Master Thesis
The information value of energy labels: A quasi-experimental approach☆

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Abstract Promoting energy efficiency in the residential housing sector is a policy objective of increasing importance. In this paper, I assess the effectiveness of energy labels in the residential housing sector of Netherlands from 2008 to 2017. Hedonic pricing models, commonly used in the literature, find large transaction price premiums for dwellings with better energy labels. However, this result is sensitive to model specifications. Hence, the premiums cannot be causally attributed to energy labels. Addressing the shortcomings of this methodology, I construct a Regression Discontinuity Design model (RDD). The energy index, which determines the energy labels, is used to compare similar dwellings with different energy labels. The RDD estimates provide no evidence for significant price premiums due to energy labels. These findings suggest that energy labels do not represent information valued in the market and question the need for this type of information policy.

Keywords: *energy labels, house prices, information value, regression discontinuity design*

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1. Introduction

In the EU, buildings account for approximately 40 percent of energy consumption and 36 percent of CO2 emissions (European Commission, 2018). To increase the energy efficiency of the build environment does not only hold financial savings potential, it has a significant role to play in achieving the goals of Paris Climate Accord and mitigate climate change. The European parliament and the council adopted the directive to promote energy efficiency in the built environment in December of 2002 (Directive 2002/91/EC). One article of this directive requires all EU member states to ensure an energy performance certificate (EPC) is made available by the owner when a building is constructed, sold or rented out. These energy labels are aimed to further encourage owners and tenants to improve the energy performance of their building.

Many studies suggest that imperfect information is one of the drivers of the so-called energy efficiency gap (Allcott & Greenstone, 2012; Ramos et al., 2015; Gerarden et al., 2017). If potential buyers of a dwelling cannot observe building-specific characteristics with regard to energy use, the level of energy efficiency will not be accurately valued in transactions. Energy labels are designed to reduce this efficiency loss by disclosing unobserved information to buyers, which, in turn, should be capitalized in transaction prices. Thus, the extent to which energy labels disclose additional, valued information to buyers can be found empirically by estimating their effect on transaction prices. I define this as the information value of energy labels. Whether energy labels posses such information value is the key question of this paper.

Over the last decade, a growing body of literature aims to assess the effectiveness of energy label policies using hedonic pricing and repeated sales models. In the commercial real estate market, a few studies find significant premiums of 'green' energy labels in transactions of office buildings and rent levels (Eichholtz et al., 2010, 2013; Kok & Jennen, 2012; Fuerst & McAllister, 2011). For the residential housing sectors, results are mixed. Brounen & Kok (2011) find significant and large premiums in transaction prices for dwellings with 'green' energy labels. These results are confirmed by Fuerst et al. (2015). On the contrary, Olaussen et al. (2017) find no empirical evidence of energy label premiums in housing prices. It is yet unclear whether these premiums in the literature are induced by energy labels or other factors, such as differences in (energy efficiency) characteristics of buildings.

In this paper, I analyse the information value of energy labels in the residential sector by estimating the effect of energy labels on transaction prices of dwellings in the Netherlands. As the Netherlands has known two distinct systems of energy labels from 2008-2014 and 2015-2017, these are studied separately. Hedonic pricing models are employed for both systems to examine the premiums associated with energy labels. Moreover, these models are estimated in the period before dwellings obtained their energy label assigning a dummy variable to each dwelling for an energy label obtained in a later period. Doing so, I investigate correlation between energy labels and unobserved time-invariant characteristics associated with transaction prices. Then, the energy index, which determines the energy labels, is used to construct a Regression Discontinuity Design (RDD) model. By comparing dwellings with a similar energy index on each side of the energy label cut-off point, I estimate the effect of achieving a better energy label on transaction prices. This quasi-experimental approach allows for the estimation of the 'true' information value of energy labels.

In line with findings in the literature, I find significant and large premiums for energy labels in both labelling systems by estimating hedonic pricing models. However, the hedonic estimates for the period before the introduction of energy labels also find some significant and large differences in transaction prices. This provides evidence for the existence of an omitted variable bias in the hedonic model as the premiums may be driven by unobserved dwelling characteristics. On the contrary, the RDD estimates show no significant premiums. As this approach does not suffer from biases found in the hedonic pricing models, it can be concluded that the effect of energy labels on transaction prices are non-significant. Hence, the energy labels do not provide significant information value to buyers.

Contributions to the literature are made in several ways. First, while many studies have investigated the relationship between transaction prices and energy labels, they have been unable to attribute the existence of premiums to energy labels as a causal effect. This paper is among the first to investigate the information value of energy labels in the residential housing sector. Second, the confounding factors of energy label premiums in the hedonic pricing model are investigated. Correlation between energy labels and real energy efficiency is checked by including the energy index. Moreover, evidence of correlation between time-invariant factors and transaction prices is given by estimating a model for a pre-label period. Third, the quasi-experimental research design of this paper is, to the best of my knowledge, a novelty in the literature. It allows for the estimation of the 'true' information value of energy labels.

The remainder of this paper is structured as follows. Section 2 discusses the literature on energy label effects. Section 3 describes the policy background of energy labels in the EU and the Netherlands. The methodology of this paper is proposed in section 4. Section 5 describes the data and section 6 shows the results. Section 7 concludes.

2. Literature overview

2.1. The Energy Efficiency Gap

The rationale for information policies such as energy labels can be found in the literature on the Energy Efficiency Gap. Gerarden et al. (2017) give an overview of mechanisms that potentially cause an Energy Efficiency Gap. Innovation spillovers, market power and externalities can lead to lower investments in energy efficiency than the socially desirable level. Also, inattention, myopia, cognitive limitations, credit constraints and imperfect information can cause investments in energy efficiency lower than the private and socially desirable level. The sum of all inefficiencies is defined as the Social Energy Efficiency Gap: a wedge between the socially optimal level of investments and the real investments. On the individual level, inefficiency is defined as the Private Energy Efficiency Gap: a wedge between the cost minimizing level of investments and the real investments (Allcott & Greenstone, 2012).

The mechanisms that drive the Energy Efficiency Gap determine the optimal policy response. If information is perfect and only externalities are present, the first-best policy would be to implement a Pigouvian tax (Pigou, 1920). If credit constraints are the cause of underinvestment, the optimal policy response would be to alleviate those constraints. If information is imperfect, the first-best policy response is to address this market failure directly with information policies.

Energy labels are aimed to resolve imperfect information analogues to the 'market for lemons' problem described by Akerlof (1970). They are aimed to introduce transparency for prospective buyers with regard to unobserved energy performance characteristics (Directive 2010/31/EU). Their effectiveness depends on whether the information captured by the label is indeed unobserved and not accurately valued in transactions.

2.2. Empirical estimates on label effects

The housing market, characterized by its heterogeneity and rigidity, is a challenging domain for econometric studies. As randomized experiments are practically impossible, researchers resort to other methods for causal inference. In the literature on energy labels, large datasets are utilized to compare transaction prices of buildings with different energy labels and similar characteristics such as construction year, type and location. Commonly used techniques are hedonic pricing models and repeated sales models. While hedonic pricing models are an OLS type of estimation based on cross-sectional data, repeated sales estimation tracks the same buildings over time and includes building-specific fixed effects.

For the non-residential sector, Eichholtz et al. (2010) employ a hedonic pricing model to document energy label effects. They investigate the effect of the Energy Star labelling program on the prices of office buildings in the US. The hedonic pricing model, including the main characteristics and locational effects, finds that offices with a 'green' label are transacted at a 6 percent premium. Since the energy savings of green office buildings are smaller than 6 percent, they conclude that some of the premium is likely to be caused by the label. In a study with a larger dataset and for a more recent period, Eichholtz et al. (2013) confirm the existence of such significant price premiums for office buildings with a 'green' label.

