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

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**Abstract**

This paper examines the information value of energy labels using administrative data on all transactions in the Dutch residential housing market from 2000 to 2017. We compare two different labeling systems, one complex and voluntary system and the other a simple and mandatory. Employing a combination of hedonic pricing models and a sharp Regression Discontinuity Design, we find robust evidence that voluntary labels had limited information value from 2008 to 2014. The information value of the mandatory labels adopted since 2015 is less clear. We observe that better-labeled houses already attracted significant price premiums before they obtained energy labels, which implies that at least part of the price premium cannot be attributed to mandatory labels.

*Keywords:* energy labels, house prices, information value, JEL: D12, Q51, R21

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## 1. Introduction

In the EU, residential buildings account for approximately 24% of energy consumption and 22% of $CO_2$ emissions (European Commission, 2018). While improving the energy efficiency of residential housing can generate significant energy savings and emission reductions (Vringer et al., 2016), homeowners appear to underinvest in energy-efficient technologies, even when there are (private) net financial benefits (Allcott and Greenstone, 2012; Ramos et al., 2015; Gerarden et al., 2017). This so-called "energy efficiency gap" arises from many barriers and market failures (Ramos et al., 2015), one of which is a gap in information that seems to be pervasive and relevant. Participants in the residential market lack consistent access to information on the energy performance of dwellings: as a result, potential buyers and sellers may be unable to (fully) value energy performance in housing transactions, which hinders investments in residential energy efficiency (Ramos et al., 2015).

To alleviate the information asymmetry between buyers and sellers, policy-makers have introduced energy labels to facilitate energy-informed housing transactions. The European Parliament and Council (2002) implemented a mandatory Energy Performance Certificate (EPC) scheme for the European Union; other initiatives, such as the Energy Star program and Leadership in Energy and Environmental Design (LEED) in the United States, promote voluntary disclosure of energy-related information. Do energy labels provide the market with new, otherwise not readily available information? Is a voluntary or a mandatory labeling scheme more effective? These are the key questions of this paper.

Despite significant effort and resources devoted to designing and implementing energy labeling programs, their effectiveness is not fully understood. While a handful of studies has documented that 'green' energy labels in the residential real estate sector generate significant and large transaction price premiums[1], these studies could not conclude whether the introduction of labels itself led to the observed effect. There are three main reasons for this. First, energy labels are correlated with location and unobserved dwelling characteristics, such as quality or aesthetics (Olaussen et al., 2017). To separate the price premiums commanded by energy labels from the price premiums generated by other, confounding factors remains challenging. Second, a number of studies provide evidence that observable energy efficiency is capitalized into transaction prices in the residential market, regardless of labeling. Therefore, separating the information value of energy labels

[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).

from the capitalization of energy efficiency has proven difficult. Last, the design of the labeling programs plays an unclear role, with a dearth of evidence on the relative merits of voluntary and mandatory labels.

This paper examines the information value of energy labels. We base our analysis on administrative data concerning all residential property transactions in the Netherlands from 2000 to 2017. The Dutch labeling system is an interesting case to study because the country introduced two different labeling programs over the period in question: a complex, but *de facto* voluntary label program from 2008 to 2014 and a simplified, but mandatory label program from 2015 onwards.

We address important empirical challenges to identification and contribute to the existing literature in several ways. First, hedonic pricing models that estimate the price premiums of "green" labels are subject to multiple confounding factors, including location and 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 how much price premium is attributed to location instead of energy labels. Existing studies often cannot precisely account for location effects. Furthermore, following the spirit of Olaussen et al. (2017), we 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 price premiums cannot be attributed to labels. The results shed more light on whether energy labels or other unobserved factors drive the price premiums. This method is particularly useful in evaluating the information value of labels in the mandatory system.

Second, there is another empirical problem that we address. The collinearity between (observable) energy efficiency and energy labels makes it difficult to identify any additional effect of energy labels on transaction prices. The lack of randomized experiments means we cannot conclude whether labels operate by eliminating information asymmetries between buyers and sellers or if they 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, similar to the methodology of (Aydin et al., 2020). The use of a sharp RDD allows us disentangling the information value of energy labels from the effects of energy efficiency on transaction prices in the voluntary system.

