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The information value of energy labels: Evidence from the Dutch residential housing market

Do energy labels contain extra information that buyers cannot observe themselves? Which labeling scheme is more effective: a voluntary or a mandatory one? In this paper we examine the information value of voluntary and mandatory energy labels using administrative data on all transactions in the Dutch residential housing market.

We show that voluntary labels introduced in the period 2008-2014 contain limited information value. Furthermore, the information value of mandatory labels adopted since 2015 is less clear-cut.

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The information value of energy labels: Evidence from the Dutch residential housing market*

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Abstract

We examine the information value of energy labels using administrative data on all transactions in the Dutch residential housing market. We compare two different labeling systems, namely voluntary and mandatory labels. Employing a combination of hedonic pricing models, matching and a sharp Regression Discontinuity Design, we find robust evidence of limited information value of voluntary labels during the period 2008-2014. The information value of mandatory labels that are adopted since 2015 is less clear-cut. We observe that better-labeled houses were already transacted with significant price premiums before obtaining energy labels. This implies that at least part of the premiums cannot be attributed to mandatory labels.

Keywords: *energy labels, house prices, information value*

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1. Introduction

Buildings account for approximately 40% of energy consumption and 36% of CO_2 emissions in the EU (European Comission, 2018), among which 60% of energy consumption and emissions are attributed to residential buildings. Improving the energy efficiency of the residential housing sector can generate significant energy savings and emission reductions (Vringer et al., 2016). However, homeowners appear to under-invest in energy-efficient technologies, even when there are (private) financial net benefits (Allcott and Greenstone, 2012; Ramos et al., 2015; Gerarden et al., 2017). This so-called 'energy efficiency gap' arises due to many barriers and market failures (Ramos et al., 2015). In particular, informational failures seem to be pervasive and relevant. Residential market participants lack consistent access to information on the energy performance of dwellings and, as a result, potential buyers and sellers may not be able to (fully) value energy performance in housing transactions, which hinders investments in residential energy efficiency (Ramos et al., 2015).

Energy labels such as the Energy Performance Certificate (EPC), implemented by the European Parliament and Council (2002), aim to improve the mandatory provision of information on the energy efficiency of (residential) buildings through an A-G (high to low efficiency) label, thereby facilitate energy-informed housing transactions. Alternative labeling programs, such as Energy Star and Leadership in Energy and Environmental Design (LEED) in the United States promote voluntary disclosure of energy-related information. Do energy labels have added value by providing new information not readily available to the market? Which labeling scheme is more effective: a voluntary or a mandatory one? These are the key questions of this paper.

Despite significant efforts and resources devoted to designing and implementing the labeling programs, the effectiveness of energy labels is not fully understood. A handful of studies have documented significant and large transaction price premiums of 'green' energy labels in the residential real estate sector (Brounen and Kok, 2011; Fuerst and McAllister, 2011).[1] However, they are unable to conclude whether the introduction of labels itself has lead to the observed price premiums for several reasons. First of all, energy labels are correlated with location and unobserved dwelling characteristics, such as quality or aesthetics. Separating the premiums of labels from the premiums of other confounding factors remains challenging. Secondly, separating the information value of energy labels from the capitalization of (observable) energy efficiency has proven to be difficult. Thirdly, there is a dearth of evidence for different designs of labeling programs. The relative merits of voluntary and mandatory labels remain under-exploited.

[1]There is strong evidence of significant and large premiums in the rental and transaction prices in the commercial sector, such as Eichholtz et al. (2010, 2013); Kok and Jennen (2012); Fuerst and McAllister (2011).

The purpose of this paper is to overcome the empirical shortcomings of the literature by employing several methods. Our analysis is based on the administrative data on all residential property transactions in the Netherlands over the period 2000-2017. The Dutch labeling system represents an interesting case to study. During this period, the country has introduced two different labeling programs: a complex, but *de facto* voluntary label program over 2008-2014 and a simplified, but mandatory label program over 2015-2017. These two systems have vastly different characteristics in terms of quality, accuracy, and utility of the information the label provides, on the one hand, and the cost and supervision, on the other hand.

We address some important empirical challenges to identification and contribute to the existing literature in several ways. First, hedonic pricing models that estimate the premiums of 'green' labels are subject to several confounding factors, such as location or unobserved dwelling characteristics. Failing to control for these factors can yield misleading results regarding the effectiveness of energy labels. We control for post-code fixed effects to minimize the price premiums which are attributed to location rather than energy labels. Existing studies are often unable to account for location effects in a precise manner. Furthermore, we use an approach in the spirit of Olaussen et al. (2017) and estimate the price premiums of dwellings that had no labels at the moment of transaction but obtained labels after the transaction. In doing so, we uncover to what extent the price premiums cannot be attributed to labels. These results shed more light on whether energy labels or other unobserved factors drive the premiums. This method is particularly useful in evaluating the information value for mandatory labels in the new system.

Second, the collinearity between (observable) energy efficiency and energy labels presents difficulties for identifying any additional effect of energy labels on transaction prices. The lack of randomized experiments does not allow us to conclude whether labels operate by eliminating information asymmetry between buyers and sellers or simply provide redundant information that buyers can gather from observable features of the dwellings. To this end, we employ a sharp Regression Discontinuity Design (RDD) to minimize potential bias from unobserved characteristics that confound causal identification. The use of a sharp RDD is a novelty in this literature. It allows us to disentangle the information value of energy labels from the effects of energy efficiency on transaction prices, especially in the old system.

Third, energy labeling programs can have substantially different designs. A key distinction is between mandatory and voluntary programs. Under mandatory programs, all regulated dwellings must comply with the programs' requirements. On the contrary, voluntary programs provide owners the option to participate. While mandatory programs in Europe and several U.S. cities and states have been operating for longer periods, voluntary programs, such as Energy Star and LEED in the United States, have been developed to supplement the existing ways, such as sharing utility bills and building inspections that property owners communicate information about building energy use to potential tenants and buyers (Stavins et al., 2013). Whether voluntary and mandatory labels result in different impacts remains less clear cut. We provide additional evidence on the information value of both voluntary and mandatory labels given the uniqueness of our data.

We present three sets of results. First, in line with the literature, it remains difficult to gauge whether the presence of energy labels has any additional effects on transaction prices in the hedonic price models. Energy efficiency, measured by the Energy Index and gas use is to a certain degree capitalized in the transaction price, independent of voluntary or mandatory labels. Second, we find no significant price premiums around the cut off value for better energy labels based on the RDD analysis during 2008-2014, suggesting that voluntary energy labels have rather limited information value. Last, we demonstrate that for the new mandatory labeling system better-labeled dwellings were sold for premiums even before the introduction of labels. This implies that at least part of the price premiums of better labels can not be attributed to labels themselves and also here the information value is limited.

2. Literature Review

Whether hard-to-observe energy efficiency is capitalized into sales prices has long been the subject of research. A body of work emerged in the early 1980s has investigated the relationship between energy efficiency and residential sales prices. At the time, energy efficiency was measured by past billing data or coarse labels describing the thermal integrity of the dwelling. Albeit with small and highly localized samples, these studies have found evidence of capitalization of (or proxies for) energy efficiency into residential sales prices (Halvorsen and Pollakowski, 1981; Johnson and Kaserman, 1983; Quigley, 1984a,b; Laquatra, 1986; Dinan and Miranowski, 1989; Quigley and Rubinfeld, 1989). Consequently, for building energy labels to influence energy use and investment decisions, they must provide additional information about the dwelling not already available in the market to potential buyers.

The topic has attracted renewed interest in the early 2010s when energy labeling became more prevalent. Larger data sets and more sophisticated hedonic price models were employed to study the effects of building energy labels on the transaction prices. A handful of studies on commercial buildings have found that LEED and Energy Star certified buildings carry substantial rental and sale price premiums in the US (Eichholtz et al., 2010, 2013). Eichholtz et al. (2010) document that offices with a 'green' energy label are transacted at a 6 percent premium. Since the present value of energy savings of these green buildings are smaller than 6 percent, they conclude that part of the premium is likely to be caused by the label in the commercial sector. Brounen and Kok (2011) are the first to estimate the effect of energy labels on transaction prices in the residential sector. Based on a large sample of residential housing transactions in 2008-2009 in the Netherlands, they identify large premiums associated with better energy labels. For example, relative to a D-label dwelling, an A-label dwelling is transacted with a 10% premium while a G-label dwelling is transacted at a 5% discount. Significant price premiums have been confirmed in subsequent studies using data from various countries, such as the Netherlands (Chegut et al., 2016), the US (Kahn and Kok, 2014; Walls et al., 2017; Myers et al., 2019), UK (Fuerst et al., 2015), Germany (Cajias et al., 2019), Australia (Fuerst and Warren-Myers, 2018), Ireland (Hyland et al., 2013; Stanley et al., 2016), and Sweden (Wahlström, 2016).

Although these studies, based on hedonic price models, provide compelling evidence of capitalization of energy labels, they are unclear, however, as to whether labels provide *additional* information to the market. If the markets fully capitalize on buildings' energy efficiency, as indicated by early studies reviewed above, energy labels may simply measure this performance. One would expect to find a strong correlation between energy labels and property values although the labels provide no new information on the energy efficiency of buildings. Consequently, the identified premiums in this literature can not be taken as evidence that the introduction of labels led to the observed differences in transaction prices.

Against this backdrop, the research effort has begun focusing on separating the price premium of energy labels from the premium of readily observable energy efficiency. This paper goes straight to the heart of this line of research by investigating the information value of both voluntary and mandatory energy labels using the whole population of transactions in the Dutch residential housing market.

Our paper is closely related to several recent studies in this area. Olaussen et al. (2017) find no empirical evidence of energy label premiums in transaction prices based on a small sample of residential housing transactions before and after the introduction of (mandatory) energy labels in Oslo, Norway. They show that houses that were sold with premiums after energy labels were introduced had that advantage before it too, suggesting that the premiums could be driven by unobserved time-invariant characteristics of the dwellings that are not controlled for in the hedonic pricing models. Focusing on the German rental market, Mense (2018) documents economically and statistically insignificant effects of energy labels. This is because consumers already did value energy efficiency and because energy cost savings have been translated into higher rents 1-by-1. Using survey data from Germany, Amecke (2012) questions the usefulness of energy labels in actual purchasing decisions of homebuyers. His findings reveal that although energy labels are reported to be well understood, they are only moderately trusted and of little to no relevance for purchasing decisions.

In the Dutch context, the seemingly contradictory results regarding the effectiveness of labels are particularly interesting. While Brounen and Kok (2011) report large and significant price premiums associated with better energy labels, their subsequent study (Aydin et al., 2018) shows that energy labels are found to only have a weak influence on prospective homebuyers, especially in the pre-purchase phase. Recently, Aydin et al. (2019) report that labeled dwellings are sold quicker than their unlabeled counterparts. Murphy (2014) documents small reported effects of energy labels in the Netherlands. Only 10 percent of the respondents state that energy labels had any influence on their purchasing decisions.

Regarding the effectiveness of mandatory labeling schemes, two recent studies should be noted: Myers et al. (2019) employ a difference-in-differences design inside and outside the city of Austin, Texas. They find that after the introduction of the labeling system within the city, markups were paid for energy efficiency compared to the area outside the city. Additionally, investments in energy efficiency were spurred by the introduction of labels. Frondel et al. (2018) find that homeowners ask a lower price after labels have become mandatory in Germany and that this decision is especially correlated with the dwellings' energy efficiency.

We differ from the existing studies in a few ways: While the Dutch studies are based on the subset of transaction data provided by the Dutch Association of Estate Agents (NVM), we use official registry data by Statistics Netherlands (CBS) that include all transactions. Additionally, we include information for both the old, voluntary and the new, mandatory system and apply an RDD that is new to this literature.

3. Energy labels in the Netherlands

The first regulation to impose energy labels in the EU was the Directive 2002/91/EC to promote energy efficiency in the built environment (European Parliament and Council, 2002). Article 7 of that directive requires all EU member states to ensure an Energy Performance Certificate (EPC) to be made available to the buyer when a building is constructed, sold or rented out. This obligation to member states remains in article 12 of the revised Directive 2010/31/EU (European Parliament and Council, 2010). The objective of the directive, in this case, the creation of a labeling scheme, is binding but the member states create individual implementation policies. The directive includes the obligation that energy labels should be determined by an independent expert and are based on building-specific energy efficiency characteristics. In all other respects, energy label systems may vary across countries.