For the residential sector, Brounen & Kok (2011) are the first to estimate the effect of energy labels on transaction prices. They study the energy labels in the Netherlands in 2008 and 2009. A hedonic pricing model including many building specific characteristics as well as time and locational fixed effects, shows large price premiums for 'green' energy labels. For example, an A label dwelling is transacted at a 10 percent premium compared to a D label dwelling. A G label dwelling is transacted at a 5 percent discount relative to a D label dwelling. Using a similar hedonic pricing model, Fuerst et al. (2015) also find price premiums of such magnitude in the UK.

Moreover, Fuerst et al. (2015) estimate a repeated sales model using transaction data from before and after the introduction of energy labels, which allows them to estimate the effect of obtaining an energy label while controlling for all time-invariant characteristics of dwellings. However, the results for this type of model appear to be less robust as time-varying factors influencing transaction prices such as investments and depreciation rates are unobserved. For example, the A/B label dwellings are found to be transacted at a 1.5 percent discount relative to D label dwellings. The authors conclude that despite this result, the estimates are sufficiently robust to confirm the existence of premiums as in the hedonic pricing model.

A critique on the hedonic pricing model comes from a study in Norway by Olaussen et al. (2017). After replicating a basic hedonic pricing model and confirming large premiums, they estimate the same hedonic model for the period before energy labels were introduced while including a dummy variable for the later obtained label. As the coefficient of the dummy variable is significant and similar to the found energy label premium, they argue the premium can be explained by unobserved time-invariant characteristics of dwellings that the hedonic pricing model does not control for. Olaussen et al. (2017) further estimate a repeated sales model with 2200 dwellings transacted before and after obtaining an energy label. As the model finds non-significant and counterintuitive results, they argue it debunks the result of the hedonic pricing model. However, since the repeated sales model does not include any (time-varying) control variables, coefficients in the repeated sales model could be biased by any factor correlated with energy labels and prices such as investments, depreciation rates and changing consumer preferences.

2.3. Survey studies on energy labels

Although research based on survey data is generally not a robust method for policy evaluation, it yields insights to understand the effects of energy labels. Amecke (2012) evaluates the effects of energy labels and Germany based on questionnaires. Although energy labels are reported to be well understood, they are only moderately trusted and of little to no relevance for purchasing decisions. For the Netherlands, Murphy (2014) documents little reported effects of energy labels. 10 percent of respondents state that the energy label had any influence on their purchasing decision.

This highlights a paradox which is particularly present in the Dutch studies. While Brounen & Kok (2011) report large and significant price premiums associated with energy labels, Murphy (2014) shows that 90 percent of buyers state to not be influenced by energy labels. Two potential explanations of the paradox are that home buyers are more influenced by energy labels than they report in survey studies or the empirical estimates report something different than premiums caused by energy labels.

3. Energy label policies

3.1. Energy label directive EU

The first regulation to impose energy label requirements in the EU is the directive to promote energy efficiency in the built environment (Directive 2002/91/EC). Article 7 of the directive requires all EU member states to ensure an energy performance certificate (EPC) is made available when a building is constructed, sold or rented out. This obligation to member states remains in the article 12 of the revised directive (2010/31/EU).

The objective to create 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 over countries.

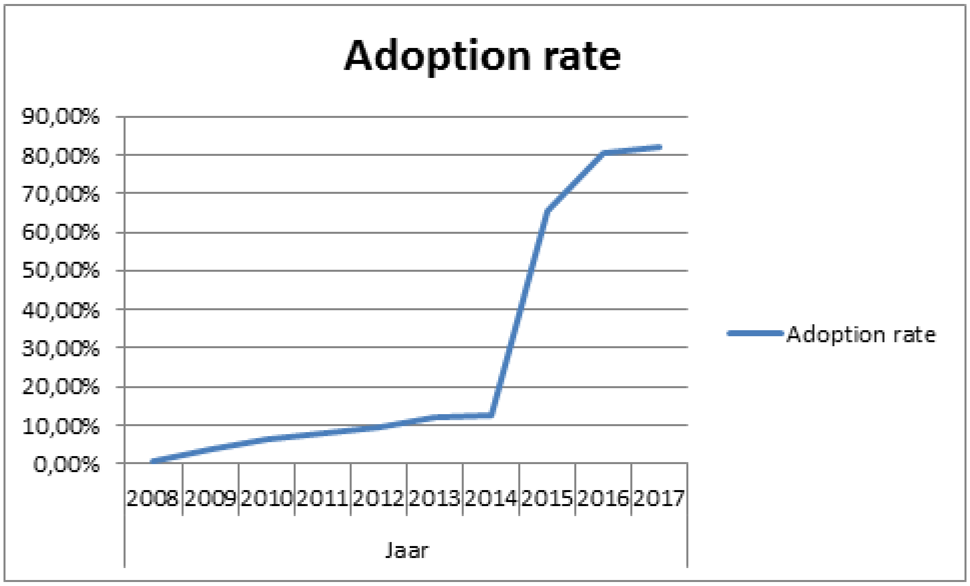
3.2. Implementation in the Netherlands

The Netherlands first implemented the European directive in 2008 ('old system') and later changed the labeling system in 2015 ('new system'). The old system formally required all build, sold or rented dwellings to apply for an energy label, ranging from A++ to G. However, failing to apply did not result in a penalty. This de facto voluntary labeling system 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 3.1).

3.2.1. Old system

In the old system, the person to sell, build or rent out a dwelling would apply for a label. Then, a certified expert physically inspects the dwelling to determine 150 building specific characteristics related to energy efficiency. The expert would enter these 150 variables in the so-called EPA-W software system, which, in turn, would calculate an

Figure 3.1: Adoption rate of energy labels in the Netherlands



energy index. This software is relatively non-transparent for the expert due to the complexity of the algorithm. Even more so, the owner of the building will not be able to know the relative importance of building characteristics in determining index.

The input menu of the EPA-W software in Figure 3.2 shows the level of detail of the input. 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, characteristics of doors, such as material, insulation and size are put in the system. Each of these factors are weighted to calculate 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 in accordance with Table 3.1, will be disclosed. Although this system is thorough, it is relatively costly with energy labels costing 180 to 400 euro per label.