Third, energy labeling programs can have substantially different policy designs. A key design distinction is between mandatory and voluntary programs. Under mandatory programs, all regulated dwellings must comply with the programs' requirements. By contrast, 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 unclear. The uniqueness of our data allows us to provide additional evidence on the information value of both voluntary and mandatory labels.

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

## 2. Literature Review

Whether hard-to-observe energy efficiency is capitalized into sales prices has long been a subject of research. A body of work emerging in the early 1980s 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 dwelling's thermal integrity. While they used small and highly localized samples, these studies found evidence of capitalization of energy efficiency (or proxies thereof) in 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 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 transaction prices. A handful of studies on commercial buildings find that LEED and Energy Star certified buildings carry substantial rental and sale price premiums in the United States (Eichholtz et al., 2010, 2013). Eichholtz et al. (2010) documented that offices with a "green" energy label are transact at a

6% premium. Since the present value of energy savings by these green buildings is smaller than 6%, they conclude that the labels likely cause part of the premium in the commercial sector. Brounen and Kok (2011) were 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 the Netherlands from 2008 to 2009, they identified large premiums associated with better energy labels. For example, relative to a D-labeled dwelling, an A-labeled dwelling transacts with a 10% premium, while a G-labeled dwelling transacts at a 5% discount. Subsequent studies confirm significant price premiums using data from various countries, such as Australia (Fuerst and Warren-Myers, 2018), Germany (Cajias et al., 2019), Ireland (Hyland et al., 2013; Stanley et al., 2016), the Netherlands (Brounen and Kok, 2011; Chegut et al., 2016), Norway (Khazal and Sønstebø, 2020), Singapore (Fesselmeyer, 2018), Sweden (Wahlström, 2016), the UK (Fuerst et al., 2015), and the United States (Kahn and Kok, 2014; Walls et al., 2017; Myers et al., 2019).

Although these studies, based on hedonic pricing models, provide compelling evidence that energy labels are capitalized, they are unclear as to whether labels provide *additional* information to the market. If markets fully capitalize on buildings' energy efficiency, as indicated by the early studies reviewed above, energy labels may simply measure this same performance. One would expect in this case to find a strong correlation between energy labels and property values, even though the labels provide no new information on the buildings' energy efficiency. Consequently, the premiums identified 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, research has begun to focus on separating the price premium of energy labels from the price premium of readily observable energy efficiency. This paper goes straight to the heart of this line of research, 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) found 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 showed that houses that sold with premiums after energy labels were introduced had that same advantage before labels were introduced. This suggests that the price premiums could be driven by unobserved time-invariant characteristics of the dwellings that were left uncontrolled for in the hedonic pricing models. Using survey data from Germany, Amecke (2012) questioned the usefulness of energy labels in affecting homebuyers' actual purchasing decisions. His findings revealed that although energy labels are reportedly well understood, they are only moderately trusted and have 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) first report large and significant price premiums associated with better energy labels, they find in a subsequent study (Aydin et al., 2020) that energy labels 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, there are two recent notable studies: Myers et al. (2019) employed a difference-in-differences design inside and outside the city of Austin, Texas, finding that after the city's introduction of the labeling system, markups were paid for energy efficiency compared to the area outside the city. The introduction of labels also spurred investments in energy efficiency. Frondel et al. (2017) found that homeowners asked for a lower price after labels became mandatory in Germany and that this decision is especially correlated with dwellings' energy efficiency.

We differ from the existing studies mainly in two 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 voluntary and mandatory system.

