

Refurbishment Effectiveness Assessment Based On Consumption Data From iESA Accounts

Filip Milojkovic, co2online, Berlin Germany

Abstract

Owners of apartments or buildings can improve the energy efficiency of their home with measures in two main areas: insulation of the building envelope to reduce heat losses and the exchange of heating system components to generate heat energy. All of these are associated with envisaged energy savings, which can be calculated demand oriented based on building physics. What the end user is mainly interested in, however, is not theoretical demand, but actual consumption. The interactive Energy Savings Account (iESA), developed and maintained by co2online, gives end consumers the opportunity to monitor the energy consumption of their household. With this online tool users can verify, whether calculated energy savings supposedly induced by refurbishment actually materialise. Currently, there are 88,000 registered users in the iESA, a third logs in regularly. In the context of this paper, data on more than one thousand households is available for analysis.

For this study we subset the data base and use information from iESA accounts that exhibit plausible values with at least monthly input of meter values, contributed by the user over a sufficient time horizon before and after the investment. We find relevant and significant savings effects for the insulation of the roof, facade and basement ceiling, while the results are inconclusive for insulation of the attic floor and windows exchange.

This data set is unique, in that to our knowledge it is the only data set in Germany with panel data of energy consumption focussed around the implementation of energy efficiency improvements. Furthermore, this data set has so far not been analysed towards this end and the literature is scarce on similarly detailed analysis of the effectiveness of refurbishment measures based on actual consumption data. In two regression models the dependent variable measures energy consumption on a monthly basis, first in absolute levels and second in deviation from the household specific mean to control for individual fixed effects.

Introduction

This paper analyses the average effect of refurbishment activity on heat energy consumption. The data is user-generated in co2online's "interactive Energy Savings Account" (short: iESA)¹, a complete energy monitoring and advice solution for everyone to use free of charge, with freemium services available. The tool was developed and is maintained by co2online,² a Berlin based NGO, with financial support from the German Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety starting in 2003. The iESA shows the user how much energy is consumed at a glance whether it is heating, electricity, water or motorised individual mobility. The Account manages data, bills and meter readings digitally and presents them graphically. The focus in this paper is on space heating. Currently, users can input data via the webinterface, the iESA smartphone-app or via .csv import. Automated communication between a smart (gas) meter and the account has been piloted and will be rolled out soon.

Primarily the purpose of the iESA is to support individual homeowners in their energy saving efforts. So data generation is driven by the motivation of the homeowner to monitor his consumption with individual building analysis and savings advice. Scientific aspects, e.g. bulk data analysis, have

¹ <http://esa.co2online.com/>

² Please refer to <http://www.co2online.com/> for the English website or .de for the more extensive German version.

thus far not been the prime objective. This paper is a first attempt to use these user-generated data for regression modelling. The selection of the subset to enable predictive analysis of energy savings for refurbishment measures is based on extensive descriptive presentation of the data, graphically and in tables.

Literature

To our knowledge there is no data set in Germany, that combines measured information on energy consumption with refurbishment activity. There are several approaches with a focus on one or the other, but the combination of panel structure energy consumption data and refurbishment as presented in this data set is unique.

Research by co2online "*Refurbishment Effectiveness*" in cooperation with Fraunhofer ISE and the Ostfalia Hochschule für angewandte Wissenschaften laid bare the discrepancy between ex ante technical potential of energy efficiency refurbishment in residential buildings and the wide range of materialized savings ex post.³ The authors assessed the refurbishment effectiveness and compared savings for a sample of 180 buildings. In cases where the heating equipment was replaced, savings ranged from 8% to 50%, for heating in combination with thermal solar between 16% and 65%. For a combination of roof-fassade-windows savings ranged from 21% to 48%. Furthermore, the gap between demand calculations and actual consumption after refurbishment diverged significantly, in some cases by around 40%. The ranges could partly be explained by a change in use pattern after the refurbishment, but more importantly by substandard quality of implementation. Therefore, based on these findings, the authors suggest: (a) to tighten quality standards for energy auditors and craftsmen; (b) to implement an ex post quality check in combination with consumption measurement as a criteria for financial support from the state (KfW and BAFA fundings); (c) to use heat meters, smart meters and feedback instruments to inform the user about his current consumption on a monthly or even weekly basis; (d) to structure tailor-made communication for the target group and provide more relevant information in the right phase of information, implementation and monitoring.

In a parallel approach, co2online runs the two tools *Heizspiegelkampagne* and *Modernisierungs-ratgeber* (engl.: heating bill analysis campaign⁴ and building modernisation advisory tool⁵): The tremendous amount of data held by co2online is generated by users of on- and offline advisory tools on energy efficiency, ranging from consumer goods via electric appliances to heating and insulation. These tools deliver snapshots of the point in time, at which the user enters the EnergiesparChecks (so-called energy savings check) and provides the necessary information to the tool. Therefore the available information does not allow comparisons of before and after refurbishment consumption, like the kind conducted in this paper on iESA account data.