Figure 3.2: Example input menu EPA-W software

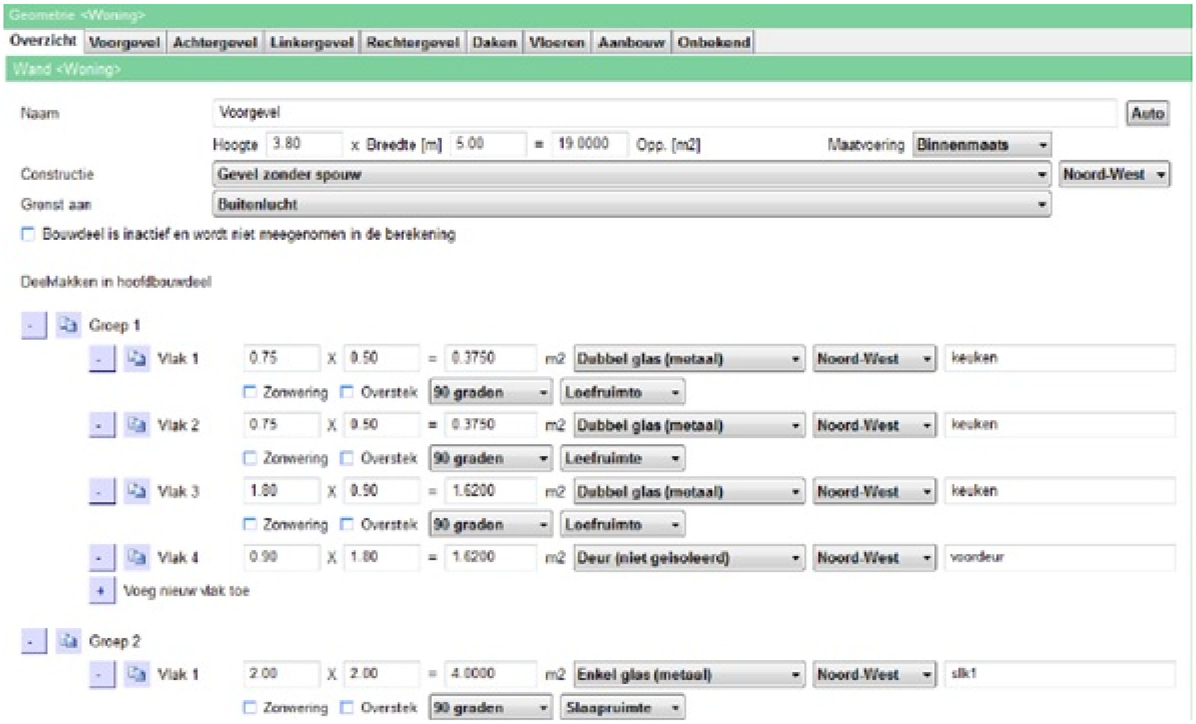


Table 3.1: Energy labels and index values

Energy label	Energy index value (EI)
A++	EI<0.5
A+	0.5<EI<0.7
A	0.7<EI<1.05
B	1.05<EI<1.3
C	1.3<EI<1.6
D	1.6<EI<2.0
E	2.0<EI<2.4
F	2.4<EI<2.9
G	EI>2.9

3.2.2. New system

In 2015, the new system of energy labels was implemented. As the old labels were relatively expensive, the main aim of the policy revision was to bring down the costs. Moreover, since the adoption rate was low in the old system, the European Commission urged the Netherlands to introduce penalties for non-adoption.

In the new system, one has to apply for an energy label online when a dwelling is build, sold or rented out. The applicant has to fill in a form with the main energy efficiency characteristics of the dwelling. Instead of the 150 variables in the old system, the new labels are based on a maximum of 10. In the online form, the applicant has to include proof of the disclosed information. Then, the uploaded proof is checked by a certified expert from a distance. Based on the characteristics specified, an energy label, ranging from A++ to G, is calculated directly. Hence, this system does not include an energy index.

Although the costs went down to 5 euro per label and the adoption rate went up, the new system appears to be more vulnerable to fraud. The judgment of an expert based on the uploaded proof of an applicant is clearly not as vigorous as a physical inspection, harming the reliability of the labels in the new system.

4. Empirical strategy

The methodology of this paper is twofold. First, hedonic pricing models are employed to analyze the relationship between energy labels and transaction prices in the old labelling system (2008-2014) and the new labelling system (2015-2018).

Second, a Sharp Regression Discontinuity Design is employed to find the causal effect of a stepwise change in energy labels on transaction prices. This quasi-experimental design exploits the energy indices to compare similar dwellings with different energy labels. As only the old energy label system includes an energy index, the RDD can only be estimated for these labels.

4.1. Hedonic pricing model

4.1.1. Theory

Hedonic pricing models measure the willingness to pay for specific features of a tradable item of a constrained, utility-maximizing consumer (Rosen, 1974). In this paper, the tradable item is a dwelling and the features of interest are the building-specific characteristics. Thus, the hedonic model will aim to estimate the willingness to pay of a buyer for each characteristic of the transacted dwelling.

4.1.2. Specification

The general specification of the hedonic model is as follows:

$$ln(P_{int}) = \alpha + \beta Label_i + \gamma X_i + \delta_n + \theta_t + \epsilon_{int} \tag{1}$$

Where $ln(P_{int})$ is the natural logarithm of the transaction price per square meter of dwelling i in neighborhood n in period t. The natural logarithm is estimated to allow a convenient interpretation of the coefficients. $Label_i$ is the energy label for dwelling i. X_i is a vector of characteristics specific to dwelling i, which includes all available variables that affect transaction prices per square meter. It includes the building type and construction year, which are the most commonly used determinants of transaction prices in the literature. Moreover, the size is included as larger building may have a lower price per square meter than smaller buildings and energy index is included in some specifications to control for energy efficiency characteristics. δ_n and θ_t denote neighborhood and time fixed effects, calculated on the 4-digit postcode level and per month respectively. Finally, ϵ_{int} is a stochastic error term, assumed to be normally distributed with a mean of zero and variance of σ^2.

Since the old energy label system and the new energy label system are fundamentally different, they are analyzed in separate estimations. Thus, Equation 1 will be estimated for the old system in a subsample of transactions from 2008 to 2014, where $Label_i$ is the energy label obtained in the old system. For the new system, Equation 1 will be estimated for a subsample of transaction from 2015 to 2017, where $Label_i$ is the energy label obtained in the new system.

4.1.3. Limitations and robustness checks

Hedonic pricing models have several limitations. Most importantly, it can suffer from omitted variable bias and selection bias. If a determinant of the dependent variable is not included in the model and correlated with an independent variable, the coefficient of the independent variable will be biased. In the specification of interest, such factors would be those that affect transactions prices and are correlated with energy labels. So, for instance, potential sources of omitted variable bias may be unobserved building quality, aesthetics and renovations.

To investigate potential sources of omitted variable bias, dwellings are assigned a variable equal to their energy label before they obtained the label. Then, a hedonic pricing model as in Equation 1 is estimated to find the correlation between the assigned variable and transaction prices. If coefficients are significant, this means dwellings that obtained a different energy label at a later time, were transacted at significantly different prices before the introduction of energy labels.

Selection bias arises if the obtained sample is not representative of the population. In the old system, the adoption rate is low and is likely to be non-random due to the de facto voluntary nature of the system. Dwellings are self-selected into the 'treatment' of an energy label. If the unobserved factor determining self-selection is correlated with transaction prices and energy labels, estimated coefficients are biased analogues to omitted variable bias.

In the new system, the researched sample is more likely to be representative as the adoption rate is around 80 percent. Though, selection bias may also arise if the sample of transacted dwellings is non-random compared to existing dwellings. Some studies suggest that the frequency of transaction is negatively related to building quality (Bourassa et al., 2006; Chernobai & Chernobai, 2013). If building quality, in turn, is a determinant of energy labels and is correlated with transaction prices, estimates are biased.

4.2. Regression Discontinuity Design (RDD)

4.2.1. Theory

RDD is a quasi-experimental research design that exploits a rule-based cut-off point to assign an intervention to a treatment group. If the observation close to the cut-off are 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 cut-off, to the sample on the left side.

In order to find the causal effect of energy labels, the assignment of labels based on the energy index cut-off points is used to estimate RDD models for each energy label step. The transacted dwelling on the left and right side of the cut-off points are assumed to be similar in their characteristics other than the energy label.

4.2.2. Specification

For each label step, a subset of all dwellings with the two relevant energy labels is constructed. Then, a RDD model is estimated and reported for the 6 subsets separately.

The main specification of the RDD model is as follows:

$$ln(P_i) = \alpha + \beta_i D_i^{label} + \gamma_i(EI_i - c) + \delta_i(EI_i - c)D_i^{label} + \epsilon_i \tag{2}$$

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 higher than the cut-off 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 cut-off point c, implying a higher tier energy label. β_i is the accompanying coefficient of interest, which measures the effect of moving from a certain energy label to a label that is one step lower. This effect thus indicates the information value of having a better energy label. 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.

The selection of the bandwidth implies a trade off between bias (increasing in the bandwidth) and variance (decreasing in the bandwidth). In order to select a bandwidth for each RDD estimation, the optimal bandwidth 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 'lead to noisy estimates, sensitivity to the degree of the polynomial and and poor coverage of confidence intervals' (Gelman & Imbens, 2017). Finally, an RDD model is constructed including an additional vector of covariates using a covariate-adjusted estimator. Inclusion of additional covariates could lead to point estimate and inference improvements (Calonico et al., 2018).