## 3. Institutional Background

The European Union demands from its members that an Energy Performance Certificate (EPC) be made available to the buyer when a building is constructed, sold or rented out.[2] How this EPC is designed specifically is the member states' responsibility. The directive requires that energy labels be determined by an independent expert and be 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 ("voluntary system") and later, in 2015, reformed the labeling system ("mandatory system"). The two systems have vastly different characteristics in terms of the quality, accuracy, and utility of the information the label provides, on the one hand, and the cost and supervision, on the other. The voluntary system formally required all homeowners

[2]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). This obligation to member states also remains in article 12 of the revised Directive 2010/31/EU (European Parliament and Council, 2010).

| | Voluntary | Mandatory |
|---|---|---|
| Simple | — | **2015–2020** |
| Complex | **2008–2014** | 2021– |

Table 1: Labeling Design

to apply for an energy label, but not applying resulted in no penalty. This complex, *de facto* voluntary labeling system—and its high costs—had a low adoption rate. When penalties were introduced alongside the simplified but mandatory system in 2015, the adoption rate, calculated as the share of dwellings transacted with a label, grew rapidly (see Figure 1). Recently, there has been another reform to make the labeling system more accurate, as depicted in Table 1.

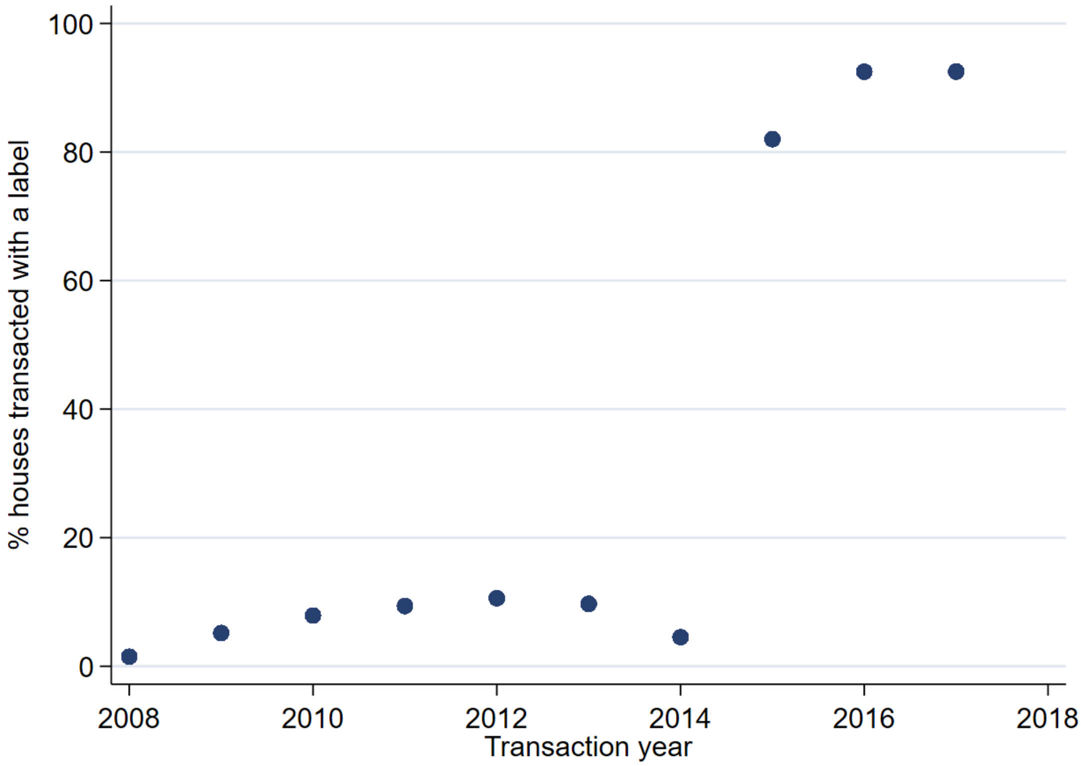



Figure 1: Adoption rate of energy labels in the Netherlands

### *3.1. Voluntary System*

In the voluntary system, any person selling, building, or renting out a dwelling was required to apply for a label, which cost €180–400. A certified expert then physically inspected the dwelling to determine 150 building-specific characteristics related to energy efficiency. The expert entered these 150 variables into the so-called EPA-W software system, which, in turn, calculated the Energy Index (EI). The algorithm calculating the EI was not transparent for the expert. The owner of the building was even less able to determine the relative effects of building characteristics on the index. This continuous Energy Index is then converted to a discrete Energy Performance Certificate, which is disclosed to both the seller and the buyer. Additionally, the applicant for the EPC receives a more extensive report written by the expert, which is not disclosed to (potential) buyers or renters.[3]