Still widely cited as the reference approach to assess the German building stock is the *Datenbasis Gebäudebestand* (engl.: Database Buildings Stock, cf. Diefenbach et al. (2010)): This representative survey of about 7,500 German buildings founds on a 16-page questionnaire and results from a joint project by the Institute for Housing and Environment (IWU)⁶ and the former Bremen Energy Institute (BEI)⁷. The questionnaire was presented to homeowners by chimney sweeps to collect details on space heating systems, geometry and insulation of their buildings. Consumption was not surveyed.

KfW and BAFA subsidies: To better the economic viability of relevant measures the state-owned bank Kreditanstalt für Wiederaufbau (KfW)⁸ and the Federal Office of Economics and Export

³ c.f. Jahnke et al. (2015)

⁴ <http://www.heizspiegel.de/heizspiegel/bundesweiter-heizspiegel/>

⁵ <http://www.co2online.de/service/energiesparchecks/modernisierungsscheck/>

⁶ For more information: www.iwu.de

⁷ <http://www.bremer-energie-institut.de/>, now part of Fraunhofer IFAM institute

⁸ www.kfw.de

Control (BAFA)⁹ provide cheap credit and grants conditioned on specific U-values of implemented new parts.¹⁰ The funding support is strictly focussed on demand calculations and disregards actual savings after the measure. Without additional surveys of recipients, there is no information about before and after refurbishment consumption.

German Residential Energy Consumption Survey: This data set was collected by the RWI Essen¹¹ and market research outfit Forsa in Berlin in 2005. Grösche and Vance (2008) combine data on 2530 observations of real investment costs for 16 retrofit measures in one and two family homes and engineering estimates of the respective energy savings with information on wage and material costs along with the sociodemographic characteristics for the sampled households. Here again, there is no information on actual consumption.

According to recent data from the *BBSR* (Federal Institute for Research on Building, Urban Affairs and Spatial Development, c.f. BBSR 2016) the overall market for energy efficiency refurbishment in Germany is in decline. Compared to 2010, the volume of investment into the building stock in 2014 hardly changed and amounted to EUR 118.2 Billion. Two underlying trends stand out: (a) The share of energy related refurbishment activity declined from a third down to 27%. Especially comprehensive measures for a full energy efficiency overhaul of residential buildings were reduced. Owner occupiers as well as (professional and private) landlords took a more nuanced stance towards refurbishment, opting only for those measures that promised value for money. (b) While activity for energy efficiency overhaul of multi family homes and non-residential buildings continued to increase, activity in one and two family homes was at the peak in 2010 and "normalized" since. Especially the building envelope was less likely to receive efficiency measures, while the renewal of heating equipment was still in high demand.

Descriptive analysis

We restrict our analysis to one and two family homes, since the unit of observation is the household and only in small buildings the household and the building coincide. The basic sample only includes households that have implemented at least one of five refurbishment measures: 1. Insulation of the roof; 2. Insulation of the attic floor (topmost ceiling); 3. Insulation of the facade; 4. Exchange of windows; 5. Insulation of the basement ceiling.

This analysis sets off on 544,018 data points with monthly heat energy consumption. 7,157 households contributed information for the timeframe January 1990 until late 2015, which on average implies data on around 181 months. The frequency of monthly data strictly increases over time until 2013. The stepwise increase coincides with the usual billing period for heating, which were entered retrospectively. The drop in observations coincides with the decline in fossil energy prices. Energy consumption became less of a burden for households so there was less motivation to take care of their iESA account. While the number of households with informative aggregated data decreases, the number of metering values grows exponentially (not shown in this paper¹²). This implies that heavy users contribute information in increasing frequency either with manually input meter values or as bulk import of smart meter data.

The variables of iESA data

This chapter will list the variables and give multivariate presentations of the raw data. The goal is to identify correlations and differences in categories of households in order to build a sensible model. The descriptive analysis leads to a subset of data, which feeds the regression model.

⁹ www.bafa.de

¹⁰ The U-value is the overall heat transfer coefficient.

¹¹ www.rwi-essen.de

¹² The page <http://www.co2online.de/statistik/nutzung-der-energiesparchecks/> gives comprehensive live information on usage of our services - only available in German as of now.