4.2.3. Robustness checks

Due to the extensiveness of the dataset, many robustness checks can be performed. First, the potential of manipulation of treatment assignment is examined by performing a density manipulation test following Cattaneo et al. (2018). Essentially, this entails a density manipulation test developed by McCrary (2008) with similar optimal bandwidth calculations as in the RDD models. Second, to test the main assumption of balanced covariates around the energy index cut-off points, RDD models are estimated to measure the effect of the cut-off points on the main characteristics of dwellings. Third, to investigate the robustness of the results, energy label effects are estimated over different time periods and in different provinces. Finally, to investigate the external validity of the results, RDD models based on non-transactional data are estimated.

5. Data

The dataset in this study is compiled and provided by the Statistics Netherlands (CBS). It consists of micro-data on all transactions of dwellings in the Netherlands from year 2000 till 2017. The data includes building specific characteristics such as building type, construction year and size. Also, the month of transaction and the postcode location is known. This dataset has been merged with a dataset on energy labels, which includes the label, month of obtainment and the energy index.

Table A1 in the appendix presents the descriptive statistics of the dataset including non-labeled dwellings. Labeled dwellings in the old system have a lower transaction price per square meter relative to non-labeled dwellings. In the new system, labeled dwellings have a higher price relative to non-labeled dwellings. Moreover, there are large differences in characteristics between labeled homes and non-labeled homes. For example, 35 percent of labeled homes in the old system are apartments, while 26 percent of non-labeled homes are apartments. In the new system, this is 25 percent and 29 percent for labeled and non-labeled homes respectively. Similar differences are found in construction years. In the old system, 9 percent of labeled dwellings are constructed between the year 1900 and 1929 and 13 percent of non-labeled homes are constructed at that time. In the new system, 11 and 16 percent of labeled and non-labeled homes are constructed in 1900 to 1929.

The sample of the hedonic pricing models excludes non-labeled dwellings to eliminate selection effects. Moreover, in both labelling systems, homes with a monumental status are not obliged to apply for an energy label. To further prevent biased estimates due to self-selection into treatment, dwellings with monumental status should therefore be excluded from the sample. Since a monumental status is not observed, these observations are largely excluded by excluding dwellings from before the year 1900.

Table 5.1 shows the descriptive statistics of dwellings in the old labeling system. A label and B label dwellings have a relatively higher transaction price per m2. Dwellings ranging from C to G labels have rather similar transaction prices per m2. As C label dwellings must have better energy efficiency compared to G label dwellings, the similar transaction prices may be explained by other factors. As the table depicts, dwellings in different label groups have large variation in their main characteristics. For example, A label dwellings consist for 61 percent of apartments while this is 33 percent 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 2000 and higher. G label dwellings frequently have a construction year between 1930 and 1969 compared to A label dwellings. Moreover, energy efficient dwellings are transacted relative often in later years. 39 percent of A label dwellings are transacted in 2014, while 23 percent of G label dwellings are transacted in 2014.

In the new system, transaction prices per m2 for each label group are less intuitive (see Table 5.2). The most expensive dwellings, on average and corrected for size, are those with an F label at €2279.06 per m2. In contrast, C label dwellings are transacted at €2023.33 per m2 on average. Also in the new system, large differences in characteristics between label groups can be observed. A large fraction of C label dwellings are terraced (0.43) and less frequently detached (0.08). In contrast, F label dwellings are less often terraced (0.30) and have a substantial fraction of detached dwellings (0.19). Moreover, the dwellings in the label groups differ severely in constructions year. In the years of transaction however, large variation is not present.

Table 5.1: Characteristics per label group in the old system

Energy label	A	B	C	D	E	F	G
	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Transaction price per m2	2717.68	2138.56	1821.25	1715.05	1777.70	1784.98	1817.10
Dwelling type (fraction)							
Apartment	0.61	0.48	0.34	0.29	0.36	0.34	0.33
Semi-detached	0.09	0.14	0.20	0.20	0.18	0.20	0.20
Duplex	0.05	0.05	0.06	0.06	0.09	0.13	0.17
Terraced	0.20	0.28	0.38	0.43	0.34	0.29	0.22
Detached	0.05	0.05	0.02	0.02	0.03	0.05	0.08
Construction year (fraction)							
1900-1929	0.36	0.13	0.05	0.08	0.11	0.14	0.20
1930-1944	0.03	0.02	0.02	0.04	0.08	0.08	0.12
1945-1959	0.02	0.05	0.08	0.13	0.22	0.28	0.37
1960-1969	0.02	0.07	0.09	0.21	0.27	0.27	0.22
1970-1979	0.03	0.10	0.18	0.31	0.29	0.21	0.08
1980-1989	0.02	0.22	0.43	0.21	0.03	0.01	0.01
1990-2000	0.09	0.30	0.14	0.02	0.00	0.00	0.00
>2000	0.43	0.12	0.01	0.00	0.00	0.00	0.01
Year of transaction (fraction)							
2008	0.01	0.02	0.02	0.03	0.03	0.03	0.03
2009	0.02	0.05	0.06	0.07	0.07	0.09	0.10
2010	0.06	0.09	0.11	0.13	0.13	0.14	0.16
2011	0.12	0.12	0.14	0.14	0.15	0.15	0.15
2012	0.14	0.16	0.17	0.16	0.16	0.17	0.16
2013	0.27	0.22	0.20	0.19	0.19	0.18	0.18
2014	0.39	0.35	0.30	0.28	0.27	0.24	0.23
Observations	1443	6456	17941	16640	10672	6241	3030

Table 5.2: Characteristics per label group in the new system

Energy label	A	B	C	D	E	F	G
	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Transaction price per m2	2265.18	2188.21	2023.33	2118.74	2194.84	2279.06	2140.43
Dwelling type (fraction)							
Apartment	0.23	0.26	0.22	0.34	0.36	0.25	0.19
Semi-detached	0.13	0.13	0.16	0.15	0.12	0.12	0.15
Duplex	0.09	0.10	0.08	0.10	0.11	0.14	0.21
Terraced	0.42	0.37	0.45	0.29	0.33	0.30	0.15
Detached	0.13	0.13	0.08	0.11	0.08	0.19	0.30
Construction year (fraction)							
1900-1929	0.01	0.02	0.04	0.14	0.17	0.33	0.44
1930-1944	0.00	0.01	0.02	0.09	0.13	0.24	0.31
1945-1959	0.00	0.01	0.04	0.14	0.25	0.17	0.13
1960-1969	0.01	0.03	0.12	0.26	0.30	0.18	0.09
1970-1979	0.01	0.08	0.29	0.27	0.14	0.07	0.02
1980-1989	0.02	0.14	0.36	0.09	0.01	0.00	0.00
1990-2000	0.13	0.51	0.13	0.01	0.00	0.00	0.00
>2000	0.81	0.21	0.01	0.00	0.00	0.00	0.00
Year of transaction (fraction)							
2015	0.22	0.23	0.24	0.25	0.24	0.24	0.24
2016	0.36	0.36	0.36	0.35	0.35	0.35	0.35
2017	0.43	0.41	0.40	0.39	0.40	0.40	0.41
N	65321	69112	127389	68503	48737	36339	30849

6. Results

The results section is structured as follows. First, the hedonic pricing model for the old system is estimated. Second, the same hedonic method is applied to the new system data. Third, the results of the Regression Discontinuity Design are shown. Finally, various robustness checks and extensions of the RDD model are reported.