The Netherlands initially implemented the European directive in 2008 ('old system') and later reformed the labeling system in 2015 ('new system'). These two systems have vastly different characteristics in terms of quality, accuracy, and utility of the information the label provides, on the one hand, and the cost and supervision, on the other hand. The old system formally required all built, sold or rented dwellings (that are older than ten years and are no monuments) to apply for an energy label, ranging from A++ to G. However, failing to apply did not result in a penalty. This defacto voluntary labeling system, combined with high costs led to low adoption rates. When penalties were introduced in the new system in 2015, the adoption rates, calculated as a percentage of transacted dwellings with a label, went up rapidly (see figure 1).

3.1. Old voluntary system

In the old system, the person selling, building or renting out a dwelling needs to apply for a label, costing 180-400 euro. A certified expert would then physically inspect the dwelling to determine 150 building specific characteristics related to energy

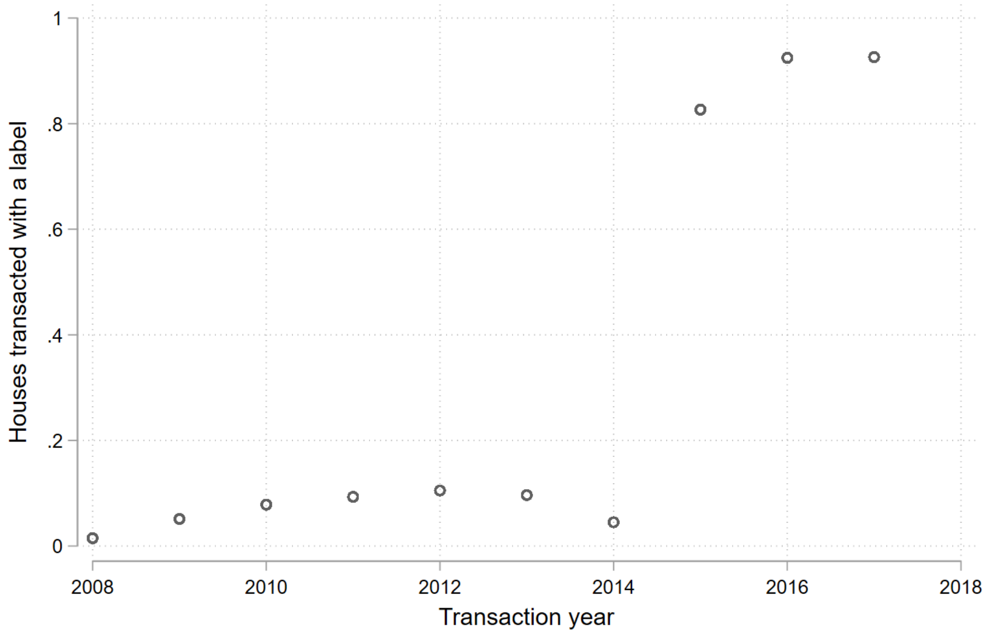

Figure 1: Adoption rate of energy labels in the Netherlands

efficiency. The expert would enter these 150 variables in the so-called EPA-W software system, which, in turn, would calculate the Energy Index (EI). The software's algorithm to calculate the energy index is non-transparent for the expert. Even more so, the owner of the building will not be able to know the relative effects of building characteristics on the index.

The input menu of the EPA-W software in Figure A.6 shows the level of details of the input characteristics. For each of the rooms of the dwelling, the length, width, and height are inserted. Furthermore, for every individual surface of the room, the expert inserts its characteristics. Characteristics of walls include their material, insulation, and size. For windows, type of glass, side of the window, shades (yes or no) and size is included. Moreover, the characteristics of doors, such as material, insulation, and size are put into the system. Each of these factors has some weight in determining the energy index.

The results of the expert inspection are written down in a report and handed to the label applicant. The report is generally not disclosed to (potential) buyers or renters. The energy label, attributed to the dwelling based on the energy index following table 1, will be disclosed.

3.1.1. New mandatory system

The old labels were relatively complex and expensive. Therefore, the main aim of the policy revision was to bring down the costs. The low adoption of voluntary labels almost led to sanctions by the European Commission, which urged the

Table 1: Energy labels and energy index values in the old system

Label	Energy index (EI)
A++	– 0.5
A+	0.5 – 0.7
A	0.7 – 1.05
B	1.05 – 1.3
C	1.3 – 1.6
D	1.6 – 2.0
E	2.0 – 2.4
F	2.4 – 2.9
G	2.9 –

Netherlands to introduce penalties for non-adoption. In 2015, the new system of energy labels was implemented. Based on the building year and type, every dwelling was assigned a provisional label. Once a dwelling is sold or rented out, one has to convert the provisional label to a definitive label online. The applicant has to fill in a form with a maximum of 10 energy efficiency characteristics of the dwelling online, in contrast to 150 variables taken by the expert in the old system. The applicant then uploads the proof of the disclosed level of energy efficiency online. Then, one chooses an expert to judge the legitimacy of the application based on the information uploaded. The cost of the expert judgment starts at 2 euro and has an average of around 5 euro. Based on the characteristics specified, an energy label, ranging from A to G, is calculated directly.

Though the costs went down and the adoption rate went up, the new system appears to be more vulnerable to fraud.[2] The judgment of an expert based on the uploaded proofs of an applicant is clearly not as vigorous as a physical inspection, questioning the information content of such mandatory labels.

It is worth noting that a new labeling system is being developed. This labeling system will expand the scope and will replace the current labeling system from July 2020.

4. Data

This study is based on all transactions of privately-owned residential dwellings in the Netherlands for the period 2000-2017, provided by Statistics Netherlands (CBS). We obtain details on the transaction (month and price) and the object (dwelling type, construction year, size and location). Then we merge this data set with the database

[2]Media report on label fraud: https://radar.avrotros.nl/uitzendingen/gemist/item/verkeerd-energielabel-voor-je-huis-wie-is-verantwoordelijk/.

on energy labels from 2008 to 2017 by the Netherlands Enterprise Agency (RVO). It contains the actual label, the label system (old or new), the application date, and the energy index, if available.

4.1. Sample Construction

In the sample, dwellings with a construction year before 1900 are excluded. In both labeling systems, homes with a monumental status are not obliged to apply for an energy label. To prevent selection bias, dwellings with monumental status should thus be excluded from the sample. Since monumental status is not observed, these observations are largely excluded by excluding dwellings from before the year 1900. Additionally, under the old system sellers only need to present an energy label if their house is older than ten years. Therefore, houses younger than a decade are excluded as well for the old labeling scheme[3].

4.2. Sample Overview

Table 2 presents the descriptive statistics of the main sample. First of all, one should note that the average selling price in the new system is higher than in the old system. This is mainly due to the financial crisis which occurred when the old system was in place. Second, the average price per square meter for unlabeled houses in the voluntary, old system is higher than for their labeled counterparts. This observation reverses in the mandatory new system where labeled houses enjoy a price premium per m^2 on average. This suggests that label application in the old system is not random, but that there is a selection effect, which will be further discussed in section 5.1 and Appendix C.

The actual Energy Performance Certificate of the labeled houses differs between the two systems. Despite the mode being a C in both schemes, the average label is better in the new system. Three possible mechanisms are at work here: (i) the reform may have made it easier to obtain a good label, (ii) homeowners may have invested in energy efficiency measures, and (iii) as only houses older than ten years need a label in the old system, the new, more energy-efficient houses are under-represented in that scheme.

The overall composition of the dwelling types is very similar under both labeling schemes. This also holds when looking at the new system separately: it does not show large differences between labeled and unlabeled houses, which makes sense as the labels are mandatory. In the old system though, apartments are over-represented

[3] In the old system 12,896 dwellings were built before the 20^{th} century, of which 489 (4%) have an energy label. Furthermore, 40,991 dwellings are ten years or younger at the time of sale and from those, 607 (1.5%) have an EPC. In the new system, there are 7,446 buildings from before 1900 that we excluded of which 1,710 (23%) were unlabeled. Excluding those observations does not meaningfully affect the sample composition as the fractions in Table 2 do not change by more than one percentage point. The only difference occurs concerning the labels: there are now on average less well-labeled houses in the old system and less badly-labeled houses in the new system. The results of all analyses are not notably altered (coefficients and standard errors are very similar overall).

Table 2: Descriptive statistics

	Old system, 2008-2014						New system, 2015-2017					
	Unlabeled		**Labeled**		**Total**		**Unlabeled**		**Labeled**		**Total**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Price per m^2	2047.734	851.3874	1825.297	737.7318	2033.482	846.3184	2018.1	1144.713	2108.978	929.1997	2099.663	953.9307
Energy index	-	-	1.88	0.54	1.88	0.54	-	-	-	-	-	-
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
Energy label												
A	-	-	388	1.0	388	1.0	-	-	53,124	15.1	53,124	15.1
B	-	-	3,500	8.8	3,500	8.8	-	-	57,564	16.4	57,564	16.4
C	-	-	11,263	28.5	11,263	28.5	-	-	103,485	29.5	103,485	29.5
D	-	-	10,937	27.6	10,937	27.6	-	-	49,029	14.0	49,029	14.0
E	-	-	7,114	18.0	7,114	18.0	-	-	35,971	10.3	35,971	10.3
F	-	-	4,284	10.8	4,284	10.8	-	-	27,783	7.9	27,783	7.9
G	-	-	2,077	5.2	2,077	5.2	-	-	23,930	6.8	23,930	6.8
Total	-	-	39,563	100.0	39,563	100.0	-	-	350,886	100.0	350,886	100.0
Dwelling type												
Apartment	135,615	23.5	12,385	31.3	148,000	24.0	9,611	24.0	73,072	20.8	82,683	21.1
Detached	66,235	11.5	1,580	4.0	67,815	11.0	7,617	19.0	46,235	13.2	53,852	13.8
Duplex	71,524	12.4	3,309	8.4	74,833	12.1	5,135	12.8	41,710	11.9	46,845	12.0
Semi-Detached	88,240	15.3	7,544	19.1	95,784	15.5	5,445	13.6	52,675	15.0	58,120	14.9
Terraced	216,356	37.4	14,745	37.3	231,101	37.4	12,268	30.6	137,194	39.1	149,462	38.2
Total	577,970	100.0	39,563	100.0	617,533	100.0	40,076	100.0	350,886	100.0	390,962	100.0
Building year												
1900-1929	64,766	11.2	2,971	7.5	67,737	11.0	5,500	13.8	31,788	9.1	37,288	9.6
1930-1944	56,119	9.7	1,928	4.9	58,047	9.4	4,250	10.7	28,364	8.1	32,614	8.4
1945-1959	55,680	9.7	5,559	14.1	61,239	9.9	4,456	11.2	27,784	7.9	32,240	8.3
1960-1969	86,919	15.1	7,287	18.4	94,206	15.3	6,590	16.6	45,800	13.1	52,390	13.4
1970-1979	106,172	18.4	9,464	23.9	115,636	18.8	6,918	17.4	57,005	16.3	63,923	16.4
1980-1989	90,145	15.6	8,380	21.2	98,525	16.0	4,519	11.4	49,936	14.2	54,455	13.9
1990-1999	87,502	15.2	3,571	9.0	91,073	14.8	4,848	12.2	54,722	15.6	59,570	15.3
2000-	29,437	5.1	364	0.9	29,801	4.8	2,712	6.8	55,205	15.7	57,917	14.8
Total	576,740	100.0	39,524	100.0	616,264	100.0	39,793	100.0	350,604	100.0	390,397	100.0
Transaction year												
2008	126,879	22.0	1,924	4.9	128,803	20.9	-	-	-	-	-	-
2009	84,963	14.7	4,598	11.6	89,561	14.5	-	-	-	-	-	-
2010	83,971	14.5	7,148	18.1	91,119	14.8	-	-	-	-	-	-
2011	78,249	13.5	8,044	20.3	86,293	14.0	-	-	-	-	-	-
2012	73,099	12.6	8,592	21.7	81,691	13.2	-	-	-	-	-	-
2013	51,468	8.9	5,507	13.9	56,975	9.2	-	-	-	-	-	-
2014	79,341	13.7	3,750	9.5	83,091	13.5	-	-	-	-	-	-
2015	-	-	-	-	-	-	18,508	46.2	84,363	24.0	102,871	26.3
2016	-	-	-	-	-	-	10,007	25.0	123,354	35.2	133,361	34.1
2017	-	-	-	-	-	-	11,561	28.8	143,169	40.8	154,730	39.6
Total	577,970	100.0	39,563	100.0	617,533	100.0	40,076	100.0	350,886	100.0	390,962	100.0

Notes: Dwellings with a construction year before 1900 are omitted. In the old system, also dwellings built less than ten years ago are excluded.

among the labeled houses (31% labeled vs. 24% unlabeled) while detached and duplex houses are under-represented. This suggests that owners of a certain dwelling type differ from owners of other dwelling types in their decision of applying for an energy label or that dwellings of a certain type are more difficult to sell.