Figure 1. Distribution of data points over time

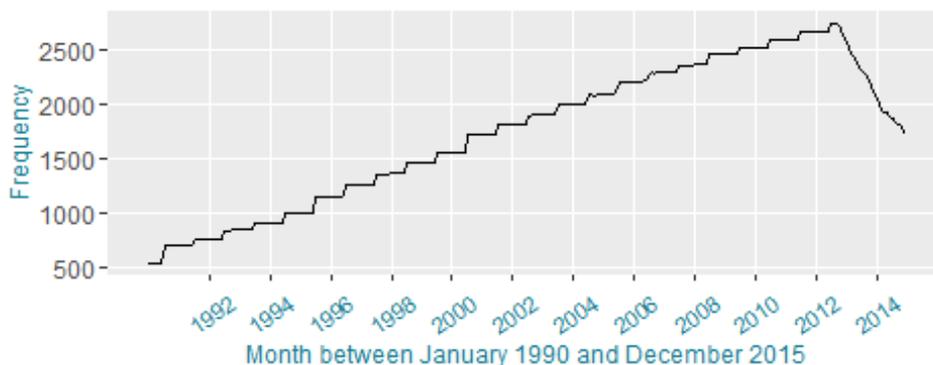
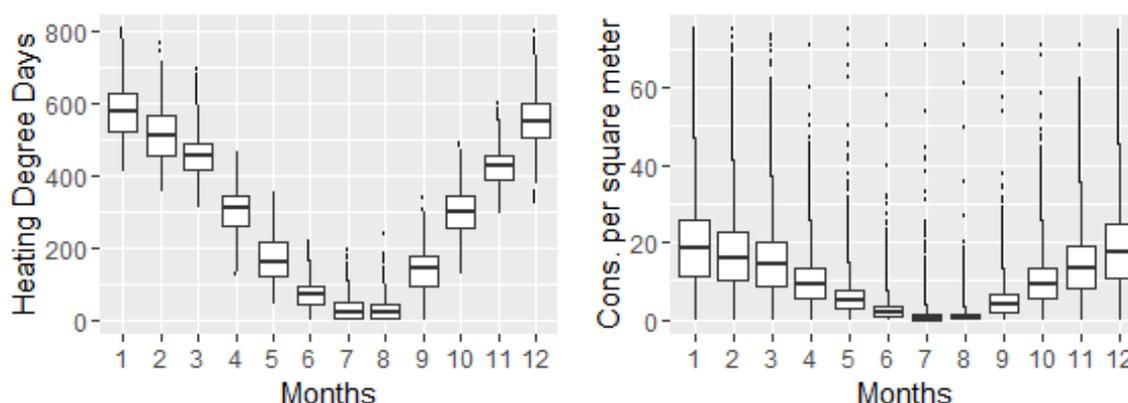


Table 1. Variables in iESA data and decoding

variable code	description
householdId	unique household ID
consumptionTotal	monthly consumption data - absolute
Consumption per m2	monthly consumption per square meter
Heating Degree Days (HDD)	monthly heating degree days for the ZIP code
Add.Heating	consumption of the additional heating system: With this unique feature to iESA, users can monitor the consumption of their stove or fireplace.
Cons.Hotwater	consumption of energy for hot water generation - only available if the technical equipment allows separate measurement
Cons.Demeaned	deviation of consumption per square meter from the household specific mean over time - used to check for robustness of the model against individual fixed effects
Roof	1 if roof was insulated
Attic	1 if attic was insulated
Fassade	1 if fassade was insulated
Basement	1 if basement Ceiling was insulated
Windows	1 if windows were exchanged
Inhabitants	inhabitants
Area	useful space
building ZIP	building ZIP code
building type	strictly one and two family homes
Construction Year	construction year
EnEV	8 possible values for construction year class for the intervals around the 7 steps tightening the German ordinance for energy efficiency
Centr.Heating	central or decentral heating
Centr.Hotwater	central or decentral hot water generation
energySource	energy source
energySourceWarmwater	energy source for hot water generation
energySourceAdditional	energy source of the additional heating system (usually wood-fired)
basementHeated	1 for basement heated

Heating degree days and Consumption of heat energy

Figure 2. Split by month: Heating Degree Days on the left; Consumption per m² on the right



The boxplots on the right in figure 2 show a number of unplausible outliers for monthly consumption, which must be due to measurement error. These outliers will distort our prediction and we therefore exclude them from the data set for modeling. The following table shows the cutoff value for every month, which is the 99.75th quantile of all observations in a given month. This implies an exclusion of one in four hundred highest energy consumptions. Since we cannot be sure that other values from the household are valid, even if they are in the legitimate range below the 99.75th percentile, we exclude the household entirely, if at least one observation is among the 0.25% highest observation for a given month. The following table shows the upper cutoff values for heat energy consumption. On the low end of consumption, we exclude households, that show negligible consumption in any January or February below 0.05 kWh/m² and month.

Table 2. 99.75th quantile of consumption per m² by month over all years

Jan	Feb	Mar	Apr	May	June
62.27	54.98	48.36	34.42	23.95	13.27
July	Aug	Sep	Oct	Nov	Dec
9.42	9.33	20.99	34.85	46.75	60.34

The filter on the highest values applies to 607 households. The filter on the low end applies to 392 households. At the same time, we exclude 11 households with unplausible consumption of energy for hot water generation (cutoff value of 5 kWh/m² and month). Both these filters exclude 211,085 observations.¹³ Figure 3 shows energy consumption for the remaining 332,933 observations, split by month over the years in the sample.

Refurbishment activity

Central to our analysis is the influence of refurbishment activity on energy consumption. The following graph shows so-called "events" that users can select in their iESA account on the web portal to identify the year in which the measure was implemented. Several peaks allow interpretation: On the one hand users seem not to be 100% accurate when they select the year of refurbishment activity, if it happened more than a decade ago. The next round number is often chosen, which explains the peaks in 1990, 1995 and 2000. Starting with 2005, however, we assume that all selected years are accurate.¹⁴ On the other hand, a decline in input meter data in very recent years explains the decline in the number of "refurbishment events" after 2013.