### *3.2. Mandatory System*

The low adoption rate of the *de facto* voluntary labels almost led to sanctions by the European Commission, which urged the Netherlands to introduce penalties for non-adoption. Thus, they were reformed with a new scheme introduced in 2015. One reason for the low adoption rate of was that the public perceived the voluntary labels to be too expensive. Therefore, the main aim of the policy revision was to reduce costs to increase acceptance. In the new scheme, every dwelling was assigned a provisional label based on building year and type. Once a dwelling is sold or rented out, the owner has to convert the provisional label to a definitive one, that requires completing an online form with a maximum of 10 energy efficiency characteristics of the dwelling. This stands in contrast to the 150 variables the expert reported in the voluntary system. The applicant then needs to upload proof (e.g., photos), and an expert remotely checks the legitimacy of the application based on the uploaded information. The cost of the expert judgment starts at €2 and averages around €5. Based on the specified characteristics, an energy label is calculated directly.[4]

### *3.3. Reform*

Notably, another new labeling system has been developed to expand the scope of assessment. This new system has replaced the previous labeling system in the Netherlands from 2021. The system includes characteristics of both previous systems. Labeling remains mandatory in the system, with a relatively thorough and expensive application process similar to the pre-2015 system. The application includes a physical inspection of an independent expert.

[3] More information about the labeling process can be found in Appendix A.

[4] Though the costs went down and the adoption rate went up, the mandatory system appears to be more vulnerable to fraud. 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. Media report on label fraud: https://radar.avrotros.nl/uitzendingen/gemist/item/verkeerd-energielabel-voor-je-huis-wie-is-verantwoordelijk/.

## 4. Data

We base this study on all transactions from 2000 to 2017 of privately-owned residential dwellings in the Netherlands, with data provided by Statistics Netherlands (CBS). We obtain details on each transaction (month and price) and property (dwelling type, construction year, size, and location). We then merge this data set with the database on energy labels from 2008 to 2017 kept by the Netherlands Enterprise Agency (RVO). This database contains the actual label, the label system (voluntary or mandatory), the application date, and the energy index (if available). Dwellings constructed before 1900 are excluded from the sample because monuments are exempt from the labeling scheme. Additionally, in the voluntary labeling scheme, we exclude houses younger than a decade because their sellers were not required to present a label.

Table 2 presents descriptive statistics of the main sample. Histograms that visualize this table can be found in Appendix C. First, one should note that the average selling price in the mandatory system is higher than that in the voluntary system. This is mainly because the financial crisis occurred when the voluntary system was in place. Second, the average price per square meter for unlabeled houses in the voluntary system is higher than for their labeled counterparts, an observation which reverses in the mandatory system, where labeled houses enjoy a price premium. This suggests that label applications in the voluntary system were not random; we further discuss the resulting selection effect in section 6.1 and Appendix E.

The average Energy Performance Certificate of the labeled houses differs between the two systems. Even though the modal score is a C in both schemes, the mean label is better in the mandatory system. Three possible mechanisms are at work here: (i) as only houses older than ten years needed labels in the voluntary system, newer, more energy-efficient houses were under-represented in that scheme; (ii) the reform may have made it easier to obtain a good label; and (iii) homeowners may have invested in energy efficiency measures.

The overall compositions of dwelling types are very similar under both labeling schemes. The mandatory system considered alone shows no large differences in dwelling type between labeled and unlabeled houses (which makes sense as the labels are mandatory). In the voluntary system, however, apartments are over-represented among labeled houses (31% labeled vs. 24% unlabeled), while detached and duplex houses are under-represented. This suggests that owners of certain dwelling types are more likely to apply for an energy label—or that dwellings of a different type are more difficult or less likely for some other reason to sell or rent.