6.1. Hedonic pricing model

6.1.1. Old system: 2008-2014

The results of the hedonic pricing model for the old system are presented in Table 6.1 (See appendix Table A2 for an extensive table). Model (1) shows significant and large premiums for most energy labels. Dwellings with energy label A are transacted at a 14.8 percent premium relative to D label dwellings. Premiums for B and C label dwellings are 5.3 percent and 1.4 percent, respectively. G label dwellings and F label dwellings are transacted at 3.3 percent and 1 percent discount relative to D label dwellings. E label dwellings are not transacted at a significantly different price.

Model (2) excludes energy labels and estimates the effect of the energy index, as a proxy for energy efficiency, on transaction prices per m2. A higher energy index has a significant negative correlation with transaction prices. Thus, energy efficiency is associated with higher transaction prices. The coefficient predicts that if the energy index of a dwellings increases with one point on its 0 to 6.50 scale, transaction price goes down by 3.8 percent.

Model (3) estimates the effect of energy labels while including the energy index as a control variable. Relative to the results of model (1), the size of the premiums become smaller. Moreover, the energy index coefficient becomes smaller compared to model (2). This suggests that some of the premium of energy labels in model (1) is explained by the correlation of energy labels with real energy efficiency.

Model (4) investigates the correlation of energy labels with unobserved characteristics that are time-invariant over the period 2008 to 2014 with energy labels and the period

Table 6.1: Hedonic pricing model for the old system

	(1) Post-label 2008-2014	(2) Post-label 2008-2014	(3) Post-label 2008-2014	(4) Pre-label 2000-2007
Energy labels				
A	0.148***		0.125***	-0.036***
	(0.008)		(0.012)	(0.010)
B	0.053***		0.038***	0.007
	(0.003)		(0.005)	(0.011)
C	0.014***		0.006	0.016***
	(0.002)		(0.004)	(0.004)
E	-0.001		0.009*	0.012**
	(0.003)		(0.004)	(0.008)
F	-0.010**		0.012	0.013**
	(0.004)		(0.007)	(0.010)
G	-0.033***		0.006	-0.006
	(0.006)		(0.012)	(0.008)
Energy index		-0.038***	-0.027***	
		(0.002)	(0.009)	
Dwelling controls	YES	YES	YES	YES
Time controls	YES	YES	YES	YES
Location controls	YES	YES	YES	YES
N	62422	62422	62422	59723
adj. R2	0.677	0.675	0.677	0.488

Notes: Robust standard errors are in the parentheses. Dwellings without an energy label are excluded. 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 construction year is 1900-1930. Time controls are dummies for every month. Location controls are dummies on the municipality level. * p <0.05, ** p <0.01, *** p <0.001

2000 to 2007 without energy labels. The energy label variable represent the energy label that each dwelling obtained in a later year. Some coefficients are significant. A label dwellings are transacted at a 3.6 percent discount relative to D label dwellings. C, E and F label dwellings are transacted at a 1.6 percent, 1.2 percent and 1.3 percent price premium respectively. Although the coefficients are not large, they suggest that the dwellings in different label groups have unobserved characteristics affecting transaction prices. In turn, this implies that estimates in model (1) are biased due to non-inclusion of these characteristics in the model.

6.1.2. New system 2015-2017

The results of the hedonic pricing model for the new system are depicted in Table 6.2 (See appendix Table A3 for extensive results). In model (1) each energy label has a significant coefficient. Dwellings with an A label, B label and C label are transacted at a 6.1 percent, 7.5 percent and 4 percent premium relative to a D label dwelling. Dwellings with an E, F and G label are transacted at a 2.1 percent, 5.4 percent and a 16.6 percent discount respectively. The model controls for main characteristics of dwellings and includes postcode and month fixed effects. However, since the new labeling system does not include an energy index, the model cannot control for energy efficiency.

Model (2) investigates the correlation of energy labels with time-invariant characteristics. Again, the dwellings have been assigned a variable which represents the energy label obtained in a later year. B and C label dwellings are transacted at a 2.9 percent and 1.3 percent price premium relative to D label dwellings. F and G label dwellings are transacted at a 0.9 percent and 5.1 percent discount. However, A and E label dwellings are not transacted at a significantly different price. These results suggest that the dwellings in some of the label groups are significantly different in characteristics associated with price. These characteristics are unobserved and not controlled for in the model. Moreover, they must be time-invariant because the price premium exists in the period 2000 to 2014 before they obtained an energy label in the new system.

Table 6.2: Hedonic pricing model for the new system

	(1)	(2)
	Post-label 2015-2018	Pre-label 2000-2014
Energy labels		
A	0.061***	0.001
	(0.002)	(0.003)
B	0.075***	0.029***
	(0.002)	(0.002)
C	0.040***	0.013***
	(0.001)	(0.001)
E	-0.021***	0.001
	(0.002)	(0.002)
F	-0.054***	-0.009***
	(0.002)	(0.002)
G	-0.166***	-0.051***
	(0.002)	(0.003)
Building controls	YES	YES
Time controls	YES	YES
Location controls	YES	YES
N	393704	275097
adj. R2	0.565	0.574

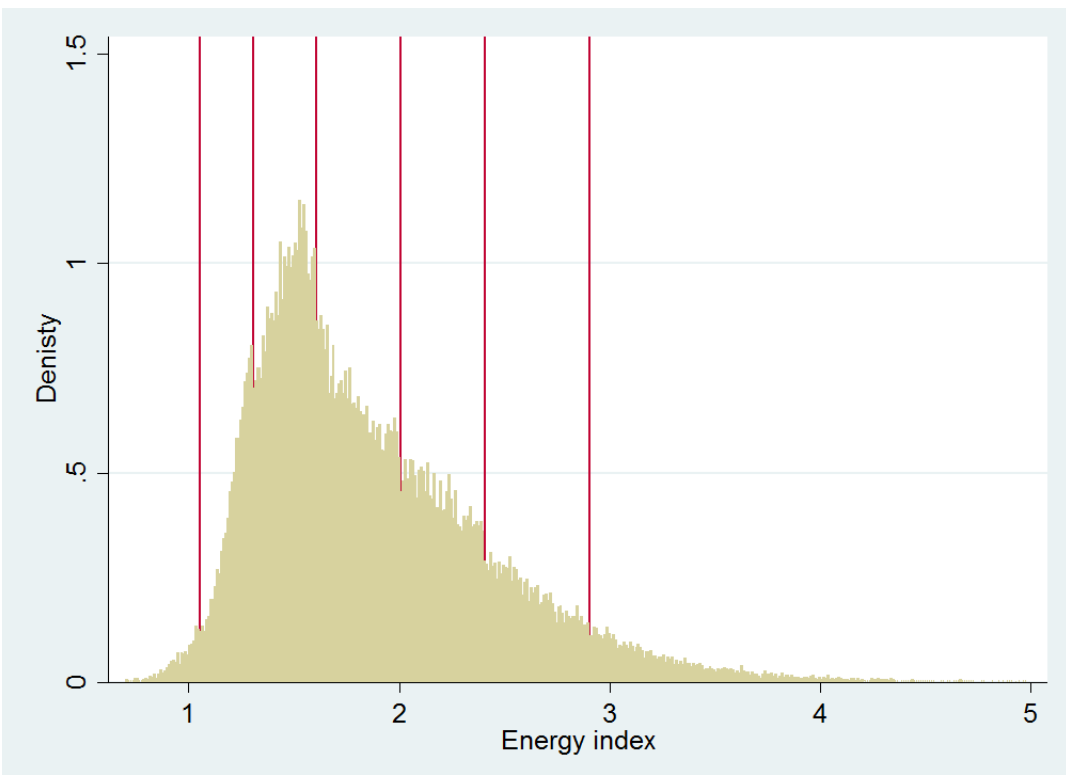
Notes: Robust standard errors are in the parentheses. Dwellings without an energy label are excluded. Dwellings with a construction year before 1900 are omitted. The reference group for energy labels is the D label. The reference group for building type is apartment. The reference group for construction year is 1900-1930. Time controls are dummies for every month. Location controls are dummies on the municipality level. * p <0.05, ** p <0.01, *** p <0.001

6.2. *Regression Discontinuity Design*

6.2.1. *Main specification*

In order to find the causal effect of energy labels on transaction prices, an appropriate counterfactual is needed. For the old labeling system, the energy index, determined by an independent expert, can be exploited to construct such a counterfactual. In figure 6.1 the frequency distribution of the energy index is depicted with the energy label cut-off points shown in vertical lines. On the left side of each cut-off point, the energy label indicating the higher level of energy efficiency is obtained. On the right side of the cut-off, the lower energy label is obtained.