¹³ Differences in sums are due to multiple filters applying to a single household.

¹⁴ This effect is well known to cause inaccuracy in research of user generated data.

Figure 3. Sample time frame 2009-2014: Distribution of consumption per square meter in kWh/month*m² living space, split by year and month

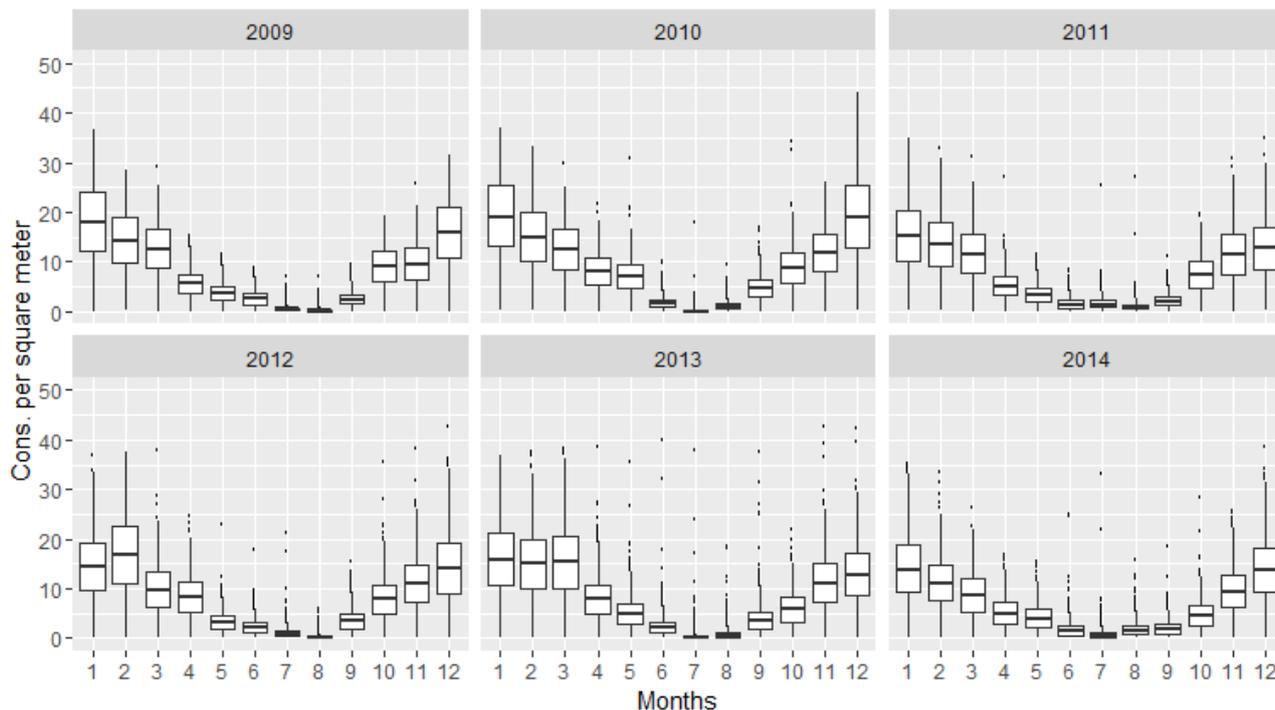
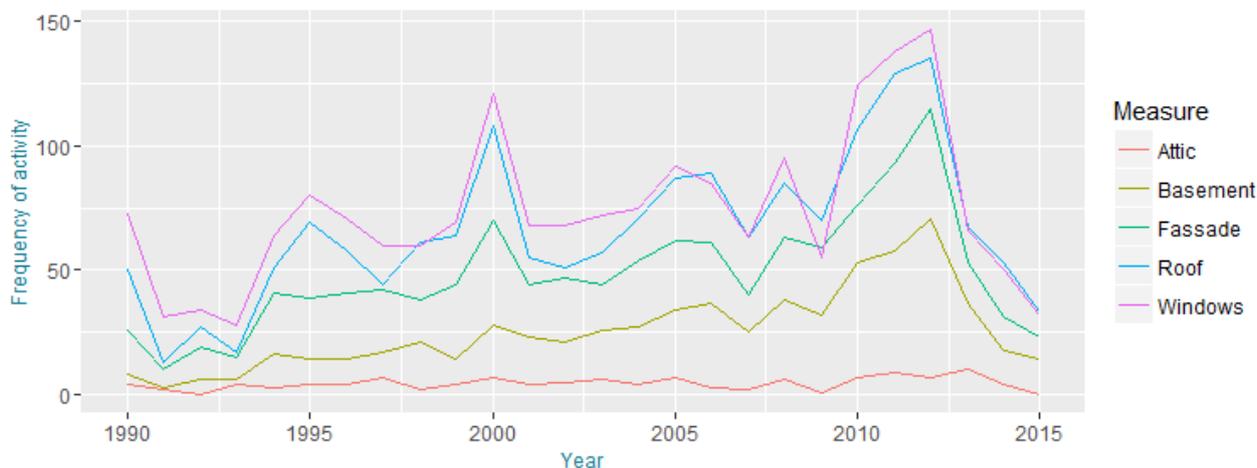


