermal comfort (such as the share of heated area, heating duration, humidity, and airflow).

3 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 rating categories, an engineer visits a dwelling and inspects its physical characteristics (e.g., size, quality of insulation, type of windows, etc.). The collected information is then used to predict the total energy consumption of the dwelling.[5] After scaling by the size and the heating loss area of the dwelling, the prediction is transformed into an energy index, which corresponds to a certain label category. The information is then reported to a government managed database. Once the information has been verified, the certificate is registered and issued to the homeowner. Appendix B, Figure B.1 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 owner of the dwelling. Dwellings that have been constructed after 1999, or that are classified as monuments, are exempted from mandatory disclosure of the energy performance certificate.[6]

In this study we use the predicted gas consumption of homes, which is provided by the EPC, as a measure of thermal efficiency. In Appendix A, we briefly describe the framework of the engineering model that is used to predict the amount of residential gas that is required to achieve a fixed level of thermal comfort.[7] As discussed by Pérez-Lombard et al. (2009), these "asset rating" engineering models are based on standard usage patterns, a standard set of operating parameters (e.g., for thermostat settings) and climatic conditions that do not depend on occupant behavior, actual weather and indoor conditions, and are developed to rate the building and not the occupant. The use of this asset rating model enables us to compare different dwellings, using a consistent methodology. For instance, the models assume that occupants heat the entire usable floor area of the dwelling at a fixed temperature. This assumption may seem unrealistic, as occupants can opt to heat just

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

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

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

some of the rooms (because of the higher cost of heating the complete space). However, in the context of our model, this assumption is acceptable and even required, as we estimate the response of the occupant to the changing cost of thermal comfort. So, if the occupant prefers to heat just part of the dwelling, we interpret this as a behavioral response to the higher cost of heating the entire 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 to obtain a correct measure of energy efficiency.

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

The accuracy of asset rating models is typically based upon evaluations of tools against accepted baseline instruments. The National Laboratory of the U.S. Department of Energy has developed a number of building energy simulation test (BESTEST) instruments for assessment and identification of errors in engineering software that is used for analysis

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

of energy efficiency in building sector (Judkoff et al., 2011).[9] Given the fact that the engineering model that is used in the calculation procedure is examined through energy simulation tests (Judkoff and Neymark, 1995; Neymark and Judkoff, 2004) and verified by pilot studies in each EU country that is implementing a similar labeling policy (Poel et al., 2007), we assume that there is no systematic measurement error that is related to the engineering model.

However, even if the predicted energy efficiency of a dwelling is based on an advanced engineering model that exploits detailed information on the thermal characteristics of the dwelling, the outcomes remain based on assumptions regarding characteristics of the dwelling that are not easy to observe. Especially for older dwellings, the inspector has to make assumptions regarding the thermal quality (U-value) of the building envelope and the rates of ventilation and infiltration. In order to verify the accuracy of assumptions made for different components of dwellings, a sample of 184 reference buildings in the Netherlands, with significant variation in type and construction period, was analyzed regarding the energy saving capacity of technical installations and insulation (Maldonado, 2013). Furthermore, the sample of reference dwellings was used the check the validity of energy saving measures from packages (combinations of thermal envelope and technical systems improvements). However, although the model assumptions are based on measurements from a representative sample of dwellings, a measurement error might still exist through engineering assumptions about the quality of new installations. The quality of insulation might be lower than expected due to a moral hazard problem (Giraudet and Houde, 2013). If this is the case, then our model will over-estimate the size of the rebound effect. Therefore, it is important to note that further research is required to verify the validity of assumptions about the quality of energy efficiency installations.

The other potential source of measurement error is the quality of the inspection.

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

In 2011, it was documented that 16.7 percent of the certified dwellings exceeded the maximum acceptable level of the deviation from the real energy index (VROM-Inspectie, 2011). Certificates that deviate from the real energy index by more than eight percent are considered as certificates with a critical defect. Examination of the data on re-inspection of a sample of certified dwellings indicates that this inspection error is not systematically and significantly correlated with the true efficiency value. Using data on 47 re-inspections, provided by VROM-Inspectie (2011), we found no significant relationship between the "true" energy index and the inspection error.[10]

4 Data

AgentschapNL, a government agency, maintains a repository that contains information on the characteristics of all dwellings certified with an energy performance certificate (EPC), as well as the predicted annual gas consumption for each home. We merge this dwelling information with information on occupant characteristics and their actual annual gas consumption, provided through the micro files of the Central Bureau of Statistics in the Netherlands (CBS). This results in a panel of 610,000 dwellings and their occupants, adopting an Energy Performance Certificate in the years 2011 or 2012. Additionally, in order to assess whether there are significant differences between the characteristics of the dwellings with and without an EPC, 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).[11] The complete dataset includes information on the dwelling characteristics, household characteristics and the household's annual gas consumption from 2008 to 2011.

We exclude the years in which occupants change their address, as it is not possible to exactly identify the amount of energy used by the occupant in that year. We also drop the observations with gas or electricity consumption of zero, and we exclude outliers that are detected based on the sample distribution of dwelling size, and actual and predicted energy

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

[11]As the buyers of these dwellings signed a waiver, the sellers were exempt from providing the certificate.

consumption (electricity and gas) – the upper and lower boundaries for the outliers are set at the first and 99th percentile. The final 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, as the diffusion of energy labels among owner-occupied dwellings in the Netherlands is relatively slow, the share of owner-occupied dwellings in our sample is only around eight percent, which is below the population average. Therefore, the rental housing stock is overrepresented in the sample. As this may 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. These sample statistics indicate that there are minor differences in the average characteristics of the two samples (rental versus owner-occupied dwellings). The annual gas consumption in the owner-occupied market seems to be higher than 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 annual gas bills.[12] 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

[12] As the predicted annual 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 annual gas consumption in each year is corrected for the annual heating degree days (HDD) in that year, in order to provide comparable descriptive statistics. We multiply the actual gas consumption of the household by the ratio of the "fixed HDD" to the "actual HDD" of that year. Fixed HDD, which is used in engineering predictions, is equal to $212 * (18 - 5.64) = 1,620$. We apply this correction in order to better evaluate the average gap between engineering predictions and realized consumption in Table 1. In the analysis, we do not apply this correction as we include year and location dummies in our model, which control for time and location-varying climatic conditions.

owner-occupied dwellings that are not labeled. The average actual annual gas consumption and the occupant characteristics are quite similar for both samples. However, the non-labeled sample contains more dwellings that are constructed after the year 2000. This is in line with expectations, as the energy label is not mandatory for dwellings constructed after 1999.

[Insert Table 1 here]

Figure 1 shows the descriptive statistics for the actual versus predicted gas 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 well with the label categorization. Of course, this is a result by design, as these predictions determine the categorization. When comparing the predictions 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 dwelling 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 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, one can consider the "predicted gas consumption" as the cost of heating the entire area of the dwelling at a fixed temperature, and the "actual/predicted" ratio can be considered an indicator of 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 resulting from energy efficiency improvements.