The age structure is also very similar between both systems on average. The main difference between the two is that there are many more houses built in the 21st century under the new system which makes sense as (i) there are no exemptions for new houses and (ii) time has progressed and more houses have been built over the years. Inspecting the two systems separately, you see different patterns. Under the voluntary mechanism, very old houses and very new houses are less likely to have an energy label. Probably because the sellers do not need it to set themselves apart from the competition. In the mandatory system, one sees a pattern of labels being more common the newer a house is. This could be because the labels have such a low cost that owners may be afraid that they send a bad signal if they do not have a label. Alternatively, it might be that newer houses are more likely to be sold in general and therefore their owners apply for labels more frequently.

In Appendix B we look at the relationship of the Energy Performance Certificate and the observable characteristics in a similar fashion. We see that the final label and a dwelling's characteristics are correlated. In subsection 5.1 we further look into the influence of those characteristics on the label that a dwelling receives.

5. Methodology and Results

In this section, we first explore factors that relate to the adoption of energy labels in subsection 5.1. In subsection 5.2 we use the usual hedonic pricing model approach. This is accompanied by results for the pre-label period where we check whether there was already a premium for better-labeled houses before they actually had a label. We call them "fictitious labels" and find limited information value there. Finally, we turn to a Regression Discontinuity Design approach in subsection 5.3.

5.1. What factors drive the adoption of the energy labels?

5.1.1. Method

To better understand the adoption of energy labels in voluntary and mandatory systems, respectively, we use fixed effects regressions to examine the factors that determine whether a transacted dwelling has an energy label and how they influence the resulting label in a sub-sample of labeled houses as follows:

$$Label_{int} = \alpha + \beta_i X_i + \delta_n + \theta_t + \epsilon_{int} \quad (1)$$

$$LabelScale_{int} = \alpha + \beta_i X_i + \delta_n + \theta_t + \epsilon_{int} \quad (2)$$

$Label_{int}$ is a binary variable with a value of one if transacted dwelling i in neighborhood (4-digit postcode) n in period t has an energy label and zero otherwise.

$LabelScale_{int}$ is a categorical variable with values 1 to 7, indicating labels A to G. Hence, a negative coefficient means that the associated variable is associated with a better label. X is a vector of dwelling specific characteristics, such as the period of construction, dwelling type, size, or transaction price. δ_n and θ_t are location and month fixed effects, respectively. Finally, ϵ_{int} is a stochastic error term, assumed to be normally distributed with a mean of zero and variance of σ^2.

5.1.2. Results

Table 3 presents the results of fixed effects regressions based on equation 2. Columns (1) and (2) show how the dwelling specific characteristics affect the application for energy labels in the first place, whereas columns (3) and (4) present how these characteristics correlate to the final label in both systems.

As column (1) shows, in the old system, the higher the transaction price the less likely the house is to be labeled. This suggests that primarily owners of cheap houses make use of energy labels. The influence of the construction year period appears to be inversely U-shaped: houses with a medium age are more likely to be labeled by their owners than very old and very new ones. This makes sense as the energy efficiency of medium-aged houses is most diffuse for potential buyers. They can expect new houses to be well insulated and old houses to be rather inefficient. Because of that, owners of medium-aged dwellings have more reasons to apply for an energy label. Furthermore, terraced and duplex houses are less likely to be labeled than apartments (with (semi-)detached houses being indistinguishable). Houses with a garden are on average more likely to be labeled and finally household size and dwelling size are negatively associated with getting a label.

For the new system, one sees in column (2) that labels are positively correlated with the price of a dwelling: the more expensive a house the more likely it is that the owner applied for a label before the sale. Also, the likelihood of taking up a label seems to be more or less linearly related to the building year, which is at odds with the results for the old system. The actual type of the dwelling is insignificant. As in the old system, the house's size reduces the likelihood of having a label. On the contrary, though, the effect of the household size is now positive in the mandatory scheme.

For the subsample of labeled houses, we now turn to the effects of dwellings' characteristics on the actual label in columns (3) and (4). The higher the eventual transaction price, the better the label of a house on average. In other words, those houses that will later be sold for a higher price, are c.p. also more energy-efficient and obtain a better label. Hence, we can already observe a positive association between a house's energy label and its transaction price. Furthermore, for both systems, we see that in general labels are better for newer houses, which does not come as a surprise. Exceptional is that very old houses (1900-1929) appear to be better-labeled than houses built shortly after that. The reason presumably is better maintenance and differences in building quality between the pre- and post-war period. The dwelling's type has no substantial influence on the actual label in the old system

Table 3: Fixed effects regression of the adoption of energy labels

VARIABLES	(1) Label (Dummy) Old System	(2) Label (Dummy) New System	(3) Label (Categorical) Old System	(4) Label (Categorical) New System
Log price/m^2	-0.0940***	0.114***	-0.457***	-0.590***
	(0.00439)	(0.00361)	(0.0483)	(0.0160)
Construction year				
1900-1929	–	–	–	–
1930-1945	0.00198	0.00679*	0.337***	0.101***
	(0.00276)	(0.00313)	(0.0814)	(0.0148)
1945-1959	0.0427***	0.00980**	0.183*	-0.783***
	(0.00364)	(0.00331)	(0.0729)	(0.0174)
1960-1969	0.0287***	0.0206***	-0.0407	-1.370***
	(0.00318)	(0.00312)	(0.0739)	(0.0183)
1970-1979	0.0355***	0.0329***	-0.491***	-2.109***
	(0.00314)	(0.00299)	(0.0746)	(0.0170)
1980-1989	0.0367***	0.0431***	-1.318***	-2.571***
	(0.00386)	(0.00301)	(0.0777)	(0.0162)
1990-1999	0.173***	0.0356***	-1.884***	-3.271***
	(0.00304)	(0.00303)	(0.0771)	(0.0172)
2000-	-0.0129***	0.0571***	-2.273***	-4.056***
	(0.00341)	(0.00307)	(0.116)	(0.0179)
Dwelling type				
Apartment	–	–	–	–
Detached	-0.00833	-0.0427**	0.258*	0.762***
	(0.00659)	(0.0152)	(0.104)	(0.0511)
Duplex	-0.0155*	-0.00499	0.182*	0.581***
	(0.00624)	(0.0151)	(0.0899)	(0.0503)
Semi-Detached	-0.00406	0.00785	0.0766	0.482***
	(0.00615)	(0.0151)	(0.0836)	(0.0500)
Terraced	-0.0183**	0.0198	-0.0301	0.204***
	(0.00606)	(0.0150)	(0.0829)	(0.0497)
Multi-family home	-0.00857	0.0153	0.000506	-0.0150
	(0.00534)	(0.0144)	(0.0746)	(0.0459)
Garden	0.0221***	-0.00413	-0.00915	-0.328***
	(0.00335)	(0.00347)	(0.0413)	(0.0234)
Household size	-0.000467	0.0190***	-0.0632***	-0.0815***
	(0.000315)	(0.000441)	(0.00531)	(0.00169)
Log size	-0.0682***	0.0117***	-0.116*	-0.377***
	(0.00347)	(0.00298)	(0.0488)	(0.0136)
Constant	1.007***	-0.362***	9.086***	12.00***
	(0.0448)	(0.0388)	(0.500)	(0.167)
Observations	576,539	370,716	37,130	334,468
R-squared	0.0405	0.0575	0.237	0.601
Transaction date FE	YES	YES	YES	YES
Postcode groups	3,816	3,775	2,759	3,755

Notes: The dependent variable in columns (1) and (2) is a binary variable (1-label, 0-no label). The dependent variable in columns (3) and (4) is a categorical variable ranging from 1 to 7, indicating A to G label. Dwellings with a construction year before 1900 are omitted. In the old system, also dwellings built less than ten years ago are excluded. The reference group for building type is *apartment*. The reference group for the construction year is *1900-1930*.
Cluster robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05.

while in the new system, apartments are on average labeled the best and the more detached a building is, the worse its label. This indicates that there might be unobserved characteristics that are correlated with both the dwelling type and the final label in the new system. Whether the house is a single- or multi-family home does not have an effect in both systems, while having a garden is associated with a better label in the new system. Finally, larger houses and larger households, in general, have a better label.

5.2. Are energy-efficient dwellings valued in the residential housing market?

5.2.1. Method

Houses are sold as a bundle of many characteristics; energy efficiency being one of them. To isolate the value of a single item in such a bundle, the hedonic pricing method has been developed. Usually, this method is used to measure how much utility-maximizing consumers are willing to pay for urban and environmental amenities (Rosen, 1974). In our case, we use this approach to estimate the price premium that buyers pay for more energy-efficient dwellings. Specifically, we are interested in whether dwellings with better energy labels enjoy a price premium. The benchmark specification is the following:

$$ln(P_{int}) = \alpha + \beta LabelScale_{int} + \gamma X_i + \delta_n + \theta_t + \epsilon_{int} \tag{3}$$

where $ln(P_{int})$ is the natural logarithm of the transaction price per square meter of dwelling i in neighborhood n in period t. $LabelScale$ indicates the energy label. For some specifications, we also include alternative measures of energy efficiency, namely the Energy Index (EI) and/or the electricity and gas use one year before the sale. As before, X is a vector of house-specific characteristics, such as building year, dwelling type, or size. δ_n and θ_t are the neighborhood and time fixed effects. Finally, ϵ_{int} is a stochastic error term, assumed to be normally distributed with a mean of zero and variance of σ^2. We estimate equation 3 for both labeling systems.

5.2.2. Results for the Old System

Table 4 reports the results of hedonic pricing models for the sub-sample of transactions with energy labels in the old labeling system during 2008-2014. Column (1) shows the baseline specification without controlling for neighborhood effects, whereas columns (2) and (3) further include regional and postcode fixed effects, respectively. We find significant and large price premiums for better energy labels. The results in column (2) for example, indicate that dwellings with energy label A are transacted at a 10% premium relative to D-label dwellings. Premiums for B- and C-label dwellings are 4% and 1% respectively. F-label dwellings and G-label dwellings are transacted at 1% and 4% discount relative to D-label dwellings. These results are in line with Brounen and Kok (2011). However, the size of the premiums associated with A and B labels decrease significantly once neighborhood effects are properly controlled for in column (3), suggesting that part of label premiums could be attributed to location. Failing to properly control for neighborhood effects at a finer geographical scale could partially explain the large premiums of energy labels found in the existing literature.

Table 4: Hedonic pricing model: Old labeling system

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
MODELS	EPC	EPC	EPC	EI	Use	EPC & EI	EPC & Use	EPC, EI & Use	Fictitious labels (2000-2008) Model (3)	Fictitious labels (2000-2008) Model (7)	Fictitious labels (2000-2008) Model (8)
VARIABLES	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$
Energy Label											
A	0.109***	0.101**	0.0651***			0.0368*	0.0648***	0.0369*	-0.0151	-0.0143	-0.0265
	(0.0211)	(0.0316)	(0.0167)			(0.0185)	(0.0167)	(0.0185)	(0.0160)	(0.0160)	(0.0207)
B	0.0451***	0.0350***	0.0349***			0.0161	0.0347***	0.0162	0.00534	0.00569	-0.00214
	(0.00690)	(0.00826)	(0.00663)			(0.00876)	(0.00659)	(0.00875)	(0.0101)	(0.00995)	(0.0133)
C	0.0254***	0.0145**	0.0175***			0.00672	0.0172***	0.00658	0.0132**	0.0130*	0.00849
	(0.00457)	(0.00479)	(0.00388)			(0.00517)	(0.00389)	(0.00517)	(0.00509)	(0.00507)	(0.00666)
E	0.00527	0.00144	-0.00576			0.00797	-0.00560	0.00795	0.00680	0.00705	0.0125
	(0.00536)	(0.00607)	(0.00412)			(0.00584)	(0.00411)	(0.00583)	(0.00543)	(0.00542)	(0.00744)
F	-0.0185**	-0.0123	-0.0199***			0.00881	-0.0191***	0.00920	0.00602	0.00648	0.0177
	(0.00673)	(0.00881)	(0.00546)			(0.0101)	(0.00544)	(0.0101)	(0.00770)	(0.00769)	(0.0134)
G	-0.0491***	-0.0377**	-0.0580***			-0.00731	-0.0570***	-0.00688	-0.0200	-0.0188	0.00105
	(0.00993)	(0.0121)	(0.00823)			(0.0172)	(0.00821)	(0.0172)	(0.0107)	(0.0107)	(0.0209)
Energy index				-0.0398***		-0.0355**		-0.0352**			-0.0140
				(0.00392)		(0.0109)		(0.0109)			(0.0136)
$\mathrm{Log}\left(\frac{\text{Electricity Use}}{m^2 * \text{household size}}\right)$					0.00985***		0.00831***	0.00820***		0.0200***	0.0200***
					(0.00191)		(0.00190)	(0.00189)		(0.00279)	(0.00279)
$\mathrm{Log}\left(\frac{\text{Gas Use}}{m^2 * \text{household size}}\right)$					-0.00698***		-0.00393*	-0.00361*		-0.0106***	-0.0106***
					(0.00187)		(0.00183)	(0.00183)		(0.00248)	(0.00248)
Constant	9.593***	9.090***	9.179***	9.256***	9.147***	9.242***	9.150***	9.211***	8.776***	8.719***	8.744***
	(0.0555)	(0.143)	(0.0608)	(0.0613)	(0.0610)	(0.0633)	(0.0606)	(0.0630)	(0.0705)	(0.0718)	(0.0784)
Observations	30230	30230	30230	30230	30230	30230	30230	30230	25589	25589	25589
R-squared	0.301	0.299	0.318	0.318	0.313	0.318	0.319	0.319	0.247	0.250	0.250
Dwelling controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Transaction date FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Municipalities		445									
Postcode groups			2661	2661	2661	2661	2661	2661	2621	2621	2621