Figure 4 includes information on 2,086 households. The point in time of refurbishment activity does not necessarily fall into the time frame for meter data input. A household would also be included here in the present sample, if there is metered data for the time frame 2008-2012 with a stated refurbishment event in the year 2000. Therefore, these numbers cannot be interpreted as the refurbishment rate.¹⁵

Table 3 gives the number of "events" split by measure. The difference between events and unique household IDs can be explained by households that have repeated or extended refurbishment activities. At present iESA does not allow the user to define the degree to which a measure was implemented, for instance the percentage of the envelope covered in insulation or the depth of the insulation layer.¹⁶

Figure 4. Refurbishment activity over time



¹⁵ 100 households in this graph correspond to around 5% of households with a certain activity.

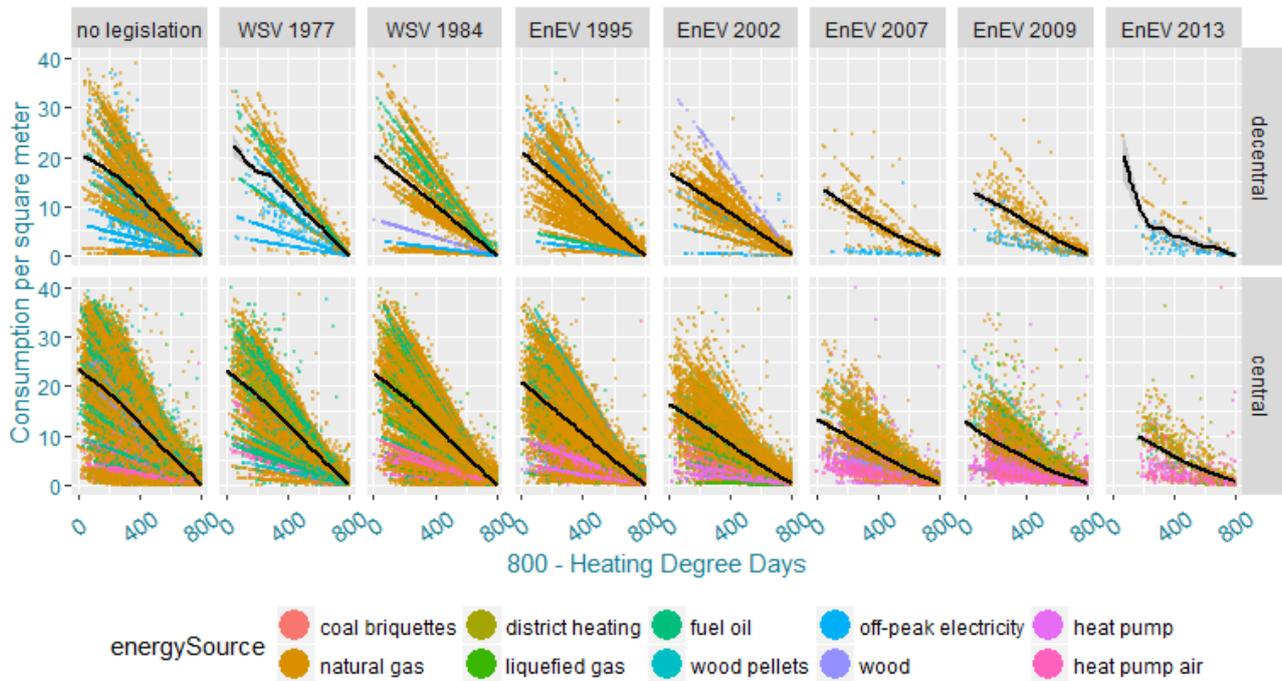
¹⁶ This feature is currently under development. More on this issue in the final paragraph of this paper.

Table 3. Number of "refurbishment events" as reported by the users

Measure	Events	Unique hh-ID	as of HH in sample
Roof	1,714	1,681	80.6 %
Attic floor	116	111	5.3 %
Fassade	1,250	1,222	58.6 %
Windows	1,921	1,885	90.4 %
Basement Ceiling	661	650	31.2 %

The relation between Consumption per m² and heating degree days

Figure 5. The relation between consumption and heating degree days, split by energy source in color and construction year class (EnEV) versus heating type in the panes