[Insert Figure 3 here]

Finally, we compare the most energy-efficient and inefficient dwellings, and their occupants, based on their observable characteristics. Table 2 documents the descriptive statistics for the dwellings that are at the lower (below 10th) and upper (above 90th) quantiles of the energy index distribution, representing energy-efficient and inefficient homes, respectively. The statistics indicate that the percentage difference in actual annual gas consumption between these samples is significantly smaller than the percentage difference in their predicted gas consumption. Considering the other dwelling characteristics, we observe that the distribution of construction year is significantly different between energy-efficient and inefficient homes. Examining household characteristics, we observe that households living in energy-efficient homes are significantly wealthier as compared to households in energy-inefficient homes.

[Insert Table 2 here]

5 Methodology and Results

The rebound effect can be described as the elasticity of demand for a particular energy service with respect to energy efficiency. In this article, 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 use of hot water (e.g. for showers). 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 annual 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 (64.4°F) for the entire space of the dwelling during the heating season (212 days), and a fixed amount of hot water per person per day. Assuming that 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:

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

As 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 consumption.

Empirical Results

In order to identify the rebound effect in residential heating demand, we estimate the relationship between actual and theoretical gas consumption 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 the 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 the EPC, but that are affecting the household's gas consumption, such as household size and composition, province, year, income, employment status of the household members, and ownership of the dwelling. 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 $(\alpha_i + \varepsilon_{it})$.[13] The results of these estimations are presented in Table 3.[14] When explaining the variation in actual gas consumption by the variation in predicted gas consumption and the province and year fixed effects (column 1), the explanatory power of the model is about 21 percent. 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 household characteristics are included.

[Insert Table 3 here]

The signs and magnitudes of the estimated effects for the 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 significantly 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. 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 related to lower gas consumption.

Importantly, our coefficient of interest (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

[13]As presented in Figure 1, the variance of actual gas consumption increases by the predicted gas consumption level. Therefore, we apply the White (1980) approach to estimate heteroskedasticity-robust standard errors. As we expect observations within each year and province to be correlated because of similar climate conditions, we also estimate the standard errors based on province-year clusters.

[14]In Appendix Table B.1, we report the results from estimating the same model by using the actual and predicted consumption variables scaled by the size of the home. The results are comparable to the estimation results that use non-scaled variables.

household characteristics, leading to a decrease in the estimated coefficient. These estimates indicate a quite sizable difference between relative changes in actual energy consumption and engineering predictions. We interpret this as evidence on the influence of household behavior on residential energy consumption.[15]

Measurement Error in Engineering Predictions

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

The assumption that G_{it}^{p} 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):

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

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

The presence of this random measurement error leads to a downward bias in the OLS estimate of β_1. In order to overcome this bias, a common approach is to use an instrumental variable (IV) method. Such an IV needs to be correlated with the predicted gas use

[15] In order to analyze whether this gap is driven by a systematic error that is related to unobserved characteristics of the older homes, we also estimate our model for a restricted sample including only those homes that are constructed after 1999. The estimates of β_1, which are provided in Appendix Table B.2, are slightly larger compared to the full sample estimates, which might be associated with the heterogeneity of the rebound effect. We examine the heterogeneity issue in more detail in the following sections of the article.

(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. In addition, we expect that the average 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^*).[16] The limitation of this approach is that we rely upon the assumption that engineering models do not include a non-random measurement error causing a systematic bias in engineering predictions. If there is a systematic (non-random) engineering error correlated with the instrumental variable, the instrument will eliminate only the impact of the random component of the measurement error.

We estimate the model in equation (6) using a two-stage least squares (2SLS) estimation approach, with year of construction (specified as dummy variables) as an instrument for theoretical gas consumption. Table 4 reports the results of the IV estimations. Compared to OLS estimates that are provided in Table 3, we now document β_1 estimates of 0.587 and 0.733 for the rental and owner-occupied samples, respectively. Although the coefficients of the control variables all remain comparable in sign and size, the use of IV estimators significantly reduces the rebound effect estimates, to 41.3 percent and 26.7 percent for the rental and owner-occupied samples, respectively. According to these results, if the efficiency of an average dwelling is increased by 50 percent, this will lead to a 29.4 percent energy saving in rental dwellings and 36.7 percent energy saving in owner-occupied dwellings, *ceteris paribus*. The difference between the estimated rebound effects for rental and owner-occupied dwellings is also in line with expectations that more wealthy households are

[16] Hausman (2001) states that the magnitude of a parameter estimate is usually smaller than expected because of the measurement error problem, even in studies using seemingly high quality data. In our case, the measurement error problem would make us more likely to over-estimate the size of rebound effect, as it will lead to a downward bias in the estimated OLS coefficient. Our IV strategy is comparable to Allcott and Wozny (2014), who address the measurement error problem using the grouping estimator, which is a generalization of Wald (1940)'s estimator to the case of many group indicator variables. By using construction year as an IV, we average the individual level measurement error over the contruction year categories, which leads to a decrease in the variance of noise (random measurement error).

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 section 5.5, we further analyze the heterogeneity of the rebound effect based on wealth and income levels.

[Insert Table 4 here]

In order to test the robustness of our IV results, we also estimate the 2SLS model based on an alternative instrument – the stringency of the building codes at the time of construction. Starting in 1965, the Dutch government introduced minimum legal requirements for the thermal efficiency level of new construction. This legislations sets a maximum allowable U-value for each component (walls, windows, floor and roof) of the construction. The U-value is defined as a measure of heat loss through one square meter of the material for a one-degree difference in temperature at either side of the material. The maximum allowable U-value for external walls decreased over time from 2.00 W/m^2 to 0.25 W/m^2 by the regulations that were introduced in 1965, 1974, 1978, 1981, 1986, 1989, 1995, 2000, 2002, and 2006. Using the variation in the legal U-value requirements for external walls as an instrument for the predicted gas consumption, we re-estimate the IV model.[17] The results provided in Appendix Table B.3 are comparable to the IV results that are estimated using the year of construction as an instrument.

Finally, we check whether our results are robust to the inclusion of dwelling size as a control variable. Households might respond to the changing cost of thermal comfort through different mechanisms. One potential response might be to change the share of the heated area. In order test whether our results are mainly driven by this kind of behavioral response, we control for the size of the dwelling in the estimations. This also enables us to test the robustness of our findings regarding the engineering assumptions on the size of heating area. In Appendix Table B.4, we report the estimation results for the models including the size of the house as a control variable (both linear and quadratic specifications). The results indicate that, keeping the dwelling size constant, the estimated rebound effect is

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

not significantly different from the results provided in Table 4. This finding implies that the estimated average rebound effect is not driven by the engineering assumptions on the size of heated space.