Notes: Dwellings with (i) a construction year before 1900 and (ii) younger than ten years are omitted. The reference group for energy labels is the *D* label. The reference group for building type is *apartment*. The reference group for the construction year is *1900-1930*.
Cluster-robust standard errors in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Energy labels may simply be a proxy for energy efficiency of dwellings in which (some of) the features are observable to homebuyers. In this respect, the high collinearity between labels and energy efficiency measures poses difficulties in interpreting the price premiums of energy labels. Columns (4) and (5) exclude energy labels and display the effects of the Energy Index and actual electricity and gas use (controlled for the size of the house and the household), as proxies for energy efficiency on transaction prices. Figure 2 shows a slightly positive linear trend in median electricity use for worse labels. In Figure 3 one can observe a more pronounced linear relationship between gas use and label classes.

We find a strong negative correlation between the Energy Index and transaction prices. Hence, energy-efficient dwellings are clearly valued in the market. The improvement in energy efficiency, for example, a decrease of the EI by one point on its 0 to 6.5 scale is on average associated with an increase of transaction prices by 4%. The effects of energy use go into different directions: A 1% increase in standardized electricity use (in kWh per m^2 and household size) leads on average to a 0.01% higher selling price.[4] A similar increase in normalized gas use (in m^3 per m^2 and household size) leads on average to a 0.007% lower transaction price. This is in line

[4]The positive relationship between energy use and transaction prices could be due to the presence of a heat pump, electric cooking appliances or an electric vehicle.

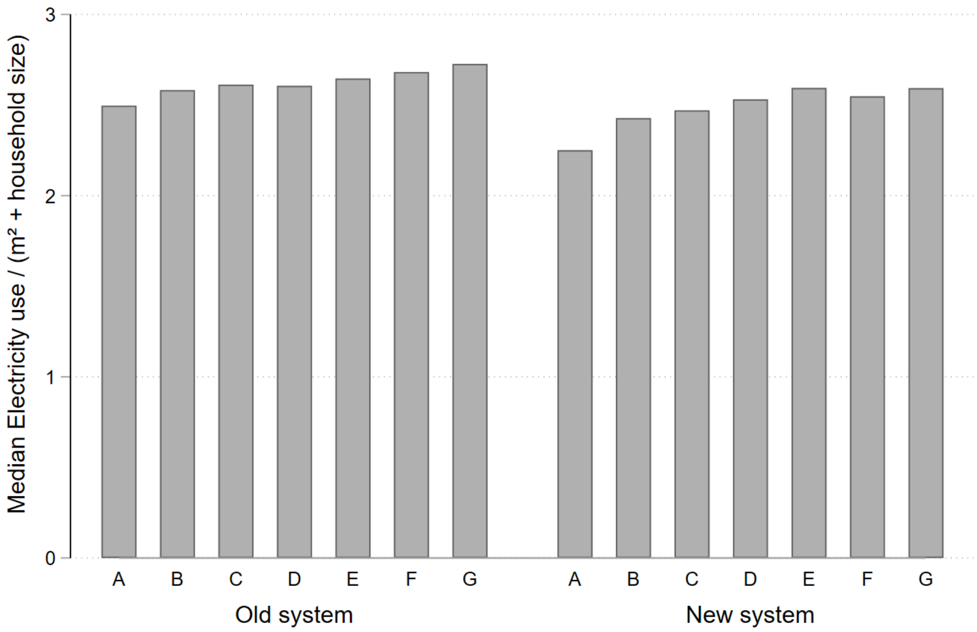

Figure 2: Median electricity use in both systems

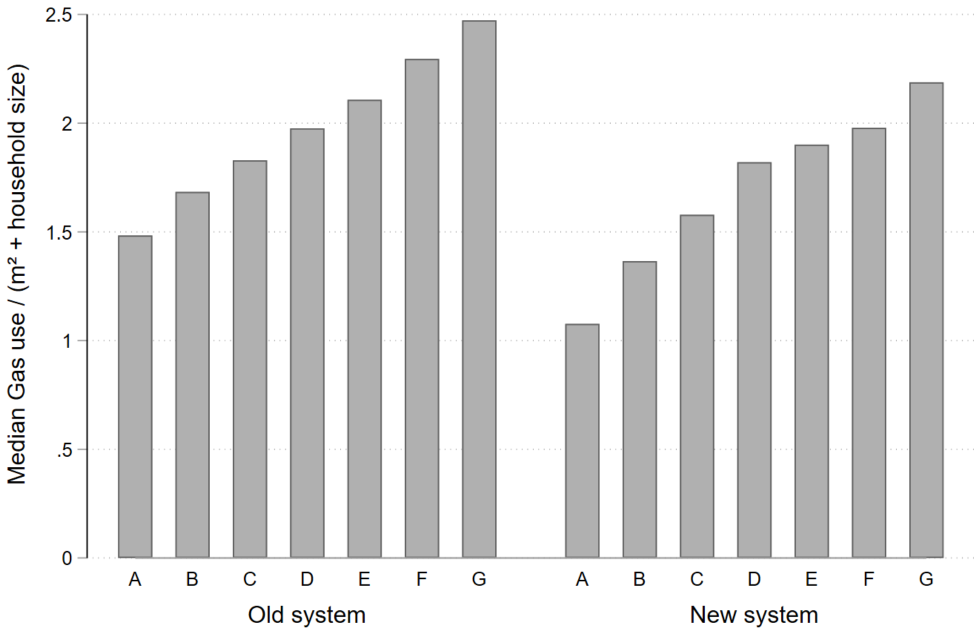

Figure 3: Median gas use in both systems

with Brounen et al. (2012) who have found the gas use to be affected largely by a house's structure while electricity use is more determined by the household setup, including its size and its income[5].

Column (6) and (7) further add energy labels into columns (4) and (5). Once we include the EI to control for energy efficiency, the premiums of energy labels become considerably smaller and mostly insignificant. The only exception are A-labeled houses that sell c.p. for a 3.7% price premium compared to D-labeled houses which is significant on the 5%-level. Above that, the magnitudes are much smaller than those reported in column (2) or (3), suggesting that part of the premium of energy labels is explained by the correlation of energy labels with energy efficiency. For the inclusion of energy use, no such effect can be observed in column (7) which is basically identical to column (5). The main difference is that the coefficient on gas use is now only significant on the 5%-level.

Lastly, column (8) presents the most comprehensive specification. It includes EPCs, EI and energy use to estimate the effect on transaction prices. Also here the results are very similar to column (6) and the inclusion of energy use does not have meaningful effects.

As a further check of the labels' information value using hedonic pricing models, we investigate whether better-labeled houses have already enjoyed a price premium before the application following the reasoning of Olaussen et al. (2017). This means that we use only houses that did not have a label at the time of their transaction but later received one. Re-runs of models (3), (7), and (8) in columns (9)-(11) find no such effects for the "fictitious labels". This indicates that while the old system was in place, where those voluntarily chose to apply for an EPC, apparently the labels provided some information that was not easily available for buyers.

To summarize, we find significant and large sale premiums for dwellings with better voluntary labels using hedonic pricing models, which is in line with the literature (Brounen and Kok, 2011). However, hedonic pricing models are prone to several confounding factors, such as location or other (unobserved) dwelling characteristics. As a result, they often yield biased estimates that overestimate the premiums associated with energy labels.[6] We demonstrate that energy efficiency, captured by the EI and gas use, appears to some extent capitalized in the market, independent of voluntary labels, consistent with recent findings in the Dutch context (Aydin et al., 2018; Havlínová and Van Dijk, 2019). More importantly, the collinearity between energy

[5]We additionally ran our analyses with energy use normalized for weather effects (using weather degree days as in Spinoni et al. (2018)) but this did not change the results. There are two explanations at hand: first of all, the Netherlands are a small country where the weather does not vary much between regions and secondly, regional fixed effects in our models account for constant differences between locations.

[6]In appendix Appendix C, we apply a matching approach to at least filter out the effect of observable characteristics on the decision to apply for an EPC. The size of premiums is considerably smaller using the matching approach.

efficiency and energy labels does not allow us to clearly identify whether the latter have any additional effect on prices. Whether voluntary labels have information value remains unsettled.

5.2.3. Results for the new mandatory system

The results of hedonic pricing models for the new mandatory labeling system are presented in Table 5. Columns (1)-(3) show the baseline results without and with neighborhood fixed effects similar to columns (1)-(3) in Table 4. Again we uncover significant price premiums for each step increase in energy labels. Exceptional is only the A category which has a lower price premium than the B category. The magnitude of the estimated premiums is somewhat larger than those found in the old labeling system in column (3) in Table 4. Moreover, it appears to be less influenced by location. As labels in the new system do not require to have the EI, we can not directly control for energy efficiency as in Table 4. Rather, columns (4) and (5) consider the role of electricity and gas use as proxies for energy efficiency. Both types of energy use have the same signs as in the old system. As before in the old system, the results suggest that actual energy use does not explain the label premiums, because the estimated premiums in column (5) are rather similar to those in column (3).

Table 5: Hedonic pricing model: New labeling system

MODELS	(1) EPC	(2) EPC	(3) EPC	(4) Use	(5) EPC & Use	(6) Fictitious labels (2000-2017) Model (3)	(7) Fictitious labels (2000-2017) Model (5)	(8) Fictitious labels (2000-2014) Model (5)
VARIABLES	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$	$\log(p/m^2)$
Energy Label								
A	0.0356***	0.0451***	0.0497***		0.0533***	0.0179***	0.0171***	0.0141***
	(0.00341)	(0.00404)	(0.00309)		(0.00309)	(0.00354)	(0.00352)	(0.00359)
B	0.0527***	0.0605***	0.0624***		0.0628***	0.0303***	0.0294***	0.0276***
	(0.00268)	(0.00363)	(0.00208)		(0.00209)	(0.00261)	(0.00260)	(0.00264)
C	0.0318***	0.0309***	0.0322***		0.0319***	0.0124***	0.0117***	0.0108***
	(0.00207)	(0.00267)	(0.00146)		(0.00147)	(0.00180)	(0.00179)	(0.00182)
E	-0.00747**	-0.0153***	-0.0165***		-0.0166***	0.00456*	0.00454*	0.00628**
	(0.00271)	(0.00345)	(0.00187)		(0.00186)	(0.00192)	(0.00191)	(0.00193)
F	-0.0460***	-0.0481***	-0.0439***		-0.0435***	0.000577	0.000658	0.00414
	(0.00334)	(0.00635)	(0.00241)		(0.00239)	(0.00263)	(0.00261)	(0.00274)
G	-0.172***	-0.146***	-0.122***		-0.121***	-0.0321***	-0.0315***	-0.0203***
	(0.00398)	(0.00953)	(0.00304)		(0.00300)	(0.00347)	(0.00345)	(0.00350)
$\mathrm{Log}\left(\frac{\text{Electricity Use}}{m^2 * \text{household size}}\right)$				0.0271***	0.0253***		0.0243***	0.0231***
				(0.00116)	(0.00108)		(0.00112)	(0.00112)
$\mathrm{Log}\left(\frac{\text{Gas Use}}{m^2 * \text{household size}}\right)$				-0.0199***	-0.0123***		-0.0212***	-0.0207***
				(0.00119)	(0.00107)		(0.00112)	(0.00114)
Constant	9.239***	8.907***	9.090***	8.946***	9.000***	9.127***	9.098***	9.125***
	(0.0232)	(0.106)	(0.0366)	(0.0356)	(0.0358)	(0.0374)	(0.0370)	(0.0366)
Observations	294654	294654	294654	294654	294654	205949	205949	192715
R-squared	0.166	0.265	0.329	0.315	0.332	0.300	0.304	0.310
Dwelling controls	YES	YES	YES	YES	YES	YES	YES	YES
Transaction date FE	YES	YES	YES	YES	YES	YES	YES	YES
Municipalities		397						
Postcode groups			3695	3695	3695	3521	3521	3490

Notes: Dwellings with a construction year before 1900 are omitted. The reference group for energy labels is the *D* label. The reference group for building type is *apartment*. The reference group for the construction year is *1900-1930*.
Cluster-robust standard errors in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Also for the new system, we check whether "fictitious labels" can explain the found price premiums. Column (6) re-estimates column (3) using all transacted dwellings that did not have a label at the time of the sale but later received one. We see that for the better-labeled houses, about one third to one half of the premium is already present before the owner applies for the EPC. This suggests that buyers can gauge the energy efficiency to some degree without having an actual piece of paper with the Energy Performance Certificate printed on it. Similar results are found in column (7) which re-estimates model (5). Even when looking only at the period before the introduction of the new labels, 2000-2014, similar coefficients are observed for the effect of "fictitious labels". This indicates that dwelling characteristics that are observed by the buyer (but unobservable for researchers) partially explain the estimated price premiums of energy labels in the new system using hedonic pricing models.