As we can see, more recently constructed buildings under building energy efficiency legislation show a lower slope (black line) than older buildings. In order to better understand what the information in the "refurbishment events" may tell us, we constructed a refurbishment index as follows: (a) A new variable builds the sum over the five refurbishment measures for each monthly observation (range of 0 to five). (b) We build 16 classes with eight categories for EnEV by two categories for heating type, as in the graph above. (c) The index is just the average of sums of refurbishment dummies for all observations in a given class. We can see that refurbishment indices are consistently above three for higher construction year classes (younger than 2002). The interpretation of these (unexpected) numbers is that many users chose an event in their iESA account to reflect the better efficiency of their buildings, even if the measure was already taken in the initial construction of the building. Subsequent refurbishment activity does not pay off for recently constructed buildings, so it is highly unlikely to see that many additional measures for buildings which had to comply with ambitious standards in the first place. Table 4 shows the refurbishment index for the aforementioned 16 subgroups

Table 4. The refurbishment index for construction year classes and centralisation of the heating system

	no legislation	WSV 1977	WSV 1984	EnEV 1995	EnEV 2002	EnEV 2007	EnEV 2009	EnEV 2013
decentral	2.2	1.8	2.8	3	3.1	3.6	3.5	3.6
central	2.3	1.7	2.3	2.9	3.3	3.3	3.6	3.6
# of HH in class	771	148	226	361	234	92	218	64

Final subsetting for the regression model

Based on the insights gained from the descriptive analysis of our iESA data, we further subset the data for the regression model to include only those households in buildings constructed before 2002, the four oldest classes. Additionally, we reduce the sample to include observations only for the time frame 2000 up to 2016. This subsetting to include only construction years before the tightening of building energy efficiency standards with the second EnEV in 2002 and the current time frame excludes 112,016 observations and leaves 220,917 observations on 1,497 households.

Table 5. The number of "refurbishment events" in the sample used for regressions

Measure	Events	Unique hh-ID	as of HH in sample
Roof	702	687	45.9 %
Attic Floor	33	33	2.2 %
Fassade	418	409	27.3 %
Windows	755	744	49.7 %
Basement Ceiling	205	201	13.4 %

Regression Analysis

Introduction to model setup

We show regression results for two types of models separated into the following two tables. Absolute monthly consumption per square meter is the dependent variable in the first table. For the second table, we calculated monthly per square meter consumption in deviation from the household specific mean over time. This procedure is also applied to all explanatory variables. The motivation for this approach is to hide individual specific fixed effects. An alternative approach would be to include a dummy variable in the regression model for each household. Since we deal with data on around 1,500 households, this approach is not feasible with commonly available computing power.

All constant factors influencing energy consumption are masked in the second model, which includes the number of residents (which hardly changes over time in our sample), the building area and the construction year class according to steps in the EnEV. This is the reason to exclude these in the regression on the deviation from the mean shown in the second table. One could think of several further factors influencing energy consumption not available to be included as explanatory variables, such as the general attitude towards climate change, income and wealth level and whether there is an infant in the household.

Tables 6 and 7 report t-values next to the coefficients. Since our data set is large, the usual interpretation of p-values could be misleading.¹⁷ Standard deviations on the estimates of the

¹⁷ The American Statistical Association has recently issued a statement warning of misleading interpretations of the p-value. The statement can be accessed at <http://amstat.tandfonline.com/doi/abs/10.1080/00031305.2016.1154108>

coefficients are very small, so p-values are low as well. In fact, most of the p-values are extremely small (below 2 times 10 to the power of -16) which does not offer meaningful interpretations. As a reference, absolute t-values of greater 3.291 lead to p-values smaller 0.001. P-values test the null-hypothesis of zero marginal effect, so for instance a p-value of 0.0001 indicates that the probability to witness the present data although the null-hypothesis is true, is one in ten thousand. Therefore, in order to better gage the explanatory power of the coefficients we resort to presenting the t-value instead.

The models are set up as to test the robustness of the marginal effects on refurbishment activity, controlling for an increasing number of explanatory variables. Both models show the fragility of the estimation of marginal effects of refurbishment on energy consumption. Not only the significance varies, but also for some measures the sign of the effect. This implies that our data exhibits a lot of noise in the measurement of refurbishments.

Discussion of regression model with absolute consumption as the dependent variable

The model with merely the refurbishment dummies as the explanatory variables has very little explanatory power, as shown in the first two columns of the output. The R-squared for this model (0.011) indicates that only about one percent of the variance in consumption can be explained by the variance in the explanatory variables. As expected, the heating degree days as a proxy for outside temperature is responsible for most of the explanatory power in the three models two to four, as indicated by the R-squared of above 0.85. In these models we include a number of categorical variables (construction year class EnEV, month of the year as well as heating type and hotwater type in the last model). Thereby, the variable EnEV serves as the reference and for each of the other categorical variables one category is omitted from model output (i.e. January, decentral heating and hotwater). The four categories of EnEV then provide the constellation of characteristics, against which the marginal effects for switching categories in the other variables can be interpreted.