Figure 6.1: Energy index density distribution



The energy index appears to follow moderately smooth log normal distribution. At some thresholds however, spikes in the distribution are visible. Table 6.3 reports the results of a density manipulation test in accordance with (Cattaneo et al., 2018). For each label step, except D to E, no significant sorting around the thresholds is detected.

The density disparity at the D to E cut-off point could be explained by several things. 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 an 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 cut-off are computed more frequently. Given the labelling process described in section, in which an independent expert determines the energy index on the basis of his or her own observations and using non-transparent software, and the fact that the frequency distribution is smooth at the other cut-off points, the latter explanation appears to be most likely.

Table 6.3: Density manipulation test

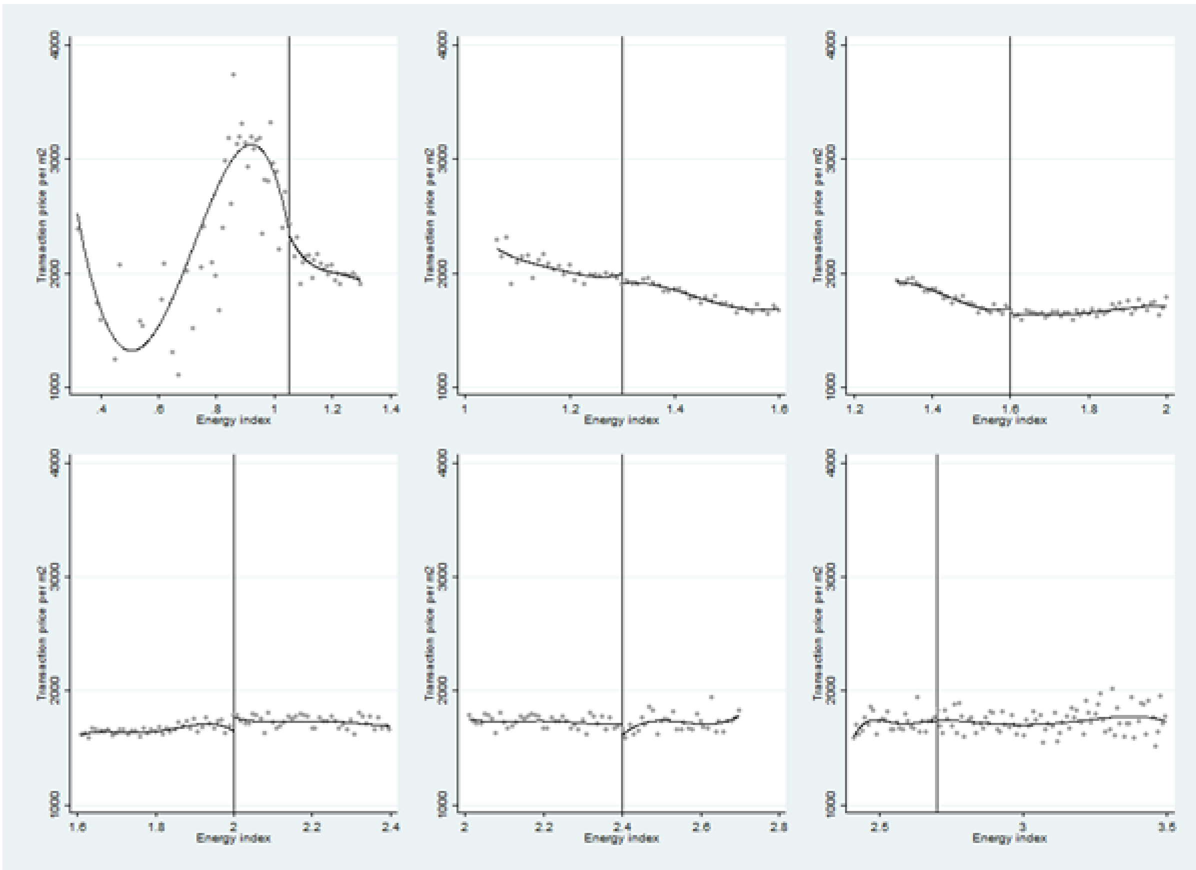
	t-value	p-value	Significant
A-B	0.07	0.95	NO
B-C	-1.06	0.29	NO
C-D	-0.16	0.87	NO
D-E	-4.65	0.00	YES
E-F	-0.92	0.36	NO
F-G	0.83	0.41	NO

Notes: The density manipulation test is performed according to Cattaneo, Jansson and Ma (2018): Simple Local Regression Distribution Estimators, Journal of American Statistical Association.

Figure 6.2 shows the unconditional variation of transaction prices per m2 around each energy label cut-off point. An energy label premium would be observed as a jump in transaction prices at the threshold. At a first glance, such jumps do not appear to be present in the figure.

Turning to the results of the RDD models, where Equation 2 is estimated for dwellings at each energy label step separately. The coefficients in Table 6.4 show the effect of

Figure 6.2: Transaction prices at each energy label step



Notes: The figures represent the plotted transaction prices at each energy label step, ordered from the A-B to the F-G label step. The vertical axis depicts the 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 4th order polynomial fit.

having an energy label that is one label step lower than the counterfactual. For example, a B label dwelling is compared to an A label dwelling that is similar in all other respects. As is shown, energy labels do not have significant price premiums at the A to B, B to C, C to D, E to F and F to G label steps. Also, E label dwellings are sold at a 5.3 percent premium compared to D label dwellings. As the density manipulation test at this threshold yielded significant results however, this estimate is unreliable.

Table 6.4: RDD results main specification

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	-0.058	0.027	-0.018	0.053**	-0.037	-0.026
	(0.046)	(0.028)	(0.013)	(0.017)	(0.022)	(0.039)
N	25387	24097	34331	27048	14840	8563

Notes: Robust standard errors are reported in the parentheses. The specification assumes linear local polynomials. No control variables are included. The optimal bandwidth, calculated in accordance with (Calonico et al., 2014), contains around 35% of the observations in each estimate.
* p <0.05, ** p <0.01, *** p <0.001

6.2.2. Robustness checks

In order to test the robustness of the RDD results, several extension and alternative specifications of the RDD model are considered.

Table 6.5 shows results of an RDD specification including construction year and dwelling type dummies as control variables. As expected, the standard errors go down. Moreover, the coefficients do not change much and still, no premiums are found at 5 out of the 6 label steps. In case of the D and E label dwellings, a counterintuitive premium remains. Again, as the density manipulation test found significant differences at this label step, it can be concluded that this result is not driven by the energy label. Moreover, the same results are found in an RDD model with a quadratic polynomial specification (see appendix table A4). Hence, the results of table 6.4 are robust for different model specifications.