5.3. Do (voluntary) energy labels have information value?

5.3.1. Method

To identify the information value of energy labels, we adopt a sharp Regression Discontinuity Design (RDD) method to identify the localized impact of energy labels on transaction prices. RDD is a quasi-experimental research design that exploits a rule-based cutoff point to assign an intervention to a treatment group. If the observation close to the cutoff can be assumed to be similar in their characteristics other than the treatment assignment, the average treatment effect can be estimated by comparing the sample close to the right side of the cutoff, to the sample on the left side.

Since energy labels in the old system are strictly determined based upon threshold values of the Energy Index (Table 1), a continuous value we observe, our RDD model is constructed by comparing the transaction prices of dwellings that are near the threshold criteria used to assign the label. These dwellings are assumed to be similar in their characteristics other than the energy label. The main specification is as follows:

$$ln(P_i) = \alpha + \beta_i D_i^{label} + \gamma_i(EI_i - c) + \delta_i(EI_i - c)D_i^{label} + \epsilon_i \tag{4}$$

where $ln(P_i)$ is the natural logarithm of the transaction price of dwelling i. D_i^{label} is a dummy variable that is equal to one if the dwelling has an energy index that is higher than the cutoff point c, implying the lower tier energy label. The dummy variable is equal to zero if the dwelling has an energy index that is lower than the cutoff point c, implying a higher tier energy label. β_i is the accompanying coefficient of interest, which thus measures the effect of moving from a certain energy label to a label that is one step lower. EI_i is the running variable, the energy index of dwelling i. γ_i is the coefficient of the running variable and δ_i is the coefficient of the interaction term. ϵ_i is a stochastic error term, assumed to be normally distributed with a mean of zero and variance of σ^2.

A non-parametric estimation is preferred over a parametric estimation as transacted dwellings are most similar around the cutoff points. The optimal bandwidth around the cutoff points is calculated following Calonico et al. (2014). Furthermore, the model is estimated using local linear polynomials and local quadratic polynomials as estimators, since high-order polynomials may be misleading (Gelman and Imbens, 2019). Finally, our RDD model includes an additional vector of covariates using a covariate-adjusted estimator. The inclusion of additional covariates could lead to an improvement in the precision of point estimates and inference (Calonico et al., 2019). We estimate the average treatment effect on the treated (ATT) for the A-B label group, and repeat the procedure for the other labels as well.

5.3.2. Results

The validity of the RDD estimates relies critically on the assumption that the sorting of transacted dwellings around the Energy Index cutoffs is random. As energy labels are strictly determined based on the EI, a tiny change of the EI can lead to assignment to a better or worse label category. If better energy labels are capitalized in the market, homeowners would have the incentive to manipulate the EI to be just on the left side of the cutoff point, i.e. a better label category. The so-called "bunching" effects around the cutoffs are found in other studies (e.g. Collins and Curtis, 2018). Although manipulation is unlikely in this case as the EI is determined by an independent expert with a non-transparent software system, we nevertheless test whether there is evidence of potential manipulation around the EI cutoffs.

Figure 4 displays the frequency distribution of the EI, together with the energy label cutoff points. Overall the EI appears to have a moderately smooth log-normal distribution although there are spikes in the distribution around some thresholds.

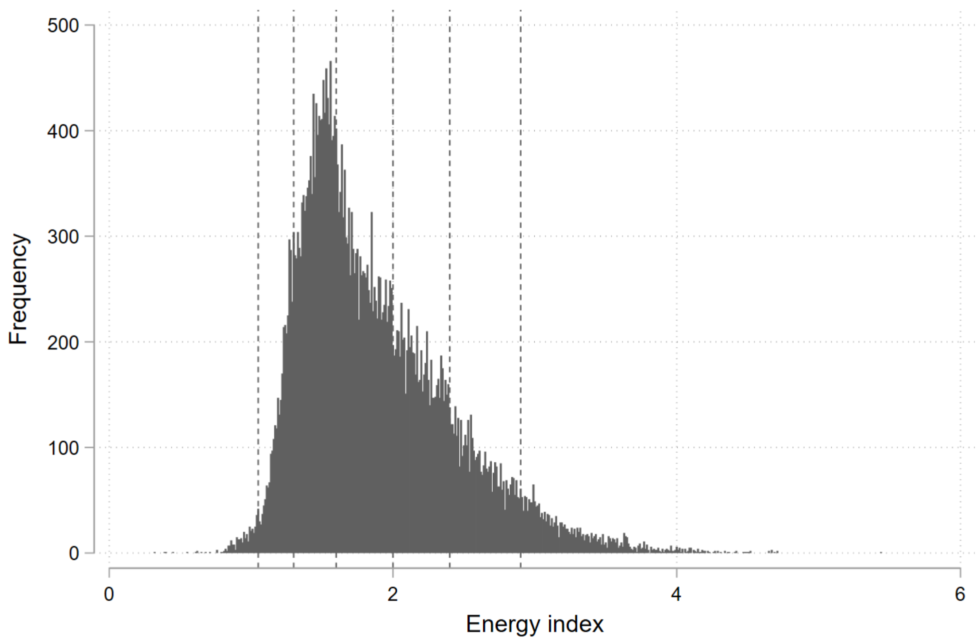

Figure 4: Distribution of the Energy Index in the Old System

To formally test whether the density of dwellings near the cutoffs is discontinuous, we employ a density manipulation test following Cattaneo et al. (2019). This test makes use of the same bandwidth calculations as in the RDD estimates (McCrary, 2008). Furthermore, this test is based on a novel local-polynomial density estimator, which does not require pre-binning of the data and is constructed intuitively based on easy-to-interpret kernel functions, which provide demonstrable improvements in both size and power, under appropriate assumptions, relative to the other approaches currently available in the literature Cattaneo et al. (2019). Table 6 shows the test results. We find that except D to E, no discontinuities exist around other cutoffs.

The density disparity at the D to E cutoff point could be explained by several reasons. First, homeowners could have invested in energy efficiency just enough to obtain the D-label instead of the E-label. Second, the independent expert could manipulate the energy indices to grant dwellings around the threshold a D-label instead of an E-label. Third, the non-transparent algorithm which determines the energy index may be programmed in such a way that energy indices on one side of the cutoff are computed more frequently. Given the labeling process described above, in which an independent expert determines the energy index based on his or her observations and using non-transparent software, and the fact that the frequency distribution is smooth at the other cutoff points, the last explanation appears to be most likely.

Table 6: Density manipulation test

	T	p-value
A-B	0.248	0.7912
B-C	-0.1465	0.8835
C-D	0.0489	0.9610
D-E	-3.4177	0.0006
E-F	-0.4243	0.6714
F-G	-1.1259	0.2602

Notes: The density manipulation test is performed according to Cattaneo et al. (2019).

Before turning to the estimates, we show the unconditional variation of the log of transaction prices per m^2 around each label cutoff point based on a linear fit in Figure 5. If energy labels have information values by providing additional information above and beyond the information contained in the EI, we would observe discontinuities in transaction prices around the cutoffs. At first glance, such jumps do not appear to be present at most of the cutoffs.

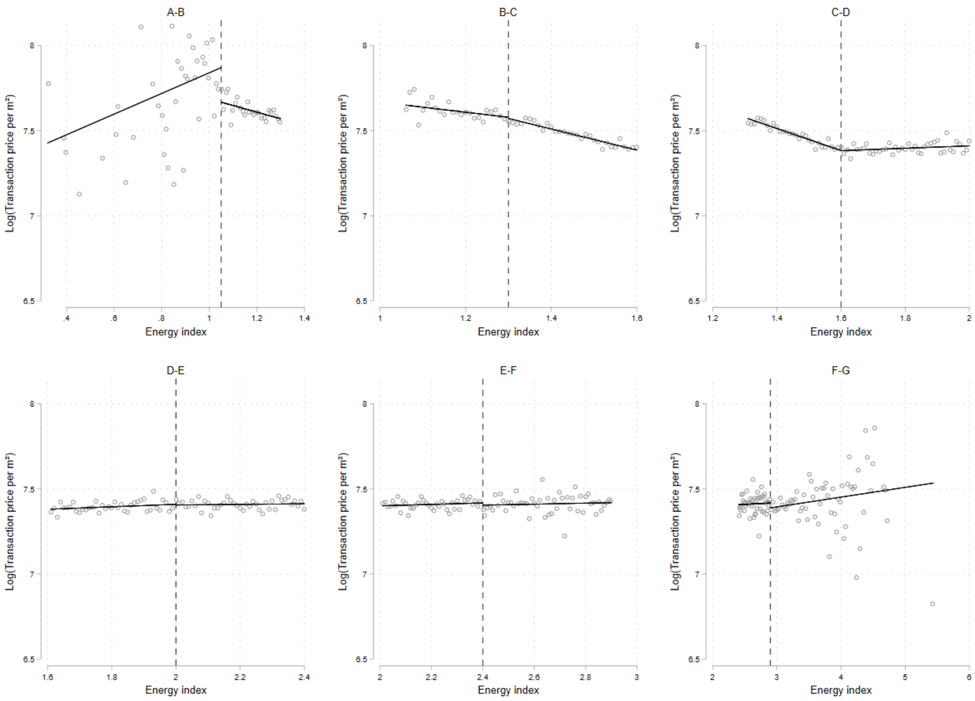

Figure 5: Transaction prices around the energy index cutoff points. The vertical axis depicts the natural logarithm of transaction prices per m². The horizontal axis depicts the energy index. Each dot represents a bin of about 1000 dwellings. The fitted line is a 1st-order polynomial fit.

Table 7 reports the coefficients of the baseline RDD model. The estimation results indicate that qualifying for a better label does not have significant effects on transaction prices around most of the label cutoffs. For example, qualifying for an A label does not bring a significant price premium over a comparable B-label dwelling, which is barely below the A-label threshold. Notably, we find some evidence of a D-label discount. An E-label dwelling is sold at a 5% premium compared to a D-label dwelling. As there appears to be potential manipulation around this cutoff indicated by the density test in Table 6, this coefficient estimate may not be reliable. When we control for covariates in table D.14 in Appendix D, also the E-label premium disappears.

We perform several robustness checks based on the baseline RDD results in Table 7 and demonstrate that our results are insensitive to alternative model specifications, selection bias, time and locational factors in Appendix D. These results suggest that the information value of voluntary labels which are adopted during 2008-2014 is rather limited as at the margin a better label does not yield a price premium in the Dutch residential housing sector.

The RDD model finds no significant variation in prices due to energy labels in the old label system. An extensive number of robustness checks show that this result is robust to model specifications, selection bias, time and locational factors. This implies that the information value of energy labels, as defined by this paper, is virtually zero.

Table 7: RDD: main specification

	A-B	B-C	C-D	D-E	E-F	F-G
D^{label}=1	0.0643	0.0184	-0.0212	0.0499*	-0.0470	0.00891
	(0.105)	(0.0440)	(0.0186)	(0.0247)	(0.0336)	(0.0479)
Observations	3,888	14,763	22,197	18,051	11,397	6,358

Notes: Cluster-robust standard errors in parentheses. The specification assumes linear local polynomials. *** p<0.001, ** p<0.01, * p<0.05.

6. Conclusion

This paper examines the information value of energy labels. We ask whether energy labels contain unobserved information that is not available to the market or not readily observed by the buyer and whether the design of a voluntary vs. mandatory label system matters for its information value. To do so, we estimate the effect of energy labels on transaction prices using administrative data on all residential property transactions in the Netherlands during 2000-2017 and employ several methodologies to address the shortcomings in the literature.