At this point we discuss only the sign of the marginal effect, while the section on "Predictions from the model" discusses whether the magnitude of the effect is relevant. Overall the results of the models are mixed:

1. For roof, facade and basement ceiling insulation the sign of the coefficient is consistently negative, which indicates lower consumption for insulated buildings, as we would expect. In all three cases high absolute t-values indicate statistical significance for all 4 specifications of the model.
2. The results for window exchange and attic insulation are inconclusive, however. The indicator variable for window replacement switches the direction of the effect from the first specification to the other specifications. According to the model, attic insulation leads to higher consumption. Estimates for both these indicators show comparatively low t-values, which lets us conclude that the precision in measurement of refurbishment activity in these categories does not suffice to detect statistically significant and economically relevant marginal effects.
3. As we could already see above, the stray-like structure in figure 5 indicates a very close relationship between outside temperature proxied by heating degree days and overall consumption. This can as well be seen from the t-values next to the robust marginal effect of Heating Degree Days in all four specifications. The steep drop in its t-value from the second to the third model can be explained with the inclusion of month of the year as an explanatory variable. As the left panel in figure 2 shows, the month of the year (naturally) proxies well for Heating Degree Days (multicollinearity).
4. Larger buildings consume less energy per square meter than smaller ones, as we would expect.
5. The marginal effects for the categorical variables EnEV and month should be interpreted in context of predictions from the model.

6. We cannot detect any decreasing trend in the data over the years. The sign of the marginal effect would point towards a reduction, but both the magnitude of the effect and its t-value do not allow a robust interpretation.
7. The marginal effect on the consumption of an additional heating system shows a high t-value, but a negligible marginal effect in all specifications.

Table 6. Coefficients and t-values for dependent variable: consumption per square meter

Variable	Coeff.1	t value	Coeff.2	t value	Coeff.3	t value	Coeff.4	t value
Intercept	9.5485	254.18	-	-	-	-	-	-
Roof	-0.3734	-10.14	-0.2	-8.96	-0.1707	-7.56	-0.1588	-7.04
Attic	0.2304	2.75	0.3893	7.81	0.4042	8.12	0.407	8.18
Fassade	-1.2155	-33.09	-0.9035	-40.49	-0.9209	-41.34	-0.9187	-41.21
Windows	-0.0475	-1.2	0.0156	0.64	0.0555	2.26	0.0408	1.66
Basement	-0.601	-13.64	-0.6021	-23.08	-0.5862	-22.51	-0.6098	-23.42
Degree Days	-	-	0.0292	641.84	0.025	159.61	0.025	159.48
Area	-	-	-0.0063	-32.86	-0.0063	-32.94	-0.0066	-34.75
Inhabitants	-	-	-0.0204	-2.52	-0.0174	-2.16	-0.0159	-1.97
no EnEV	-	-	1.9821	47.59	41.386	9.34	41.1789	9.3
WSV 1977	-	-	1.7545	37.11	41.1715	9.29	40.9596	9.25
WSV 1984	-	-	1.7359	37.1	41.1101	9.28	40.9319	9.25
EnEV 1995	-	-	0.9418	19.56	40.3411	9.11	40.1358	9.08
Feb	-	-	-	-	-0.3354	-7.22	-0.3392	-7.31
Mar	-	-	-	-	-0.7843	-15.99	-0.7907	-16.14
Apr	-	-	-	-	-1.6527	-26.12	-1.6672	-26.37
May	-	-	-	-	-2.2209	-28.35	-2.2418	-28.64
June	-	-	-	-	-2.4091	-26.42	-2.4349	-26.72
July	-	-	-	-	-2.4607	-25.36	-2.4885	-25.66
Aug	-	-	-	-	-2.488	-25.64	-2.5158	-25.94
Sep	-	-	-	-	-2.2393	-27.15	-2.2613	-27.43
Oct	-	-	-	-	-1.6271	-25.71	-1.6415	-25.96
Nov	-	-	-	-	-0.9191	-17.84	-0.9269	-18.01
Dec	-	-	-	-	-0.1867	-4.08	-0.1884	-4.12
Year	-	-	-	-	-0.0183	-8.3	-0.0184	-8.34
Centr.Heating	-	-	-	-	-	-	0.2147	5.72
Centr.Hotwater	-	-	-	-	-	-	0.3049	8.96
Add.Heating	-	-	-	-	-	-	-1e-04	-17.97
R squared	0.011	-	0.852	-	0.853	-	0.853	-
RSE	7.47	-	4.406	-	4.395	-	4.39	-

Discussion of regression model with deviation from mean consumption as the dependent variable

As mentioned before, the goal of the following model based on the so-called "within transformation" of our panel data is to account for the possibility of household specific fixed effects, without including a dummy variable for each individual household. This robustness check confirms the results from the model in absolute values.

1. The remarkable difference between models is the consistent negative effect of window exchange on energy consumption in the demeaned model. All marginal effects (despite for windows) are in about the same range of magnitude as in the full specification of the previous model.
2. Here again, and as expected, heating degree days drive the explanatory power of the model.
3. As well, we cannot detect a decreasing trend over the years.