To test the balance of covariates around the cut-off points, I estimate a series of RDD models with respect to dwelling characteristics. For each construction year and dwelling type a dummy variable is constructed which equals one if the dwellings is the specified type or has the construction year and is zero otherwise. Then, dwellings on the right side of the cut-off point are compared to those on the left. In general, dwellings are similar in these main characteristics around the thresholds but some coefficients are significant (see appendix Table A5 and Table A6). The majority of estimates are in-

Table 6.5: RDD estimates including covariates

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	-0.018 (0.047)	0.016 (0.025)	-0.018 (0.014)	0.056*** (0.017)	-0.036 (0.021)	-0.015 (0.032)
N	25387	24097	34331	27048	14840	8563

Notes: Robust standard errors are reported in the parentheses. The specification assumes linear local polynomials. Included control variable are dwelling types and construction years. * p <0.05, ** p <0.01, *** p <0.001

significant, suggesting that the characteristics of dwellings around the cut-off point are not systematically different. Notably, at the D to E cut-off point multiple significant coefficients are reported. The group of E label dwellings has a 10.4 percentage point smaller fraction of observations with a construction year between 1960 and 1969, relative to the group of D label dwellings. At the same time, E label dwellings have a 6.7 and 5.6 percentage points larger fraction of construction years between 1945 – 1959 and 1970 – 1979 respectively. This may explain the counterintuitive premium in the RDD estimation of label D to E: the sample is relatively non-random around the threshold.

Moreover, the robustness of the non-premium result is tested for multiple locations and periods. In the provinces of Zuid-Holland and Gelderland, 11 out of 12 energy labels are estimated to not yield a significant premium (See Table A9 and A10 of the appendix). Only at the D to E label step, a counterintuitive premium is found which is significant at a 10 percent level. Since the D to E label step failed on the density manipulation test, this result cannot be interpreted as a causal effect. Furthermore, no evidence for label premiums are found in specifications in different time periods (see Table A11 and A12 of the appendix). From 2008 to 2010, with an economy recovering from the 2008 economic crises, demand in the housing market was low. From 2012 to 2014, demand for dwellings was relatively high. Hence, energy label premiums are not present in the case of high demand or low demand market conditions.

To investigate the external validity of the results, RDD models based on WOZ-value data are estimated. The WOZ-value of a dwelling is assessed by the municipality in which the dwelling is located and is supposed to reflect the market value. Hence, these estimations measure the effect of energy labels on the market value assessment of dwellings by municipalities. However, because the WOZ-value is a far less accurate reflection of market prices, the exact coefficients are less reliable. In Table 6.6, results similar to Table 6.4 are found. This finding is robust for a specification with covariates and quadratic polynomials (see appendix Table A7 and A8). Thus, it can be concluded that energy labels also do not affect the market value assessed by municipalities.

Table 6.6: RDD estimates WOZ value

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	0.007 (0.077)	0.018 (0.030)	-0.025* (0.012)	0.041** (0.015)	-0.039 (0.022)	-0.036 (0.032)
N	23702	27864	33905	26796	14721	8495

Notes: Robust standard errors are reported in the parentheses. The specification assumes linear local polynomials. No control variable are included. * p <0.05, ** p <0.01, *** p <0.001

To summarize, the main results of Table 6.4 are robust to different model specifications. Moreover, the main assumption of the RDD model is satisfied, since dwellings characteristics are balanced around the cut-off points. Also, the non-premium result holds for multiple locations and time periods. Finally, the results are externally valid in respect to the market value of non-transacted dwellings.

7. Conclusion

Promoting energy efficiency in the residential sector has become an important target for policy makers. However, the effectiveness of policies is determined by the relative presence of the potential market failures. In the directive to promote energy efficiency in the built environment, European policy makers address inefficiencies that may arise from imperfect information by introducing mandatory energy labels.

This paper investigates the information value of energy labels by estimating their effect on transaction prices of dwellings and addresses the methodological shortcomings in the recent literature on this topic. Drawing upon a dataset which includes all transaction of dwellings in the Netherlands since 2000, hedonic pricing models are constructed for the old and new labelling system. While energy labels are associated with large price premiums, this result is to be sensitive to model specifications. Moreover, some of the price premiums are present for dwellings in label groups before they obtained the energy label, suggesting labels are correlated with unobserved time-invariant factors.

The RDD models find no significant effect of energy labels on transaction prices in the old label system. An extensive number of robustness checks show that this result is robust to model specifications, time and locational factors and holds for non-transactional market values. This implies that the information value energy labels, as defined by this paper, are virtually zero.

These results have important policy implications. If imperfect information on energy efficiency is not present or energy labels fail to address this issue, other policy options to promote energy efficiency are preferred. As energy labels in the old system in the Netherlands are determined in a relatively vigorous manner, by an independent expert based on over 150 dwelling characteristics, energy labels are unlikely to contain information value in other labelling systems. However, further research is required whether this holds for different labeling systems and countries other than the Netherlands.

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Appendix

Table A1: Descriptive statistics of the main sample

	Old system: 2008-2014				New system: 2015-2017			
	Labeled		Non-labeled		Labeled		Non-labeled	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Transaction price per m2	1806.44	799.90	2043.48	1084.61	2095.88	1085.27	2024.31	1270.27
Dwelling type (fraction)								
Apartment	0.34	0.47	0.26	0.44	0.25	0.43	0.29	0.45
Semi-detached	0.19	0.39	0.14	0.35	0.15	0.35	0.13	0.33
Duplex	0.08	0.27	0.12	0.33	0.11	0.31	0.11	0.32
Terraced	0.36	0.48	0.35	0.48	0.37	0.48	0.29	0.45
Detached	0.03	0.18	0.12	0.33	0.13	0.33	0.18	0.38
Construction year (fraction)								
1900-1929	0.08	0.28	0.12	0.34	0.10	0.32	0.14	0.36
1930-1944	0.05	0.21	0.10	0.31	0.08	0.29	0.10	0.32
1945-1959	0.15	0.36	0.09	0.31	0.09	0.30	0.11	0.32
1960-1969	0.18	0.39	0.14	0.37	0.14	0.37	0.15	0.38
1970-1979	0.22	0.42	0.16	0.39	0.16	0.39	0.16	0.38
1980-1989	0.21	0.41	0.14	0.36	0.14	0.38	0.11	0.33
1990-1999	0.08	0.28	0.13	0.36	0.14	0.37	0.11	0.33
>2000	0.03	0.17	0.11	0.32	0.16	0.37	0.12	0.32
Year of transaction (fraction)								
2008	0.03	0.16	0.21	0.41				
2009	0.07	0.26	0.14	0.35				
2010	0.12	0.32	0.14	0.34				
2011	0.14	0.35	0.13	0.33				
2012	0.16	0.37	0.12	0.33				
2013	0.20	0.40	0.11	0.31				
2014	0.28	0.45	0.15	0.36				
2015					0.24	0.43	0.42	0.49
2016					0.35	0.48	0.28	0.45
2017					0.40	0.49	0.30	0.46
Energy label (fraction)								
A	0.02	0.11			0.15	0.18		
B	0.10	0.29			0.16	0.35		
C	0.29	0.46			0.29	0.47		
D	0.27	0.45			0.15	0.39		
E	0.17	0.38			0.11	0.33		
F	0.10	0.30			0.08	0.29		
G	0.05	0.22			0.07	0.27		
Energy index	1.84	0.54						
N	62422		690003		393704		112620	

Table A2: Hedonic pricing model for the old system (extensive table)