We find robust evidence of limited information value of voluntary labels during the period 2008-2014 in Dutch residential housing sector. In particular, the RDD analysis suggests that a better label does not associate with a price premium at the margin. While energy efficiency is well-capitalized, energy labels do not seem to provide additional information that is not already priced in the market. This result may not be surprising given the limitation in the design and execution of voluntary labels, and subsequently low adoption rate in the market.

The information value of the new labeling system is less clear-cut. While the RDD analysis we performed for the voluntary labels relies critically on the availability of the underlying Energy Index, the EI is not available in the new system. Therefore, we could not perform a similar analysis as for voluntary labels. Whether the findings hold for the new labeling system remains unclear. On the one hand, mandatory labels have much less information content than voluntary labels, which are determined in a relatively vigorous manner, by an independent expert based on over 150 dwelling characteristics. It is unlikely that mandatory labels on the basis of 10 characteristics contain more information value, in a way that potential homebuyers can not easily observe. On the other hand, mandatory labels are more salient to homebuyers given their high adoption rate and their use in the determination of ranking on the largest real estate website Funda.nl. Nevertheless, we show that significant price premiums were present for transacted dwellings before they obtained energy labels, implying that at least part of the premiums cannot be attributed to energy labels.

It is worth noting that in this paper the information value of energy labels is defined based on the transaction prices. To what extent energy labels have any impact on the investments of insulation and the associated value created by potential buyers is not considered here. It is possible that the presence of energy labels makes easier for buyers to invest in insulation or makes possible for buyers to easily assess the value of such insulation. This opens up future research on a broader understanding of information value of energy labels in the housing market.

References

Allcott, H., Greenstone, M., 2012. Is there an energy efficiency gap?, in: Journal of Economic Perspectives, pp. 3–28. URL: http://pubs.aeaweb.org/doi/10.1257/jep.26.1.3, doi:10.1257/jep.26.1.3.

Amecke, H., 2012. The impact of energy performance certificates: A survey of German home owners. Energy Policy 46, 4–14. URL: http://dx.doi.org/10.1016/j.enpol.2012.01.064https://linkinghub.elsevier.com/retrieve/pii/S0301421512000924, doi:10.1016/j.enpol.2012.01.064.

Aydin, E., Brounen, D., Kok, N., 2018. Information Asymmetry and Energy Efficiency : Evidence from the Housing Market.

Aydin, E., Correa, S.B., Brounen, D., 2019. Energy performance certification and time on the market. Journal of Environmental Economics and Management , 102270URL: https://doi.org/10.1016/j.jeem.2019.102270https://linkinghub.elsevier.com/retrieve/pii/S0095069618305084, doi:10.1016/j.jeem.2019.102270.

Bils, M., Klenow, P.J., 1998. Using consumer theory to test competing business cycle models. Journal of Political Economy 106, 233–261. doi:10.1086/250009.

Brounen, D., Kok, N., 2011. On the economics of energy labels in the housing market. Journal of Environmental Economics and Management 62, 166–179. URL: http://dx.doi.org/10.1016/j.jeem.2010.11.006https://linkinghub.elsevier.com/retrieve/pii/S0095069611000337, doi:10.1016/j.jeem.2010.11.006.

Brounen, D., Kok, N., Quigley, J.M., 2012. Residential energy use and conservation: Economics and demographics. European Economic Review 56, 931–945. URL: http://dx.doi.org/10.1016/j.euroecorev.2012.02.007https://linkinghub.elsevier.com/retrieve/pii/S0014292112000256, doi:10.1016/j.euroecorev.2012.02.007.

Cajias, M., Fuerst, F., Bienert, S., 2019. Tearing down the information barrier: the price impacts of energy efficiency ratings for buildings in the German rental market. Energy Research & Social Science 47, 177–191. URL: https://www.sciencedirect.com/science/article/pii/S2214629618309095https://linkinghub.elsevier.com/retrieve/pii/S2214629618309095, doi:10.1016/j.erss.2018.08.014.

Calonico, S., Cattaneo, M.D., Farrell, M.H., Titiunik, R., 2019. Regression Discontinuity Designs Using Covariates. The Review of Economics and Statistics 101, 442–451. URL: https://www.mitpressjournals.org/doi/abs/10.1162/rest{_}a{_}00760, doi:10.1162/rest_a_00760.

Calonico, S., Cattaneo, M.D., Titiunik, R., 2014. Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. Econometrica 82, 2295–2326. URL: http://doi.wiley.com/10.3982/ECTA11757, doi:10.3982/ECTA11757.

Cattaneo, M.D., Jansson, M., Ma, X., 2019. Simple Local Polynomial Density Estimators. Journal of the American Statistical Association 0, 1–7. URL: https://doi.org/10.1080/01621459.2019.1635480https://www.tandfonline.com/doi/full/10.1080/01621459.2019.1635480, doi:10.1080/01621459.2019.1635480.

Chegut, A., Eichholtz, P., Holtermans, R., 2016. Energy efficiency and economic value in affordable housing. Energy Policy 97, 39–49. URL: https://www.sciencedirect.com/science/article/pii/S0301421516303482?via{%}3Dihubhttps://linkinghub.elsevier.com/retrieve/pii/S0301421516303482, doi:10.1016/j.enpol.2016.06.043.

Collins, M., Curtis, J., 2018. Bunching of residential building energy performance certificates at threshold values. Applied Energy 211, 662–676. URL: https://www.sciencedirect.com/science/article/pii/S0306261917316768?via{%}3Dihubhttps://linkinghub.elsevier.com/retrieve/pii/S0306261917316768, doi:10.1016/j.apenergy.2017.11.077.

Dinan, T.M., Miranowski, J.A., 1989. Estimating the implicit price of energy efficiency improvements in the residential housing market: A hedonic approach. Journal of Urban Economics 25, 52–67. URL: https://linkinghub.elsevier.com/retrieve/pii/0094119089900430, doi:10.1016/0094-1190(89)90043-0.

Eichholtz, P., Kok, N., Quigley, J.M., 2010. Doing Well by Doing Good? Green Office Buildings. American Economic Review 100, 2492–2509. URL: http://pubs.aeaweb.org/doi/10.1257/aer.100.5.2492, doi:10.1257/aer.100.5.2492.

Eichholtz, P., Kok, N., Quigley, J.M., 2013. The Economics of Green Building. Review of Economics and Statistics 95, 50–63. URL: http://www.mitpressjournals.org/doi/10.1162/REST{_}a{_}00291, doi:10.1162/REST_a_00291.

European Comission, 2018. Energy performance of buildings — Energy. URL: https://ec.europa.eu/energy/en/topics/energy-efficiency/energy-performance-of-buildings/overview.

European Parliament and Council, 2002. Directive 2002/91/EC. URL: http://data.europa.eu/eli/dir/2002/91/oj.

European Parliament and Council, 2010. Directive 2010/31/EU. URL: http://data.europa.eu/eli/dir/2010/31/oj.

Frondel, M., Gerster, A., Vance, C., 2018. The Power of Mandatory Quality Disclosure: Evidence from the German Housing Market. SSRN Electronic Journal , 1–42URL: https://www.ssrn.com/abstract=2796532, doi:10.2139/ssrn.2796532.

Fuerst, F., McAllister, P., 2011. Green Noise or Green Value? Measuring the Effects of Environmental Certification on Office Values. Real Estate Economics 39, 45–69. URL: http://doi.wiley.com/10.1111/j.1540-6229.2010.00286.x, doi:10.1111/j.1540-6229.2010.00286.x.

Fuerst, F., McAllister, P., Nanda, A., Wyatt, P., 2015. Does energy efficiency matter to home-buyers? An investigation of EPC ratings and transaction prices in England. Energy Economics 48, 145–156. URL: https://www.sciencedirect.com/science/article/pii/S0140988314003296https://linkinghub.elsevier.com/retrieve/pii/S0140988314003296, doi:10.1016/j.eneco.2014.12.012.

Fuerst, F., Warren-Myers, G., 2018. Does voluntary disclosure create a green lemon problem? Energy-efficiency ratings and house prices. Energy Economics 74, 1–12. URL: https://www.sciencedirect.com/science/article/pii/S014098831830166X?via{%}3Dihubhttps://linkinghub.elsevier.com/retrieve/pii/S014098831830166X, doi:10.1016/j.eneco.2018.04.041.

Gelman, A., Imbens, G., 2019. Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs. Journal of Business & Economic Statistics 37, 447–456. URL: https://doi.org/10.1080/07350015.2017.1366909https://www.tandfonline.com/doi/full/10.1080/07350015.2017.1366909, doi:10.1080/07350015.2017.1366909.

Gerarden, T.D., Newell, R.G., Stavins, R.N., 2017. Assessing the energy-efficiency gap. Journal of Economic Literature 55, 1486–1525. URL: http://pubs.aeaweb.org/doi/10.1257/jel.20161360, doi:10.1257/jel.20161360.

Halvorsen, R., Pollakowski, H.O., 1981. The Effects of Fuel Prices on House Prices. Urban Studies 18, 205–211. URL: http://journals.sagepub.com/doi/10.1080/00420988120080361, doi:10.1080/00420988120080361.

Havlínová, J., Van Dijk, D., 2019. Verplichte energielabels hebben positief effect op verduurzaming van huizen. Technical Report. ESB. Amsterdam.

Hyland, M., Lyons, R.C., Lyons, S., 2013. The value of domestic building energy efficiency — evidence from Ireland. Energy Economics 40, 943–952. URL: http://dx.doi.org/10.1016/j.eneco.2013.07.020https://linkinghub.elsevier.com/retrieve/pii/S0140988313001655, doi:10.1016/j.eneco.2013.07.020.

Johnson, R.C., Kaserman, D.L., 1983. Housing Market Capitalization of Energy-Saving Durable Good Investments. Economic Inquiry 21, 374–386. URL: http://doi.wiley.com/10.1111/j.1465-7295.1983.tb00639.x, doi:10.1111/j.1465-7295.1983.tb00639.x.

Kahn, M.E., Kok, N., 2014. The capitalization of green labels in the California housing market. Regional Science and Urban Economics 47, 25–34. URL: http://dx.doi.org/10.1016/j.regsciurbeco.2013.07.001https://linkinghub.elsevier.com/retrieve/pii/S0166046213000574, doi:10.1016/j.regsciurbeco.2013.07.001.

Kok, N., Jennen, M., 2012. The impact of energy labels and accessibility on office rents. Energy Policy 46, 489–497. URL: http://dx.doi.org/10.1016/j.enpol.2012.04.015https://linkinghub.elsevier.com/retrieve/pii/S0301421512003151, doi:10.1016/j.enpol.2012.04.015.

Laquatra, J., 1986. Housing market capitalization of thermal integrity. Energy Economics 8, 134–138. URL: https://linkinghub.elsevier.com/retrieve/pii/0140988386900113, doi:10.1016/0140-9883(86)90011-3.

McCrary, J., 2008. Manipulation of the running variable in the regression discontinuity design: A density test. Journal of Econometrics 142, 698–714. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304407607001133, doi:10.1016/j.jeconom.2007.05.005.

Mense, A., 2018. What is the Information Value of Energy Efficiency Certificates in Buildings? URL: https://www.econstor.eu/bitstream/10419/181214/1/1028143273.pdf.

Murphy, L., 2014. The influence of the Energy Performance Certificate: The Dutch case. Energy Policy 67, 664–672. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421513011841, doi:10.1016/j.enpol.2013.11.054.

Myers, E., Puller, S., West, J., 2019. Effects of Mandatory Energy Efficiency Disclosure in Housing Markets. Technical Report. National Bureau of Economic Research. Cambridge, MA. URL: http://www.nber.org/papers/w26436.pdf, doi:10.3386/w26436.

Olaussen, J.O., Oust, A., Solstad, J.T., 2017. Energy performance certificates – Informing the informed or the indifferent? Energy Policy 111, 246–254. URL: https://www.sciencedirect.com/science/article/pii/S030142151730589Xhttps://linkinghub.elsevier.com/retrieve/pii/S030142151730589X, doi:10.1016/j.enpol.2017.09.029.

Quigley, J.M., 1984a. Residential Energy Standards and the Housing Market: A Regional Analysis. International Regional Science Review 9, 201–216. URL: http://journals.sagepub.com/doi/10.1177/016001768400900302, doi:10.1177/016001768400900302.

Quigley, J.M., 1984b. The Production of Housing Services and the Derived Demand for Residential Energy. The RAND Journal of Economics 15, 555. URL: http://doi.wiley.com/10.2307/2555526, doi:10.2307/2555526.