Table 7. Coefficients and t-values for dependent variable: consumption per square meter in deviation from individual mean

Variable	Coeff.1	t value	Coeff.2	t value
Intercept	-	-	11.8342	3.7
Roof	-0.4152	-5.71	-0.2374	-7.15
Attic	-0.0486	-0.12	0.2569	1.44
Fassade	-1.0751	-10.91	-0.9521	-21.7
Windows	-0.6699	-8.47	-0.5111	-14.25
Basement	-0.4729	-3.61	-0.4955	-8.53
Degree Days	-	-	0.0295	950.25
Year	-	-	-0.0059	-3.7
Add.Heating	-	-	-0.0001	-13.6
R squared	0.002	-	0.8040	-
RSE	6.72	-	2.9760	-

Summary: Predictions from the model

In two models with varying specifications this paper analyses the saving potential of energy efficiency refurbishment measures in one and two family homes empirically, based on energy consumption data from the iESA tool (interactive Energy Savings Account). 220,917 observations of monthly energy consumption for 1,497 households allow the robust conclusion that the insulation of roof, facade and basement lead to statistically significant and economically relevant energy savings on average. For window replacement and insulation of the attic floor ceiling the results from our data are mixed and inconclusive.

Marginal effects as calculated from the regression models:

1. **Roof:** The coefficients from both models in all specification vary around -0.25. Since we observe monthly values, the estimated average annual savings from this measure is 12 times the marginal effect: **3 kWh/m²*year**.
2. **Attic floor:** Only 2.2 %¹⁸ of households in the sample stated they insulated the attic floor (i.e. the topmost ceiling). We cannot identify any effect from this measure, which is not surprising given the low number of cases in this category.

¹⁸ c.f. "Table of refurbishment events in the sample": 33 out of 1497

3. **Fassade:** The results from the calculations confirm our expectations that facade insulation is the most effective of the 5 measures in terms of energy savings. On average the marginal effect of facade insulation on energy consumption is around one kWh/m²*month, which leads to estimated average savings of around **12 kWh/m²*year**.
4. **Windows:** In regressions on the absolute level of consumption (model 1), the effect of window exchange is inconclusive. In model 2 on the demeaned observations, the effect is estimated around 6 kWh/m²*year.
5. **Basement ceiling:** The negative effect of insulation of the basement ceiling on energy consumptions is robust and statistically valid in all models and specifications. The estimated magnitude is around -0.6 in the first model and just below -0.5 in the demeaned model. Therefore a conservative estimate of the marginal effect of this measure is around **6 kWh/m²*year**.

Conclusion and Outlook

To our knowledge, this data set is the most comprehensive in Germany for energy consumption in one and two family homes in combination with refurbishment activity. The results show that refurbishment indeed saves energy. However, the identification of the measure as a binary code ("0" without the measure and "1" for implementation) does not allow the user to declare the degree to which the measure was implemented.¹⁹ Given this degree of imprecision in measurement, we believe the calculated 12 kWh/year and square meter resemble a realistic average estimate for facade insulation. In order to improve the precision of the information on refurbishment, iESA account users will soon have the opportunity to state a percentage value of refurbishment (e.g. 70% of window area was replaced).

Furthermore, the accuracy of measurement would greatly benefit from automated communication of consumption data with iESA. This feature will soon become available for households with gas smart meters. Based on high frequency data in combination with the exact point in time and degree of refurbishment activity will enable much more accurate replication of this analysis.

The quality of implementation is a serious issue, as highlighted by previous research by co2online (see literature section). Currently, financial support for energy efficiency refurbishment in Germany is granted strictly on the basis of demand calculations. The real effect on consumption, which is the ultimate objective of the funding, does not enter the equation. Current developments in measurement technology offer the opportunity to further develop state funded financing schemes in order to combine user-independent demand calculations with consumption based quality and impact control of refurbishment activity.

Literature

BBSR - Federal Institute for Research on Building, Urban Affairs and Spatial Development (2016). BBSR Analysen Kompakt - Energetische Sanierungen rückläufig [Engl.: Energy efficiency refurbishment declining]. Bonn, Germany.

Diefenbach, N., K.-D. Clausnitzer, H. Cischinsky, and M. Rodenfels (2010). Datenbasis Gebäudebestand: Datenerhebung zur energetischen Qualität und zu den Modernisierungstrends im deutschen Wohngebäudebestand [Engl.: Data base building stock: Survey for energetic quality and

¹⁹ As an example consider facade insulation: Some households only insulate the north-facing part of the building envelope. In the current form of the data, this measure receives the "1", as well as a full insulation of the building including all outer walls.

refurbishment trends in the German building stock]. IWU (Inst. Wohnen und Umwelt), technical report, Darmstadt

Grösche, P. and C. Vance (2008). Willingness-to-pay for energy conservation and freeridership on subsidization: evidence from Germany. *The Energy Journal* 0, 135-154.

Jahnke, K. et al. (2015). Wirksam Sanieren: Chancen für den Klimaschutz. Feldtest zur energetischen Sanierung von Wohngebäuden [Engl.: Effective refurbishment: Chances for climate protection. Field test on energy efficiency refurbishment in residential buildings]. co2online Technical Report, Berlin, Germany.

Woolridge, J. (2008). *Introductory Econometrics*. 4th edition, South-Western Cengage Learning, Mason, USA.