Endogeneity

Another econometric issue that may cause a biased estimation of the rebound effect 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 may 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 could be sorting into more affordable housing with a lower thermal quality and thus lower efficiency (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 a correlation exists 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 variation in theoretical gas consumption due to the change in the characteristics of the dwelling in which the household resides. We can thus observe the change in the energy efficiency of the dwelling, and the resulting change in actual gas consumption, keeping the characteristics of the household fixed. By using a FE estimator, we are able to eliminate any unobserved household-specific effects (α_i) that are correlated with the thermal quality of the dwelling. This setting allows us to obtain consistent estimates of β_1 in the presence of a relationship between household-specific effects and the thermal efficiency of the dwelling.

Table 5 reports the descriptive statistics for the households that changed their address between 2008 and 2011. These statistics indicate that households in both sectors (rental and owner markets) moved, on average, to a newly constructed dwelling with a higher level of energy efficiency, as measured by "predicted gas consumption per m^2". Additionally, the new home has, on average, a larger living area compared to the previous home. Comparing the over-time changes in predicted and actual gas use per m^2, we observe that the relative change in energy efficiency is higher then the realized relative change in actual energy use per m^2, which can be considered an indication of potential rebound effect. Finally, comparing the average characteristics of these households with the households in the full sample (see Table 1), we observe that moving households typically have a smaller household size, live in smaller homes, and consume less energy.

[Insert Table 5 here]

The FE estimation results in Table 6 show that the rebound effect for households in rental dwellings is nearly the same as the rebound effect based the pooled OLS estimates.[18] The rebound effect for homeowners is higher as compared to the OLS estimations. However, the standard error of this point estimate is relatively large due to the limited number of homeowners that changed addresses. This leads to a larger confidence interval for the estimated rebound effect for homeowners. Testing for differences between OLS and FE estimates, we conclude that there is no systematic difference between these estimates, according to the Hausman test statistics. We also estimate a random-effects (RE) model, assuming that the household-specific effects are randomly distributed and are independent of the theoretical gas consumption. In Appendix Table B.5, the results show that the RE estimates of the rebound effect are comparable to the pooled OLS results.

[Insert Table 6 here]

However, as the sample characteristics of moving households differ from the averages of the full sample, the fixed-effects results should be interpreted as the response of this specific group of households to the changes in energy efficiency of the home. If there is heterogeneity among households in terms of reactions to the efficiency improvements, then the estimated parameter in the fixed-effects model may not be representative of the full

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

population. In the following sections, we will discuss this heterogeneity issue in more detail. Second, the main identifying assumption of the fixed-effects estimator is that there is no temporal change in unobserved household characteristics that might be correlated with the change in energy efficiency level and also affects consumption behavior. By using a fixed-effects estimator, we aim to eliminate the potential impact of the correlation between households energy consumption habits and their choice of efficiency level, which is assumed to be fixed over time. Therefore, if this potential correlation changes in a systematic way within the period of analysis, the identifying assumption will be violated and the estimated parameter will thus be biased.

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 that there is no evidence of omitted variable bias, we further examine the rebound effect from energy efficiency improvements through a quasi-experimental setting. Although the fixed-effects estimator controls for potential differences in the unobserved household characteristics that might be correlated with the energy efficiency level, it is not able to eliminate the unobserved home characteristics that might also lead to a bias in the estimated parameter. Therefore, using a quasi-experimental setting, we aim to control for the unobserved home and household characteristics at the same time.

In 2008, the Dutch government initiated a program called "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 improving the energy label of their dwelling by one or two categories received a rebate 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 non-participant 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 non-participant group consists of 4,593 owner-occupied dwellings that were transacted in 2008 (with an EPC) and did not apply for any of the energy efficiency subsidy programs (e.g., tailored advice, double glazing, solar panel subsidies, etc.) offered by the government during the period of the analysis.[19] For both participant and non-participant groups, we exclude the dwellings in which the household composition changed from 2009 to 2011.

In Table 7, we report the summary statistics for the participant and non-participant groups. The participant sample shows a slightly higher actual gas consumption and a lower level of energy efficiency (i.e., a higher energy index) compared to the non-participant group. The subsidy applicants appear to be wealthier than the households in our control group. The change in average gas consumption for the non-participant group between 2009 and 2011, which is around nine percent, is assumed to be due to other time-varying 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 participant group. This 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 participant group. This suggests at an average rebound effect of 57 percent for the treated dwellings.

[Insert Table 7 here]

We then estimate the rebound effect based on a regression analysis in order to control for other factors that might affect the reduction in residential energy consumption. We use a first-difference estimator to identify the average rebound effect for the treated dwellings,

[19] As the mandatory EPC policy started in 2008, we can only use transactions in this year in order to obtain a sample of comparison homes with an energy index. We limit the sample to the transactions that took place in 2008, as the energy consumption of homes transacted in 2009 or later might introduce a systematic bias in the quasi-experimental analysis, following changes in energy demand related to vacancy in the transacted home.

isolating the exogenous variation in the energy efficiency of the dwellings in our participant group, generated by the efficiency improvements:

$$\Delta ln(G_i) = \beta_0 + \beta_1 \Delta ln(EI_i) + \sum_{j=2}^{J} \beta_j \Delta Z_{ji} + \Delta\epsilon_i \tag{10}$$

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.[20] For the dwellings in the non-participant 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 participation to the subsidy program 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 participant and non-participant 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 that might arise due to observable differences, we apply a propensity score matching (PSM) method, where the probability of being treated is estimated by using a logit model including dwelling characteristics as regressors. This probability is used as a balancing score between groups, as discussed by Rosenbaum and Rubin (1983). For the dwellings in participant and non-participant groups with the same balancing score, the distribution of the dwelling characteristics are the same. Thus, by applying the PSM method, we rely on the assumption that conditional on the dwelling characteristics, the counterfactual change in actual gas consumption is independent of the program participation. In other words, we assume that program participation is not correlated with unobserved determinants of household's gas consumption, which might change during the period of analysis.

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

Finally, using a control function (CF) approach (Heckman, 1976, 1979; Heckman and Robb, 1985), we test the effect of unobservable factors that might affect the program participation. This approach is used to deal with the unobserved factors that might lead to systematic differences between the participant and non-participant groups. Our ability to deal with this concern is limited by the available data. Using the initial energy efficiency and actual gas consumption levels as selection variables, we first estimate a probit model to predict selection into the subsidy program. Using the inverse Mills ratio calculated from the first step as control function, we then estimate a selection-corrected model of change in gas consumption. Under certain conditions, controlling for the inverse Mills ratio can yield consistent estimates of regression coefficients, even in the presence of nonrandom sample selection (Heckman, 1979). A key limitation of this approach, however, is that we rely upon assumptions about the functional form of the distribution of the residuals for identification, as we do not have an instrument for selection into the subsidy program.