Quigley, J.M., Rubinfeld, D.L., 1989. Unobservables in Consumer Choice: Residential Energy and the Demand for Comfort. The Review of Economics and Statistics 71, 416. URL: https://www.jstor.org/stable/1926898?origin=crossref, doi:10.2307/1926898.

Ramos, A., Gago, A., Labandeira, X., Linares, P., 2015. The role of information for energy efficiency in the residential sector. Energy Economics 52, S17–S29. URL: http://dx.doi.org/10.1016/j.eneco.2015.08.022https://linkinghub.elsevier.com/retrieve/pii/S0140988315002455, doi:10.1016/j.eneco.2015.08.022.

Rosen, S., 1974. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. Journal of Political Economy 82, 34–55. URL: http://www.journals.uchicago.edu/t-and-chttps://www.journals.uchicago.edu/doi/10.1086/260169, doi:10.1086/260169.

Spinoni, J., Vogt, J.V., Barbosa, P., Dosio, A., McCormick, N., Bigano, A., Füssel, H.M., 2018. Changes of heating and cooling degree-days in Europe from 1981 to 2100. International Journal of Climatology 38, e191–e208. URL: http://doi.wiley.com/10.1002/joc.5362, doi:10.1002/joc.5362.

Stanley, S., Lyons, R.C., Lyons, S., 2016. The price effect of building energy ratings in the Dublin residential market. Energy Efficiency 9, 875–885. URL: http://dx.doi.org/10.1007/s12053-015-9396-5http://link.springer.com/10.1007/s12053-015-9396-5, doi:10.1007/s12053-015-9396-5.

Stavins, R.N., Schatzki, T., Borck, J., 2013. An Economic Perspective on Building Labeling Policies. Technical Report. Analysis Group, Inc.

Vringer, K., van Middelkoop, M., Hoogervorst, N., 2016. Saving energy is not easy: An impact assessment of Dutch policy to reduce the energy requirements of buildings. Energy Policy 93, 23–32. URL: http://dx.doi.org/10.1016/j.enpol.2016.02.047, doi:10.1016/j.enpol.2016.02.047.

Wahlström, M.H., 2016. Doing good but not that well? A dilemma for energy conserving homeowners. Energy Economics 60, 197–205. URL: http://dx.doi.org/10.1016/j.eneco.2016.09.025https://linkinghub.elsevier.com/retrieve/pii/S0140988316302705, doi:10.1016/j.eneco.2016.09.025.

Walls, M., Gerarden, T., Palmer, K., Bak, X.F., 2017. Is energy efficiency capitalized into home prices? Evidence from three U.S. cities. Journal of Environmental Economics and Management 82, 104–124. URL: http://dx.doi.org/10.1016/j.jeem.2016.11.006https://linkinghub.elsevier.com/retrieve/pii/S0095069616304508, doi:10.1016/j.jeem.2016.11.006.

Appendix A. EPA-W Software

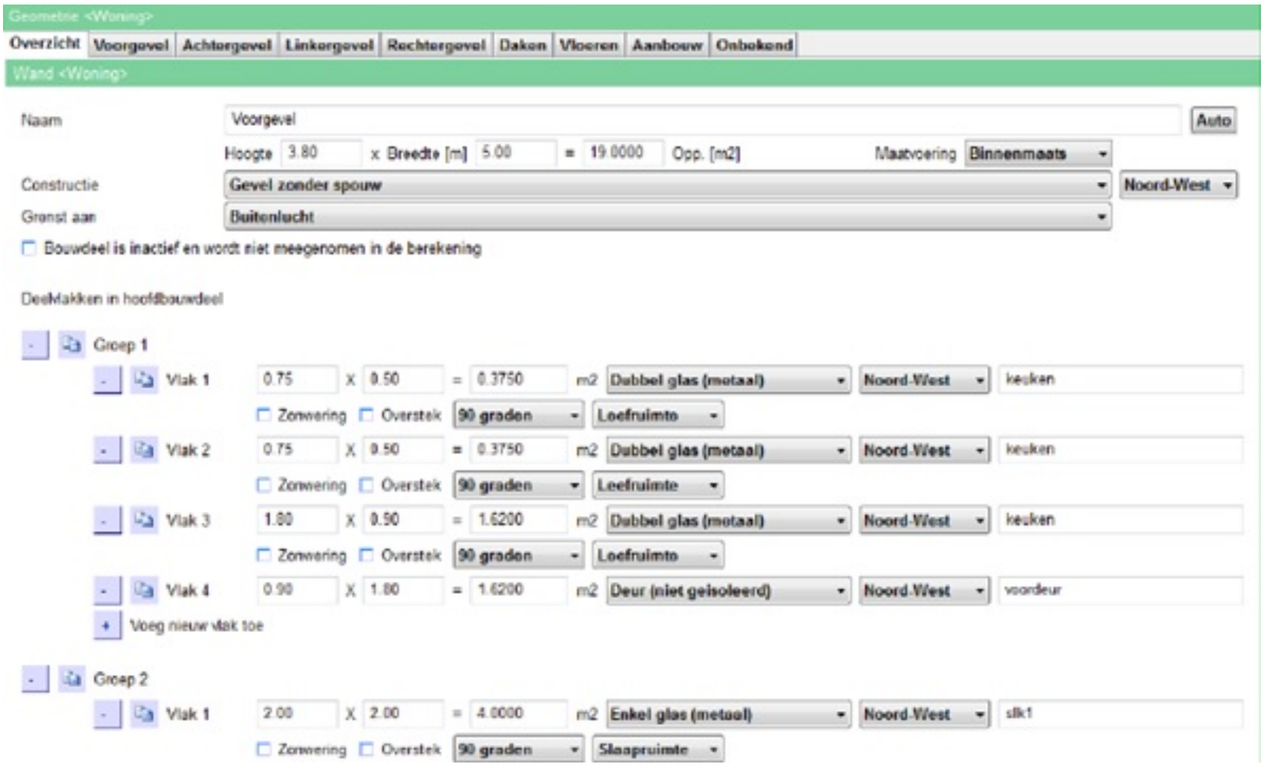

Figure A.6: Example input menu EPA-W software.

Appendix B. Further Summary Statistics: Sample Overview by Label Groups

Furthermore, between energy label groups dwellings vary in all of their observed characteristics (Table B.8 and Table B.9). In the old system, A-label dwellings, for example, consist of 51% apartments while this is 30% for G-label dwellings. Moreover, A-label dwellings are relatively frequently old with a construction year of 1900 to 1929 or relatively new with a construction year of 1990 and higher. G-label dwellings are relatively old. Moreover, energy-efficient dwellings are transacted relatively often in later years. 88% of A-label dwellings are transacted in 2011 or later, while only 57% of G-label dwellings are transacted in that time.

Clearly, these descriptive statistics could be explained by many factors. Also in the new system, large differences in characteristics between label groups can be observed. A large fraction of C-label dwellings are terraced (49%) and less frequently detached (9%). In contrast, G-label dwellings are less often terraced (15%) and have a substantial fraction of detached dwellings (30%). Moreover, the dwellings in the label groups differ severely in construction year with a positive correlation between building year and the actual EPC. For the years of the transaction, however, no large variation between labeled and unlabeled houses is observed.

Table B.8: Characteristics per label group in the old system

	Energy label															
	A		B		C		D		E		F		G		Total	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Dwelling type																
Apartment	197	50.8	1,436	41.0	3,537	31.4	2,880	26.3	2,366	33.3	1,355	31.6	614	29.6	12,385	31.3
Detached	36	9.3	284	8.1	337	3.0	264	2.4	246	3.5	233	5.4	180	8.7	1,580	4.0
Duplex	35	9.0	208	5.9	733	6.5	747	6.8	674	9.5	557	13.0	355	17.1	3,309	8.4
Semi-Detached	33	8.5	521	14.9	2,191	19.5	2,164	19.8	1,307	18.4	867	20.2	461	22.2	7,544	19.1
Terraced	87	22.4	1,051	30.0	4,465	39.6	4,882	44.6	2,521	35.4	1,272	29.7	467	22.5	14,745	37.3
Total	388	100.0	3,500	100.0	11,263	100.0	10,937	100.0	7,114	100.0	4,284	100.0	2,077	100.0	39,563	100.0
Class of the building year																
1900-1929	132	34.5	317	9.1	419	3.7	672	6.1	592	8.3	497	11.6	342	16.5	2,971	7.5
1930-1944	12	3.1	54	1.5	197	1.7	463	4.2	543	7.6	417	9.7	242	11.7	1,928	4.9
1945-1959	25	6.5	148	4.2	763	6.8	1,232	11.3	1,524	21.5	1,118	26.1	749	36.1	5,559	14.1
1960-1969	9	2.3	275	7.9	965	8.6	2,292	21.0	1,986	28.0	1,223	28.6	537	25.9	7,287	18.4
1970-1979	19	5.0	316	9.0	2,161	19.2	3,568	32.7	2,218	31.2	994	23.2	188	9.1	9,464	23.9
1980-1989	14	3.7	783	22.4	4,929	43.8	2,408	22.0	210	3.0	23	0.5	13	0.6	8,380	21.2
1990-1999	95	24.8	1,386	39.7	1,778	15.8	279	2.6	20	0.3	10	0.2	3	0.1	3,571	9.0
2000-	77	20.1	215	6.2	47	0.4	14	0.1	10	0.1	0	0.0	1	0.0	364	0.9
Total	383	100.0	3,494	100.0	11,259	100.0	10,928	100.0	7,103	100.0	4,282	100.0	2,075	100.0	39,524	100.0
Transaction year																
2008	7	1.8	158	4.5	528	4.7	549	5.0	332	4.7	249	5.8	101	4.9	1,924	4.9
2009	7	1.8	337	9.6	1,198	10.6	1,291	11.8	834	11.7	603	14.1	328	15.8	4,598	11.6
2010	33	8.5	488	13.9	1,967	17.5	2,045	18.7	1,323	18.6	836	19.5	456	22.0	7,148	18.1
2011	97	25.0	634	18.1	2,323	20.6	2,279	20.8	1,473	20.7	828	19.3	410	19.7	8,044	20.3
2012	90	23.2	800	22.9	2,627	23.3	2,303	21.1	1,513	21.3	871	20.3	388	18.7	8,592	21.7
2013	78	20.1	618	17.7	1,652	14.7	1,510	13.8	949	13.3	485	11.3	215	10.4	5,507	13.9
2014	76	19.6	465	13.3	968	8.6	960	8.8	690	9.7	412	9.6	179	8.6	3,750	9.5
Total	388	100.0	3,500	100.0	11,263	100.0	10,937	100.0	7,114	100.0	4,284	100.0	2,077	100.0	39,563	100.0

Notes: Dwellings with (i) a construction year before 1900 and (ii) younger than ten years are omitted.

Table B.9: Characteristics per label group in the new system

	Energy label															
	A		**B**		**C**		**D**		**E**		**F**		**G**		**Total**	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Dwelling type																
Apartment	7,803	14.7	11,496	20.0	18,111	17.5	14,905	30.4	11,467	31.9	5,518	19.9	3,772	15.8	73,072	20.8
Detached	7,206	13.6	7,890	13.7	8,775	8.5	6,304	12.9	3,146	8.7	5,818	20.9	7,096	29.7	46,235	13.2
Duplex	5,583	10.5	6,779	11.8	9,420	9.1	5,554	11.3	4,508	12.5	4,377	15.8	5,489	22.9	41,710	11.9
Semi-Detached	7,556	14.2	8,188	14.2	16,954	16.4	8,061	16.4	4,366	12.1	3,583	12.9	3,967	16.6	52,675	15.0
Terraced	24,976	47.0	23,211	40.3	50,225	48.5	14,205	29.0	12,484	34.7	8,487	30.5	3,606	15.1	137,194	39.1
Total	53,124	100.0	57,564	100.0	103,485	100.0	49,029	100.0	35,971	100.0	27,783	100.0	23,930	100.0	350,886	100.0
Class of the building year																
1900-1929	226	0.4	267	0.5	2,322	2.2	5,803	11.9	5,070	14.1	8,485	30.6	9,615	40.3	31,788	9.1
1930-1944	86	0.2	129	0.2	1,562	1.5	4,939	10.1	5,256	14.6	7,800	28.1	8,592	36.0	28,364	8.1
1945-1959	95	0.2	183	0.3	3,606	3.5	6,823	13.9	9,577	26.7	4,555	16.4	2,945	12.3	27,784	7.9
1960-1969	219	0.4	1,195	2.1	11,977	11.6	13,559	27.7	11,436	31.8	5,061	18.2	2,353	9.9	45,800	13.1
1970-1979	585	1.1	4,239	7.4	31,839	30.8	14,128	28.9	4,177	11.6	1,748	6.3	289	1.2	57,005	16.3
1980-1989	857	1.6	7,563	13.1	37,643	36.4	3,448	7.0	353	1.0	39	0.1	33	0.1	49,936	14.2
1990-1999	7,939	14.9	32,511	56.5	13,966	13.5	217	0.4	20	0.1	28	0.1	41	0.2	54,722	15.6
2000-	43,100	81.2	11,463	19.9	523	0.5	44	0.1	28	0.1	28	0.1	19	0.1	55,205	15.7
Total	53,107	100.0	57,550	100.0	103,438	100.0	48,961	100.0	35,917	100.0	27,744	100.0	23,887	100.0	350,604	100.0
Transaction year																
2015	12,438	23.4	13,471	23.4	24,886	24.0	11,849	24.2	8,721	24.2	6,954	25.0	6,044	25.3	84,363	24.0
2016	18,344	34.5	20,269	35.2	36,482	35.3	17,361	35.4	12,618	35.1	9,800	35.3	8,480	35.4	123,354	35.2
2017	22,342	42.1	23,824	41.4	42,117	40.7	19,819	40.4	14,632	40.7	11,029	39.7	9,406	39.3	143,169	40.8
Total	53,124	100.0	57,564	100.0	103,485	100.0	49,029	100.0	35,971	100.0	27,783	100.0	23,930	100.0	350,886	100.0

Notes: Dwellings with a construction year before 1900 are omitted.