	(1) Post-label 2008-2014	(2) Post-label 2008-2014	(3) Post-label 2008-2014	(4) Pre-label 2000-2007
Energy labels				
A	0.148***		0.125***	-0.036***
	(0.008)		(0.012)	(0.010)
B	0.053***		0.038***	0.007
	(0.003)		(0.005)	(0.011)
C	0.014***		0.006	0.016***
	(0.002)		(0.004)	(0.004)
E	-0.001		0.009*	0.012**
	(0.003)		(0.004)	(0.008)
F	-0.010**		0.012	0.013**
	(0.004)		(0.007)	(0.010)
G	-0.033***		0.006	-0.006
	(0.006)		(0.012)	(0.008)
Energy index		-0.038***	-0.027***	
		(0.002)	(0.009)	
Construction year				
1931-1945	-0.010	-0.012	-0.009	0.018
	(0.007)	(0.007)	(0.007)	(0.015)
1946-1960	-0.152***	-0.156***	-0.152***	-0.012
	(0.005)	(0.005)	(0.005)	(0.014)
1961-1970	-0.184***	-0.189***	-0.184***	-0.065***
	(0.005)	(0.005)	(0.005)	(0.013)
1971-1980	-0.161***	-0.168***	-0.162***	-0.010
	(0.005)	(0.005)	(0.005)	(0.013)
1981-1990	-0.116***	-0.126***	-0.118***	0.023
	(0.005)	(0.005)	(0.005)	(0.014)
1991-1999	0.010	0.010	0.008	0.192***
	(0.005)	(0.005)	(0.005)	(0.015)
>2000	-0.027**	0.006	0.028***	0.128***
	(0.008)	(0.008)	(0.008)	(0.015)
Building type				
Semi-detached	0.081***	0.079***	0.081***	0.098***
	(0.003)	(0.003)	(0.003)	(0.011)
Duplex	0.182***	0.181***	0.182***	0.212***
	(0.005)	(0.005)	(0.005)	(0.014)
Terraced	0.043***	0.040***	0.042***	0.055***
	(0.003)	(0.003)	(0.003)	(0.009)
Detached	0.442***	0.445***	0.443***	0.380***
	(0.008)	(0.008)	(0.008)	(0.019)
Size (log)	-0.298***	-0.299***	-0.298***	-0.260***
	(0.005)	(0.005)	(0.005)	(0.014)
Time controls	YES	YES	YES	YES
Location controls	YES	YES	YES	YES
_cons	8.481***	8.538***	8.528***	7.888***
	(0.047)	(0.047)	(0.048)	(0.081)
N	62422	62422	62422	59723
adj. R2	0.677	0.675	0.677	0.488

Table A3: Hedonic pricing model for the new system (extensive table)

	(1) Post-label 2015-2018	(2) Pre-label 2000-2014
Energy labels		
A	0.061***	0.001
	(0.002)	(0.003)
B	0.075***	0.029***
	(0.002)	(0.002)
C	0.040***	0.013***
	(0.001)	(0.001)
E	-0.021***	0.001
	(0.002)	(0.002)
F	-0.054***	-0.009***
	(0.002)	(0.002)
G	-0.166***	-0.051***
	(0.002)	(0.003)
Construction Year		
1931-1945	0.007**	0.010***
	(0.002)	(0.002)
1946-1960	-0.083***	-0.036***
	(0.002)	(0.002)
1961-1970	-0.158***	-0.061***
	(0.002)	(0.002)
1971-1980	-0.156***	-0.038***
	(0.002)	(0.002)
1981-1990	-0.113***	0.019***
	(0.002)	(0.002)
1991-1999	-0.032***	0.137***
	(0.002)	(0.002)
>2000	-0.011***	0.094***
	(0.003)	(0.004)
Building type		
Semi-Detached	0.159***	0.098***
	(0.002)	(0.002)
Duplex	0.250***	0.196***
	(0.002)	(0.002)
Terraced	0.095***	0.049***
	(0.001)	(0.001)
Detached	0.396***	0.376***
	(0.002)	(0.003)
Size (log)	-0.240***	-0.289***
	(0.002)	(0.002)
Time controls	YES	YES
Location controls	YES	YES
_cons	8.058***	7.963***
	(0.021)	(0.023)
N	393704	275097
adj. R2	0.565	0.574

Table A4: RDD estimates quadratic local polynomials

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	-0.014	-0.022	-0.022	0.059**	-0.039	-0.077
	(0.086)	(0.030)	(0.021)	(0.023)	(0.040)	(0.069)
N	25387	24097	34331	27048	14840	8563

Table A5: 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
A-B	-0.061	-0.042	0.040	0.013	-0.036	0.087**	0.011
	(0.068)	(0.042)	(0.031)	(0.029)	(0.053)	(0.027)	(0.062)
B-C	-0.032	0.000	0.031	0.002	-0.042*	0.008	0.045
	(0.021)	(0.007)	(0.018)	(0.021)	(0.020)	(0.030)	(0.034)
C-D	-0.021*	0.002	0.007	0.034*	-0.001	0.039	-0.032
	(0.010)	(0.007)	(0.012)	(0.018)	(0.025)	(0.035)	(0.019)
D-E	-0.016	-0.005	0.067**	-0.104***	0.056*	0.008	-0.008
	(0.014)	(0.012)	(0.023)	(0.025)	(0.022)	(0.014)	(0.004)
E-F	-0.003	-0.000	0.053	-0.082	-0.026	0.005	0.004
	(0.018)	(0.016)	(0.035)	(0.043)	(0.035)	(0.007)	(0.003)
F-G	0.020	-0.066	-0.011	0.024	0.001	0.010	-0.012
	(0.037)	(0.041)	(0.046)	(0.041)	(0.042)	(0.007)	(0.009)

Table A6: RDD estimates of dwelling type dummies

	(1) Apartment	(2) Semi-detached	(3) Duplex	(4) Terraced	(5) Detached
A-B	-0.029	0.051	-0.010	0.017**	-0.013
	(0.069)	(0.038)	(0.032)	(0.007)	(0.054)
B-C	-0.118**	0.018	0.025*	-0.010	0.160***
	(0.037)	(0.030)	(0.012)	(0.007)	(0.045)
C-D	0.029	-0.089***	-0.014	-0.001	0.061*
	(0.019)	(0.025)	(0.013)	(0.004)	(0.027)
D-E	-0.020	0.037*	0.009	-0.003	-0.005
	(0.020)	(0.019)	(0.015)	(0.007)	(0.025)
E-F	-0.073	-0.008	0.045	-0.007	0.070
	(0.038)	(0.025)	(0.025)	(0.009)	(0.040)
F-G	0.057	0.019	-0.040	-0.012	-0.032
	(0.046)	(0.043)	(0.035)	(0.017)	(0.050)

Table A7: RDD estimates WOZ value (including covariates)

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	-0.068	0.045	-0.019	0.047**	-0.037	-0.022
	(0.039)	(0.025)	(0.011)	(0.015)	(0.020)	(0.032)
N	23702	27864	33905	26796	14721	8495

Table A8: RDD estimates WOZ value (quadratic polynomial)

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	-0.010	0.028	-0.028	0.052*	-0.017	-0.035
	(0.079)	(0.037)	(0.016)	(0.021)	(0.035)	(0.041)
N	l23702	27864	33905	26796	14721	8495

Table A9: RDD estimates Zuid-Holland

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	0.263	-0.043	-0.036	0.096*	-0.053	-0.039
	(0.135)	(0.060)	(0.031)	(0.042)	(0.061)	(0.055)
N	3703	3645	5926	5055	2944	1820

Table A10: RDD estimates Gelderland

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	-0.132	0.027	-0.025	-0.022	-0.027	0.005
	(0.394)	(0.070)	(0.037)	(0.048)	(0.077)	(0.115)
N	2206	2176	3595	2906	1476	789

Table A11: RDD estimates period 2008-2010

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	-0.400	0.036	0.034	0.092*	0.011	-0.036
	(0.308)	(0.050)	(0.027)	(0.038)	(0.052)	(0.080)
N	1015	4466	7217	6087	3487	2324

Table A12: RDD estimates period 2012-2014

	(1) A-B	(2) B-C	(3) C-D	(4) D-E	(5) E-F	(6) F-G
$D^{label} = 1$	0.049	-0.047	-0.046*	0.039	-0.031	0.066
	(0.077)	(0.032)	(0.018)	(0.024)	(0.035)	(0.068)
N	16551	15883	22313	17129	9223	5073