Table 8 reports the findings. The simple 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 documented to be 44.5 percent. The use of the propensity score matching (PSM) and control function (CF) approaches lead to comparable estimates (44.9 and 43.9 percent, respectively). These results indicate that the average rebound effect is around 55 percent for the dwellings in our participant group. The estimated average rebound effect for the participant group is thus larger as compared to the average estimate documented for the full sample of owner-occupied dwellings (27 percent). This difference might be related to the heterogeneity of the rebound effect in the population. In the following section, we investigate the potential heterogeneity in the magnitude of the rebound effect.

[Insert Table 8 here]

Heterogeneous Effects

An important issue regarding the identification of the rebound effect relates to the heterogeneity of the effect within the population. As shown by the results in previous sections, 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 the price elasticity of energy demand indicates that the price elasticity parameter strongly depends on the socio-economic characteristics of the consumer (Madlener and Hauertmann, 2011; Ida et al., 2013). We expect that wealthier households are less sensitive to cost changes (having lower price elasticity), 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. The utility that can be gained from heating the dwelling above a comfortable room temperature will therefore be lower. In order to test for the impact of wealth and income on the rebound effect, we estimate our IV model separately for different wealth and income cohorts, and analyze whether there is a significant difference between the estimated rebound effects.

In Panel A of Table 9, we provide the results for different wealth cohorts among homeowners. We divide our 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, whereas it is "just" 19 percent for the upper quantile.[21]

[Insert Table 9 here]

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, as there is limited variation in the wealth level of tenants. The results provided in Panel B of Table 9 indicate that the rebound effect is heterogeneous among different income groups. For the lowest quantile, the rebound effect is nearly 49 percent, whereas it is in the range of 38-40 percent for the upper quantiles. These results imply that wealth and income matter for the behavioral response of homeowners and tenants to the energy efficiency of a dwelling.

[21] 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.

Another source of heterogeneity relates to the actual gas consumption level of the household. Using IV and FE-IV estimators (in Table 4 and Table 5), 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 consume 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 construction year as an IV). This method 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:

$$min_{\beta_j} \sum_{i=1}^{n} \sum_{t=1}^{t} |\alpha_i + \varepsilon_{it}| \tag{11}$$

which can be also written as:

$$min_{\beta_j} \sum_{i=1}^{n} \sum_{t=1}^{t} |ln(G^a_{it}) - [\beta_0 + \beta_1 \widehat{ln(G^p_{it})} + \sum_{j=2}^{j} \beta_j Z_{jit}]| \tag{12}$$

Another advantage of the quantile regression approach is its robustness in the presence of outliers. Therefore, we are also able to check for 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 10, we estimate the rebound effect for the 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.[22] These results imply that the response of households to improvements in energy efficiency depends on their actual gas consumption intensity level. This can be partially 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 10 here]

These results can also partially explain our finding in the quasi-experimental analysis indicating a larger rebound effect as compared to the estimates based on full sample. As the dwellings that benefited from the subsidy program have a higher actual gas consumption as compared to the other dwellings, we can expect a larger rebound effect for these households. The median actual gas consumption for the subsidy 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.

6 Conclusions and Implications

In the current debate on the reduction of externalities from global carbon emissions, economists and policy makers increasingly focus on energy efficiency improvements as a means to affect the energy consumption of 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 (Khazzoom, 1980; Wirl, 1997). This phenomenon has been termed the "rebound effect."

[22] In Appendix Table B.6, we report the non-IV quantile regression estimation results. As expected, the coefficient estimates are lower compared to the IV estimates because of the potential measurement error in the predicted gas consumption variable. For the sample of homeowners, the relative magnitude of the quantile coefficients is similar to the IV estimation results. However, we do not observe the same order for the rental sample, although the estimated rebound effect is still lower for the lowest quantile of the distribution. This might be associated with the unknown differences in the relative magnitude of the measurement error bias.

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 approach, as it may lead to biased estimates (Sorrell, 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.

Examining the association between the engineering predictions on residential energy consumption with the realized gas consumption of some 560,000 dwellings in the Netherlands, we estimate the direct rebound effect. In order to account for random measurement error in the engineering predictions, we use an instrumental variable approach, including dwelling age and the stringency of building codes at the time of construction as instruments. 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 reduction in the energy consumption of rental dwellings and a 73 percent reduction in energy consumption of 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. Benefiting from the panel structure of our data set, we then estimate a fixed-effects model to test for unobserved household heterogeneity that might also lead to a bias in the estimated rebound parameter. We document that the fixed-effects estimation results are comparable to the cross-sectional estimates. Finally, we confirm our findings by applying a quasi-experimental analysis, which enables us to take unobserved household and dwelling characteristics into account.

Using data obtained from an energy efficiency subsidy program, we show that the efficiency improvements lead to a rebound effect of around 55 percent.

We also estimate our model separately for different wealth and income 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, whereas 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, whereas 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. These results also support our finding of larger rebound effect in quasi-experimental analysis, as the households that applied for the subsidy program are at the upper quantiles of the actual gas consumption distribution in the population.

Our findings underline the importance of considering the rebound effect in the design of efficiency improvement policies in the residential sector. Policy makers have to incorporate this effect into the assessment of the outcomes of energy efficiency improvement measures and programs, including subsidies and rebates. As confirmed by the quasi-experimental evidence, there is significant potential for energy savings in residential sector through energy efficiency improvements, but the behavioral response of households offsets part of the projected energy savings. The heterogeneity of the rebound effect also has some policy implications. The results in this article 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 in estimates of the predicted savings.