Appendix C. Matching

The hedonic pricing models applied in section 5.2 can only make use of the subset of labeled dwellings. Table 3 already showed that the observable characteristics influence an owner's decision of applying for a label. To account for this effect, we use a propensity-score matching approach. In the first stage, a logit model is estimated that models the propensity of label adoption as explained by the observable features of a dwelling. After that, the potential label of unlabeled houses is estimated given the label of houses with similar characteristics. The resulting average treatment effect is the difference in transaction prices between two neighboring label groups (as in the RDD approach).

The matching results for the old system are shown in Table C.10. Here we see that there are only significant price premiums for the medium labels and that those are relatively small in magnitude. This suggests that the actual price premiums (almost) disappear once we control for the different propensities of actually applying for a label. In line with the results of column (8) in Table 4, this implies that hedonic pricing models usually overestimate the labels' information value.

Table C.10: Matching results: old system

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
Premium	0.0315	0.0254	0.0167***	0.00695*	0.00738**	-0.00718
	(0.0576)	(0.0148)	(0.00285)	(0.00327)	(0.00280)	(0.0193)
Observations	891	10,921	19,879	15,323	9,528	4,550
Dwelling controls	YES	YES	YES	YES	YES	YES
Postcode groups	YES	YES	YES	YES	YES	YES

Notes: Dwellings with (i) a construction year before 1900 and (ii) younger than ten years are omitted.
Cluster-robust standard errors in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

In Table C.11 the matching results for the new system are depicted. For all label improvements (excluding the A-B one) we now find significant premiums on the transaction price. The results are very similar to what we found using the regular hedonic pricing model in column (5) of Table 5. This should not come as a surprise because in the new system the majority of houses are labeled and hence the need to control for the decision to apply for an EPC is less relevant compared to the old system.

Table C.11: Matching results: new system

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
Premium	-0.000655	0.0312***	0.0398***	0.0114***	0.0278***	0.0731***
	(0.00213)	(0.00211)	(0.00265)	(0.00225)	(0.00275)	(0.00328)
Observations	104,483	157,772	148,651	82,433	61,561	49,682
Dwelling controls	YES	YES	YES	YES	YES	YES
Postcode groups	YES	YES	YES	YES	YES	YES

Notes: Dwellings with a construction year before 1900 are omitted.
Cluster-robust standard errors in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Appendix D. Further RDD Results

Appendix D.1. Robustness checks

To check the robustness of our results, we test whether the covariates are balanced across the cutoffs. More specifically we examine whether dwellings are similar in terms of construction year and type across the cutoffs. We estimate a series of RDD models where construction year and type variables are used as outcome variables. We test the null hypothesis that there are no discontinuities in these characteristics around the cutoffs. Table D.12 and D.13 report the results of a total of 72 RDD estimates. The majority of the RDD estimates are insignificant, suggesting that the allocation of dwellings with different characteristics is not systematically different. Notably, we find several significant coefficients around the D-E cutoff. D-label dwellings, which were built between 1945 and 1959, have a 9.7 percentage point larger fraction than E-label ones. In contrast, D-label dwellings, which were built between 1960 and 1969, have an 8.2 percentage point smaller fraction than E-label ones. This may explain the counter-intuitive premium between label D and E: the sample is relatively non-random around the threshold.

Table D.12: RDD: estimates of construction year dummies

	(1) 1900-1929	(2) 1930-1944	(3) 1945-1959	(4) 1960-1969	(5) 1970-1979	(6) 1980-1989	(7) 1990-1999	(8) 2000-	N
A-B	0.146	-0.087	0.100	0.017	-0.190	0.030	-0.088	-0.067	3,877
	(0.125)	(0.061)	(0.056)	(0.029)	(0.108)	(0.030)	(0.113)	(0.092)	
B-C	-0.043	0.003	0.058**	-0.011	-0.056	-0.030	0.071	0.022	14,753
	(0.027)	(0.009)	(0.020)	(0.031)	(0.030)	(0.041)	(0.048)	(0.017)	
C-D	-0.021	0.005	-0.016	0.046	-0.006	0.078	-0.050	-0.001	22,184
	(0.011)	(0.010)	(0.019)	(0.023)	(0.035)	(0.049)	(0.027)	(0.001)	
D-E	-0.031	-0.013	0.099**	-0.081**	0.050	0.007	-0.009	-0.000	18,031
	(0.018)	(0.016)	(0.030)	(0.027)	(0.030)	(0.017)	(0.007)	(0.000)	
E-F	-0.006	0.010	0.015	0.050	-0.100*	0.010	0.003	-0.003	11,384
	(0.025)	(0.023)	(0.033)	(0.042)	(0.050)	(0.009)	(0.005)	(0.002)	
F-G	0.079*	-0.067	-0.133*	0.052	0.098*	-0.003	0.010	0.002	6,354
	(0.039)	(0.037)	(0.054)	(0.062)	(0.049)	(0.009)	(0.008)	(0.002)	

Notes: Each coefficient represents the result of an RDD estimation on that dummy that equals 1 if the observation has the above-mentioned construction year group and 0 otherwise.
Notes: Cluster-robust standard errors in parentheses. The specification assumes linear local polynomials. *** p<0.001, ** p<0.01, * p<0.05.

Furthermore, as robustness checks, we include the period of construction and type variables in the right-hand side of our baseline RDD model and report the results in Table D.14. Results are very similar to those reported in Table 7. We find no significant premiums at 5 out of the 6 label cut-offs. However, a significant D-label discount remains. Overall, our results do not seem to be driven by the inclusion of additional control variables.

Next, we test whether our RDD results are robust to a quadratic polynomial specification. Results are reported in Table D.15, and again they are quantitatively similar. Hence, the main results in Table 7 are unlikely to be driven by model specifications.

One potential source of bias is the selection issue that transacted dwellings with energy labels are not a random sample of the total dwelling stock. Particular types of dwellings (with energy labels) are likely to be sold more frequently, which could result in biased estimates regarding the effects of energy labels. To alleviate this concern, we re-estimate the RDD model based on non-transactional data. Instead of transaction prices, we use the so-called WOZ values of dwellings. The WOZ values

Table D.13: RDD: estimates of dwelling type dummies

	(1) Apartment	(2) Detached	(3) Duplex	(4) Semi-Detached	(5) Terraced	N
A-B	0.092	-0.041	-0.012	0.096	-0.110	3,888
	(0.117)	(0.062)	(0.063)	(0.061)	(0.094)	
B-C	-0.080*	0.012	0.072***	0.000	0.021	14,763
	(0.041)	(0.021)	(0.020)	(0.041)	(0.037)	
C-D	0.026	-0.007	-0.049*	-0.043	0.052	22,197
	(0.025)	(0.011)	(0.021)	(0.028)	(0.035)	
D-E	0.000	0.011	-0.010	0.011	0.005	18,051
	(0.031)	(0.010)	(0.019)	(0.027)	(0.031)	
E-F	-0.157**	0.020	0.075*	0.015	0.045	11,397
	(0.049)	(0.017)	(0.034)	(0.032)	(0.045)	
F-G	0.070	0.025	-0.059	-0.024	-0.016	6,358
	(0.055)	(0.034)	(0.045)	(0.052)	(0.057)	

Notes: Each coefficient represents the result of an RDD estimation on that dummy that equals 1 if the observation has the above-mentioned dwelling type and 0 otherwise.
Notes: Cluster-robust standard errors in parentheses. The specification assumes linear local polynomials. *** p<0.001, ** p<0.01, * p<0.05.

Table D.14: RDD: including covariates

	A-B	B-C	C-D	D-E	E-F	F-G
D^{label}=1	-	-0.0173	-0.0215	0.0439	-0.0536	-0.00116
	-	(0.0379)	(0.0237)	(0.0287)	(0.0353)	(0.0517)
Observations	3,888	14,629	22,074	17,969	11,340	6,327

Notes: Cluster-robust standard errors in parentheses. The specification assumes linear local polynomials. *** p<0.001, ** p<0.01, * p<0.05.

Table D.15: RDD: using quadratic local polynomials

	A-B	B-C	C-D	D-E	E-F	F-G
D^{label}=1	0.0723	-0.00167	-0.00977	0.0551	-0.0335	0.00675
	(0.116)	(0.0409)	(0.0261)	(0.0343)	(0.0459)	(0.0602)
Observations	3,888	14,763	22,197	18,051	11,397	6,358

Notes: Cluster-robust standard errors in parentheses. The specification assumes quadratic local polynomials. *** p<0.001, ** p<0.01, * p<0.05.

are determined every year by local municipalities and are used for levying property tax and are rather accurate compared to the transaction price (Smeitink, 2019). The results reported in Table D.16 are rather similar to those in Table 7. Therefore, selection bias is unlikely to influence our results.

Table D.16: RDD: using WOZ value

	A-B	B-C	C-D	D-E	E-F	F-G
D^{label}=1	-0.0644	-0.0125	-0.0283	0.0335	-0.0325	-0.0316
	(0.0933)	(0.0338)	(0.0219)	(0.0276)	(0.0339)	(0.0461)
Observations	3,784	14,558	21,969	17,864	11,271	6,289

Notes: Cluster-robust standard errors in parentheses. The specification assumes linear local polynomials. *** p<0.001, ** p<0.01, * p<0.05.

Another potential bias may arise from the equal treatment of houses in regions with very different housing market conditions. Olaussen et al. (2017) argue that potential buyers may not care about energy ratings when they buy a home. Other factors play much bigger roles in a market like Norway, with fast bidding rounds. To further investigate the effect of housing market conditions on price premiums of energy labels, we construct two subsamples, one including houses in a region with relatively high housing demand comparing to supply (i.e. the province of Zuid-Holland), and the other one including houses in a region where housing demand is low (the province of Gelderland). The results are shown in Table D.17 and D.18. We find the estimated coefficients are very similar using these two sub-samples, meaning that these main results presented in Table 7 can not be attributed to different housing market conditions.[7].

Table D.17: RDD: South-Holland

	B-C	C-D	D-E	E-F	F-G
D^{label}=1	-0.0401	-0.0535	0.101	0.00675	-0.0125
	(0.0562)	(0.0548)	(0.0521)	(0.0626)	(0.0714)
Observations	2,338	3,783	3,342	2,403	1,409

Notes: Cluster-robust standard errors in parentheses. The specification assumes linear local polynomials. *** p<0.001, ** p<0.01, * p<0.05.

Table D.18: RDD: Gelderland

	B-C	C-D	D-E	E-F	F-G
D^{label}=1	0.0472	0.0626	-0.0780	0.0519	0.0504
	(0.101)	(0.0642)	(0.0740)	(0.0849)	(0.101)
Observations	1,407	2,436	2,047	1,155	590

Notes: Cluster-robust standard errors in parentheses. The specification assumes linear local polynomials. *** p<0.001, ** p<0.01, * p<0.05.

[7]The downturn in housing markets and the subsequent decrease in transaction prices may also have an impact on the willingness to pay for more efficient, green homes. It has been documented that prices are more procyclical for durables and luxuries as compared to prices of necessities and nondurables (Bils and Klenow, 1998). Kahn and Kok (2014) show that among private homeowners, demand for 'green' is lower in recessions, but increases as the economy accelerates. In contrast, it has been documented for the commercial market that green-certified office buildings experienced rental decreases similar to conventional office buildings during the most recent downturn in the economy (Eichholtz et al., 2013).