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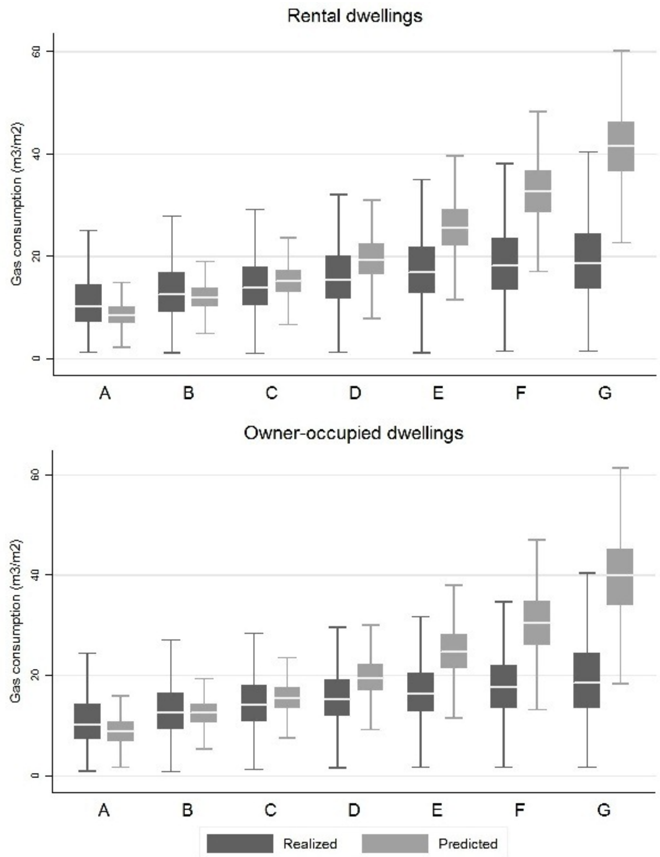
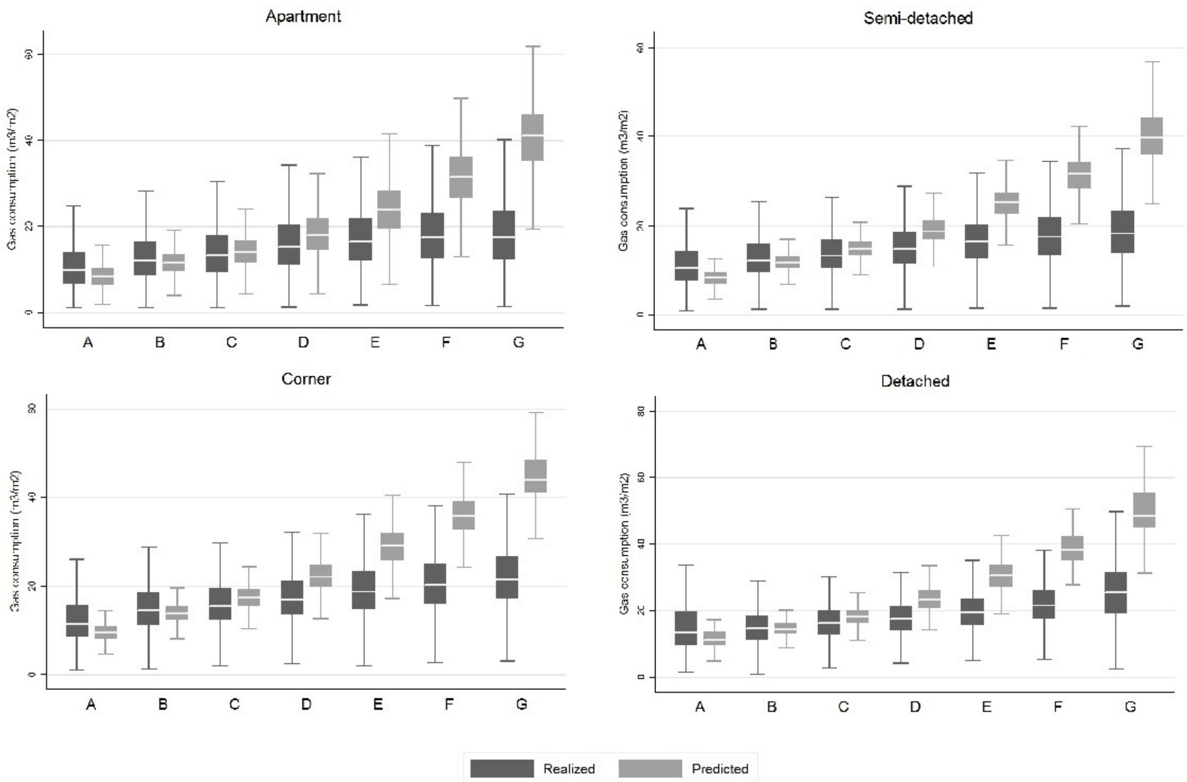
Figure 1: Predicted versus Actual Annual Gas Consumption



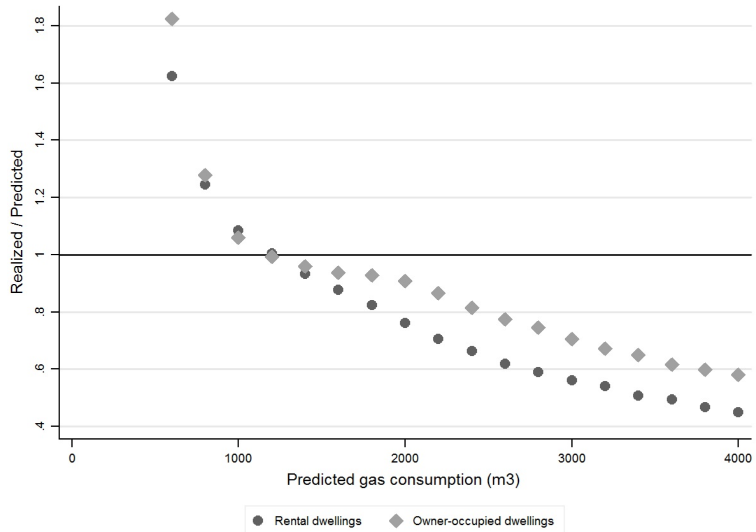
Notes: Figure 1 shows the descriptive statistics of actual versus predicted annual gas consumption across label categories, in cubic meters per unit of floor area, measured in square meters. The figure also includes the 95-percent confidence interval. The label categories range from "A" for exceptionally energy-efficient dwellings, to "G" for highly inefficient buildings. These statistics are based on the sample of labeled dwellings that adopted an EPC in 2011 or 2012. The statistics on actual annual gas consumption are calculated based on both the cross-sectional and the time-series variation (2008, 2009, 2010, 2011) in the sample. Source: Bureau of Statistics Netherlands (CBS), AgentschapNL, authors' calculations.

Figure 2: Predicted versus Actual Annual Gas Consumption by Dwelling Type



Notes: Figure 2 shows the descriptive statistics of actual versus predicted annual gas consumption across label categories, in cubic meters per square meter, for different dwelling types. The figure also includes the 95-percent confidence interval. The label categories range from "A" for exceptionally energy-efficient dwellings, to "G" for highly inefficient buildings. These statistics are based on the sample of labeled dwellings that adopted an EPC in 2011 or 2012. The statistics on actual annual gas consumption 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. Source: Bureau of Statistics Netherlands (CBS), AgentschapNL, authors' calculations.

Figure 3: Actual/Predicted Annual Gas Consumption



Notes: Figure 3 shows the relationship between the predicted annual gas consumption and the ratio of actual versus predicted gas consumption. These statistics are based on the sample of labeled dwellings that adopted an EPC in 2011 or 2012. The statistics on actual annual gas consumption are calculated based on both the cross-sectional and the time-series variation (2008, 2009, 2010, 2011) in the sample. Source: Bureau of Statistics Netherlands (CBS), AgentschapNL, authors' calculations.

Table 1: Descriptive Statistics

	Rental (With EPC)		Owner-Occupied (With EPC)		Owner-Occupied (Without EPC)	
Number of Dwellings	*519,512*		*43,498*		*122,119*	
Variables	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Actual Annual Gas Consumption (m^3)	1,245	(526)	1,588	(665)	1,573	(632)
Predicted Annual Gas Consumption (m^3)	1,492	(624)	1,887	(759)		
Actual Annual Gas Consumption (m^3/m^2)	15.7	(7.1)	15.3	(6.2)		
Predicted Annual 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 (Age<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 (€1,000)	23.8	(11.5)	36.9	(17.1)	37.3	(26.2)
Household Wealth (€1,000)	22.6	(91.6)	177.8	(393.8)	191.3	(531.5)
Share of Households Receiving Rent Subsidy	0.41					

Notes: This table reports the descriptive statistics for rental homes with an EPC and for owner-occupied homes transacted with and without EPC. The sample of labeled dwellings consists of the dwellings that adopted an EPC in 2011 or 2012. The sample of dwellings without a label includes dwellings that were sold in 2011 or 2012. As the label categories "A+" and "A++" represent a small share of the full sample, we merge these categories with label "A". The statistics on actual annual 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 set. Source: Bureau of Statistics Netherlands (CBS), AgentschapNL, authors' calculations.

Table 2: Descriptive Statistics for Energy-efficient and Inefficient Dwellings

	Rental		Owner-occupied	
	Efficient (EI<1.2)	Inefficient (EI>2.3)	Efficient (EI<1.2)	Inefficient (EI>2.3)
Number of Dwellings	*59,595*	*53,502*	*4,381*	*4,713*
Actual Annual Gas Consumption (m^3)	1,046	1,396	1,391	1,546
	(499)	(567)	(688)	(601)
Predicted Annual Gas Consumption (m^3)	873	2,513	1,240	2,598
	(249)	(639)	(538)	(771)
Actual Annual Gas Consumption (m^3/m^2)	12.9	19.1	12.3	18.2
	(6.3)	(7.9)	(6.0)	(7.1)
Predicted Annual Gas Consumption (m^3/m^2)	10.7	34.3	10.6	30.8
	(2.8)	(8.0)	(2.9)	(8.3)
Size (m^2)	84.0	75.2	117.4	87.5
	(22.6)	(18.8)	(40.3)	(25.6)
Dwelling Type:				
Apartment	0.58	0.54	0.37	0.48
Semi-detached	0.27	0.24	0.17	0.20
Corner	0.15	0.22	0.25	0.27
Detached	0.00	0.00	0.21	0.05
Construction Period:				
1900-1929	0.03	0.13	0.06	0.15
1930-1944	0.01	0.07	0.03	0.14
1945-1959	0.06	0.39	0.08	0.26
1960-1969	0.08	0.27	0.10	0.21
1970-1979	0.09	0.12	0.12	0.23
1980-1989	0.14	0.02	0.07	0.01
1990-1999	0.31	0.00	0.19	0.00
>2000	0.28	0.00	0.35	0.00
Household Characteristics:				
Number of Household Members	1.80	1.92	2.36	2.04
	(1.04)	(1.14)	(1.23)	(1.12)
Number of Elderly (Age>64)	0.55	0.44	0.33	0.32
	(0.55)	(0.68)	(0.65)	(0.62)
Number of Children (Age<18)	0.29	0.35	0.53	0.33
	(0.72)	(0.80)	(0.93)	(0.73)
Number of Females in Household	0.99	1.00	1.16	1.02
	(0.69)	(0.76)	(0.77)	(0.71)
Number of Working Household Members	0.75	0.82	1.43	1.30
	(0.88)	(0.90)	(1.00)	(0.93)
Household Annual Net Income (€1,000)	23.7	23.0	38.0	32.9
	(11.0)	(11.1)	(18.1)	(16.4)
Household Wealth (€1,000)	30.3	20.4	220.3	135.7
	(110.9)	(69.6)	(310.1)	(120.5)
Share of Households Receiving Rent Subsidy	0.40	0.38		

Notes: This table reports the descriptive statistics for the least and the most energy-efficient homes in our sample. Energy-efficient and inefficient homes are selected based on the distribution of energy index (EI). Energy-efficient homes have an energy index lower than the 10^{th} quantile of the distribution (EI<1.2), and energy-inefficient homes have an energy index higher than the 90^{th} quantile of the distribution (EI>2.3). The statistics on actual annual 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. Standard deviations are reported in parentheses. Source: Bureau of Statistics Netherlands (CBS), AgentschapNL, authors' calculations.

Table 3: Pooled OLS Estimations

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

Notes: The dependent variable is the logarithm of actual annual gas consumption. Years included in the analysis are 2008, 2009, 2010, and 2011. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year. * P<0.10 ** P<0.05 *** P<0.01

Table 4: Instrumental Variable Estimations

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

Notes: The dependent variable is the logarithm of actual annual gas consumption. Years included in the analysis are 2008, 2009, 2010, and 2011. "Predicted Annual Gas Consumption" is instrumented by "Year of Construction". Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year. *P<0.10 ** P<0.05 *** P<0.01

Table 5: Descriptive Statistics for Moving Households

	Rental		Owner-occupied	
Number of Observations	*6,507*		*202*	
	Before	After	Before	After
Actual Gas Consumption (m^3)	1,129	1,014	1,289	1,030
	(490)	(457)	(655)	(471)
Predicted Gas Consumption (m^3)	1,416	1,244	1,690	1,477
	(609)	(558)	(706)	(645)
Actual Gas Consumption (m^3/m^2)	15.5	13.6	14.4	11.8
	(7.1)	(6.5)	(6.2)	(5.3)
Predicted Gas Consumption (m^3/m^2)	19.3	16.6	19.2	16.8
	(8.4)	(7.6)	(7.6)	(6.9)
Size (m^2)	76.2	77.7	92.2	90.1
	(21.9)	(19.5)	(33.1)	(25.5)
Construction Year (median)	1968	1977	1963	1972
Dwelling Type:				
Apartment	0.58	0.64	0.51	0.40
Semi-detached	0.27	0.22	0.21	0.39
Corner	0.15	0.14	0.12	0.02
Detached	0.00	0.00	0.15	0.19
Household Characteristics:				
Number of Household Members	1.66		1.87	
	(0.93)		(1.12)	
Number of Elderly (Age>64)	0.46		0.41	
	(0.68)		(0.69)	
Number of Children (<18)	0.30		0.43	
	(0.74)		(0.91)	
Number of Females in Household	0.97		1.02	
	(0.66)		(0.79)	
Number of Working Household Members	0.63	0.65	0.97	1.13
	(0.75)	(0.73)	(0.60)	(0.64)
Household Annual Net Income (1000 Euro)	21.1	21.7	27.7	26.8
	(8.9)	(9.3)	(11.1)	(10.8)
Household Wealth (1000 Euro)	17.2	21.5	133.3	58.1
	(56.0)	(80.1)	(181.5)	(147.9)
Share of Households Receiving Rent Subsidy	0.48	0.47		
	(0.48)	(0.50)		

Notes:
The statistics are provided for the years before $(t-1)$ and after $(t+1)$ the households move to a new home between 2008 and 2011. We exclude the households that had a change in their composition between 2008 and 2011. "Apartment" category is a combination of four different apartment types which are reported in the AgentschapNL data.

Table 6: Fixed-Effects (IV) Estimations

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

Notes: The dependent variable is the logarithm of actual annual gas consumption. Years included in the analysis are 2008, 2009, 2010, and 2011. "Predicted Annual Gas Consumption" is instrumented by "Year of Construction". We exclude the households that had a change in their composition between 2008 and 2011. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year.* P<0.10 ** P<0.05 *** P<0.01

Table 7: Descriptive Statistics for Quasi-Experimental Analysis

	Participant Group			Non-participant 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 Performance Index	2.34	1.52	-35.04	1.90	1.90	0.00
	(0.39)	(0.30)		(0.58)	(0.58)	
Household Annual Net Income (€1,000)	40.1	39.8		31.5	33.8	
	(19.5)	(17.4)		(14.8)	(16.8)	
Household Wealth (€1,000)	285.8			80.3		
	(265.8)			(252.8)		
Number of Household Members	2.41			2.04		
	(1.08)			(1.11)		
Size (m^2)	127.8			104.6		
	(35.4)			(33.2)		
Construction Year (Median)	1961			1970		

Notes: The table reports the descriptive statistics for the owner-occupied homes in the participant group (that benefited from the subsidy program in 2010) and the non-participant group. The non-participant group consists of owner-occupied dwellings, that were transacted in 2008 (with a label) and did not apply to any of the energy efficiency subsidy programs offered by the government during the period of the analysis. For both participant and non-participant groups, we exclude the dwellings in which the household composition changed from 2009 to 2011. The energy index of the dwellings in the non-participant group is assumed to be constant between 2009 and 2011. We report the information on household wealth for 2009 only, as it is not available for 2011. Standard deviations are indicated in parentheses. Source: Bureau of Statistics Netherlands (CBS), AgentschapNL, authors' calculations.

Table 8: Quasi-Experimental Analysis

	(1) First-Diff.	(2) IV	(3) PSM	(4) CF
Δ Log (Energy Index)	0.408***	0.445***	0.449***	0.439***
	[0.031]	[0.032]	[0.036]	[0.032]
Inverse Mills Ratio				-0.074***
				[0.008]
R^2	0.034	0.034	0.032	0.051
Number of Households	5,198	5,198	5,198	5,198

Notes: The dependent variable is the change in the logarithm of actual gas consumption. Years included in the analysis are 2009 and 2011. The change in income and working status of the household are included as control variables in all regressions. For the IV, PSM and CF estimations, we use participation to subsidy program as an instrument for the change in energy performance index. For the PSM estimation strategy, we use dwelling characteristics (age, size, type, province) as determinants of program participation. In order to calculate the Inverse Mills Ratio (IMR) in column (4), we use the initial actual gas consumption, initial energy performance index to predict the program participation. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year. *P<0.10 ** P<0.05 *** P<0.01

Table 9: IV Estimations for Wealth and Income Cohorts

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

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

Notes: The dependent variable is the logarithm of actual annual gas consumption. Households are assigned to the groups based on their wealth and income levels (percentiles). Control variables are included in all regressions. Years included in the analysis are 2008, 2009, 2010, and 2011. 2010, 2011 are excluded from the analysis of wealth cohorts, as the information is not available for these years. “Predicted Annual Gas Consumption” is instrumented by “Year of Construction”. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year.* P<0.10 ** P<0.05 *** P<0.01

Table 10: Quantile (IV) Regression Estimations for Actual Gas Consumption Levels

Panel A: Sample of Home Owners					
	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Actual Gas Consumption (m^3)	*(707)*	*(1,039)*	*(1,481)*	*(2,003)*	*(2,454)*
Log (Predicted Annual Gas Cons.)	0.922***	0.826***	0.750***	0.644***	0.492***
	[0.046]	[0.031]	[0.031]	[0.023]	[0.019]

Panel B: Sample of Tenants					
	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Actual Gas Consumption (m^3)	*(590)*	*(846)*	*(1,166)*	*(1,539)*	*(1,917)*
Log (Predicted Annual Gas Cons.)	0.699***	0.647***	0.599***	0.553***	0.494***
	[0.022]	[0.019]	[0.018]	[0.014]	[0.010]

Notes: The dependent variable is the logarithm of actual annual gas consumption. Quantiles are chosen based on the actual gas use distribution of the households. The values in parentheses represent the actual annual gas consumption level (m^3) for each quantile. Control variables are included in all regressions. Years included in the analysis are 2008, 2009, 2010, and 2011. 2010, 2011 are excluded from the analysis of wealth cohorts, as the information is not available for these years. "Predicted Annual Gas Consumption" is instrumented by "Year of Construction". Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year.* P<0.10 ** P<0.05 *** P<0.01

Appendix A

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).

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

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

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

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.

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

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

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

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:

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

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}).

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

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:

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

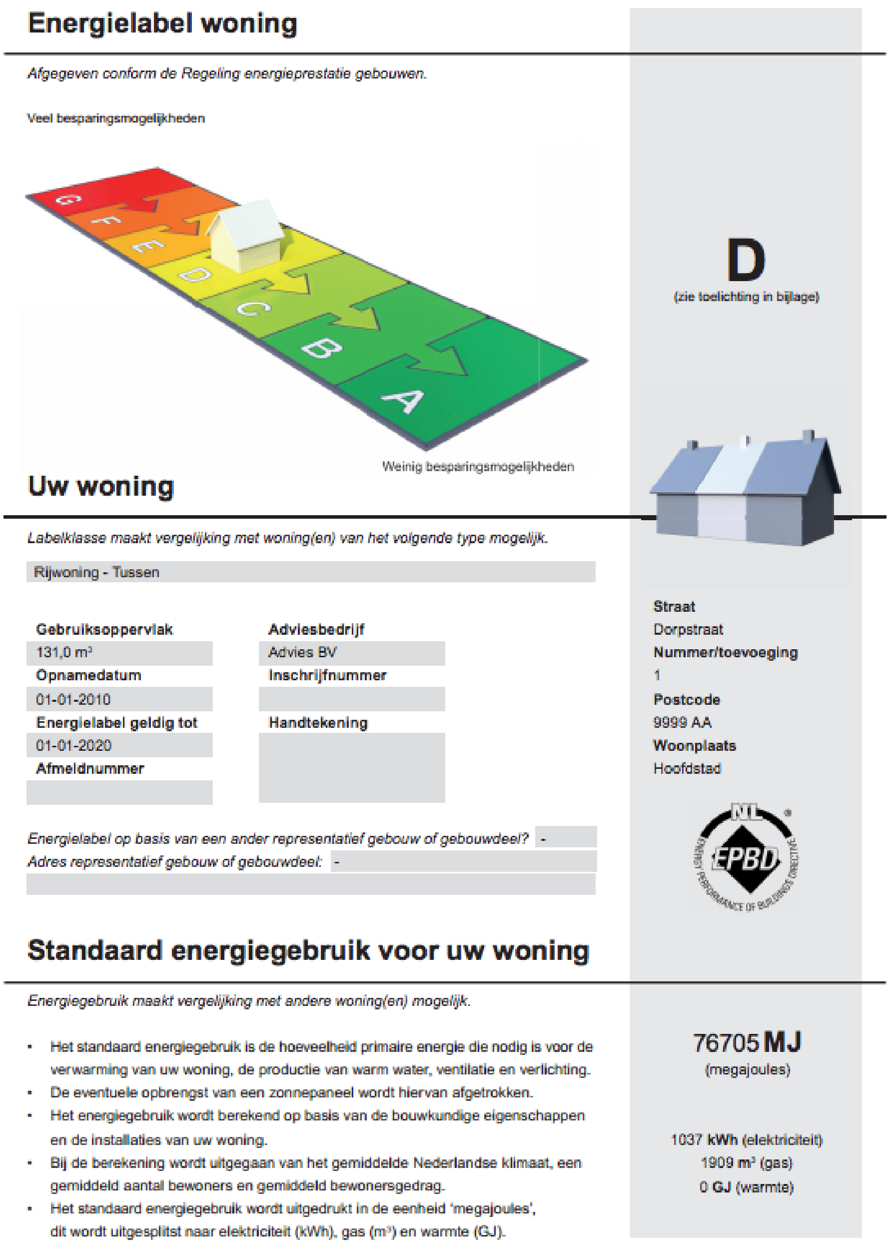
$$Q = Q_k + Q_b + N(Q_p + Q_s F_s N_s + Q_{ba} N_b D_b) \tag{A.8}$$

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).

Appendix B

Supplementary Figures and Tables

Figure B.1: Cover Page of the EPC



Energielabel woning

Afgegeven conform de Regeling energieprestatie gebouwen.

Veel besparingsmogelijkheden

G F E D C B A

Weinig besparingsmogelijkheden

D

(zie toelichting in bijlage)

Uw woning

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

Rijwoning - Tussen

Gebruiksoppervlak	**Adviesbedrijf**
131,0 m^2	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: -

NL EPBD ENERGY PERFORMANCE OF BUILDINGS DIRECTIVE

Standaard energiegebruik voor uw woning

Energiegebruik maakt vergelijking met andere woning(en) mogelijk.

- Het standaard energiegebruik is de hoeveelheid primaire energie die nodig is voor de verwarming van uw woning, de productie van warm water, ventilatie en verlichting.
- De eventuele opbrengst van een zonnepaneel wordt hiervan afgetrokken.
- Het energiegebruik wordt berekend op basis van de bouwkundige eigenschappen en de installaties van uw woning.
- Bij de berekening wordt uitgegaan van het gemiddelde Nederlandse klimaat, een gemiddeld aantal bewoners en gemiddeld bewonersgedrag.
- Het standaard energiegebruik wordt uitgedrukt in de eenheid 'megajoules', dit wordt uitgesplitst naar elektriciteit (kWh), gas (m^3) en warmte (GJ).

76705 **MJ**
(megajoules)

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

Source: AgentschapNL

Table B.1: Pooled OLS Estimations (Consumption per m^2)

	(1) Rental	(2) Owner-Occupied	(3) Rental	(4) Owner-Occupied
Log (Predicted Annual Gas Consumption per m^2)	0.468***	0.500***	0.471***	0.505***
	[0.008]	[0.008]	[0.007]	[0.007]
Number of Household Members			0.070***	0.082***
			[0.003]	[0.007]
Number of Household Members^2			-0.006***	-0.007***
			[0.000]	[0.001]
Number of Children (<18)			-0.008***	-0.016***
			[0.001]	[0.003]
Number of Elderly (Age>64)			0.022***	0.023***
			[0.002]	[0.003]
Number of Females in Household			0.017***	0.010***
			[0.001]	[0.002]
All Household Members Are Working (1=yes)			-0.032***	-0.025***
			[0.001]	[0.004]
Log (Household Income)			0.038***	0.022***
			[0.002]	[0.005]
Receiving Rent Subsidy (1=yes)			-0.023***	
			[0.002]	
Province Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Constant	1.473***	1.318***	1.707***	1.385***
	[0.023]	[0.019]	[0.034]	[0.056]
R^2	0.184	0.205	0.198	0.217
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: The dependent variable is the logarithm of actual annual gas consumption per m^2. Predicted and actual annual gas consumption variables are scaled by the size of the home. Years included in the analysis are 2008, 2009, 2010, and 2011. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year. *P<0.10 ** P<0.05 *** P<0.01

Table B.2: Pooled OLS Estimations (Dwellings Constructed after 1999)

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

Notes: The dependent variable is the logarithm of actual annual gas consumption. We restrict the sample to the dwellings constructed after 1999. Years included in the analysis are 2008, 2009, 2010, and 2011. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year. * P<0.10. ** P<0.05. *** P<0.01

Table B.3: Instrumental Variable Estimations (U-value Requirement for External Walls)

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

Notes: The dependent variable is the logarithm of actual annual gas consumption. Years included in the analysis are 2008, 2009, 2010, and 2011. "Predicted Annual Gas Consumption" is instrumented by "Maximum U-value requirement for external walls at the time of construction". Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year.* P<0.10 ** P<0.05 *** P<0.01

Table B.4: IV Estimations (Controling for Dwelling Size)

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

Notes: The dependent variable is the logarithm of actual annual gas consumption. Years included in the analysis are 2008, 2009, 2010, and 2011. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year. * P<0.10 ** P<0.05 *** P<0.01

Table B.5: Random-Effects (IV) Estimations

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

Notes: Dependent variable is logarithm of actual annual gas consumption. Years included in the analysis are 2008, 2009, 2010, and 2011. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year. * P<0.10 ** P<0.05 *** P<0.01

Table B.6: Quantile Regression (Non-IV) Estimations for Actual Gas Consumption Levels

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

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

Notes: Dependent variable is logarithm of actual annual gas consumption. Quantiles are chosen based on the actual gas use distribution of the households. Control variables are included in all regressions. Years included in the analysis are 2008, 2009, 2010, and 2011. 2010, 2011 are excluded from the analysis of wealth cohorts, as the information is not available for these years. Heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered by province-year.* P<0.10 ** P<0.05 *** P<0.01