The dwelling age distributions are also broadly similar between the two labeling systems. The mandatory system has many more houses built in the 21$^{st}$ century, which makes sense as (i) the system has no exemptions for new houses and (ii) time has progressed, so more houses have been built this century. Inspecting the

| | Voluntary system, 2008-2014 | | | | | | Mandatory system, 2015-2017 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Unlabeled** | | **Labeled** | | **Total** | | **Unlabeled** | | **Labeled** | | **Total** | |
| | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| Price per m$^2$ | 2045.95 | 848.09 | 1825.30 | 737.73 | 2031.72 | 843.15 | 2018.10 | 1144.71 | 2109.00 | 929.20 | 2099.66 | 953.93 |
| 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 | 133,232 | 23.2 | 12,385 | 31.3 | 145,617 | 23.7 | 9,611 | 24.0 | 73,072 | 20.8 | 82,683 | 21.1 |
| Detached | 65,927 | 11.5 | 1,580 | 4.0 | 67,507 | 11.0 | 7,617 | 19.0 | 46,235 | 13.2 | 53,852 | 13.8 |
| Duplex | 71,241 | 12.4 | 3,309 | 8.4 | 74,550 | 12.2 | 5,135 | 12.8 | 41,710 | 11.9 | 46,845 | 12.0 |
| Semi-Detached | 87,861 | 15.3 | 7,544 | 19.1 | 95,405 | 15.6 | 5,445 | 13.6 | 52,675 | 15.0 | 58,120 | 14.9 |
| Terraced | 215,528 | 37.6 | 14,745 | 37.3 | 230,273 | 37.5 | 12,268 | 30.6 | 137,194 | 39.1 | 149,462 | 38.2 |
| **Total** | 573,789 | 100.0 | 39,563 | 100.0 | 613,352 | 100.0 | 40,076 | 100.0 | 350,886 | 100.0 | 390,962 | 100.0 |
| *Building year* | | | | | | | | | | | | |
| 1900-1929 | 63,989 | 11.2 | 2,971 | 7.5 | 66.960 | 10.9 | 5,500 | 13.8 | 31,788 | 9.1 | 37,288 | 9.6 |
| 1930-1944 | 55,570 | 9.7 | 1,928 | 4.9 | 57,498 | 9.4 | 4,250 | 10.7 | 28,364 | 8.1 | 32,614 | 8.4 |
| 1945-1959 | 55,172 | 9.6 | 5,559 | 14.1 | 60,731 | 9.9 | 4,456 | 11.2 | 27,784 | 7.9 | 32,240 | 8.3 |
| 1960-1969 | 86,189 | 15.1 | 7,287 | 18.4 | 93,476 | 15.3 | 6,590 | 16.6 | 45,800 | 13.1 | 52,390 | 13.4 |
| 1970-1979 | 105,370 | 18.4 | 9,464 | 23.9 | 114,834 | 18.8 | 6,918 | 17.4 | 57,005 | 16.3 | 63,923 | 16.4 |
| 1980-1989 | 89,740 | 15.7 | 8,380 | 21.2 | 98,120 | 16.0 | 4,519 | 11.4 | 49,936 | 14.2 | 54,455 | 13.9 |
| 1990-1999 | 87,191 | 15.2 | 3,571 | 9.0 | 90,762 | 14.8 | 4,848 | 12.2 | 54,722 | 15.6 | 59,570 | 15.3 |
| 2000- | 29,394 | 5.1 | 364 | 0.9 | 29,758 | 4.8 | 2,712 | 6.8 | 55,205 | 15.7 | 57,917 | 14.8 |
| **Total** | 572,615 | 100.0 | 39,524 | 100.0 | 612,758 | 100.0 | 39,793 | 100.0 | 350,604 | 100.0 | 390,397 | 100.0 |
| *Transaction year* | | | | | | | | | | | | |
| 2008 | 125,907 | 21.9 | 1,924 | 4.9 | 128,803 | 20.9 | - | - | - | - | - | - |
| 2009 | 84,295 | 14.7 | 4,598 | 11.6 | 89,561 | 14.5 | - | - | - | - | - | - |
| 2010 | 83,318 | 14.5 | 7,148 | 18.1 | 91,119 | 14.8 | - | - | - | - | - | - |
| 2011 | 77,677 | 13.5 | 8,044 | 20.3 | 86,293 | 14.0 | - | - | - | - | - | - |
| 2012 | 72,596 | 12.7 | 8,592 | 21.7 | 81,691 | 13.2 | - | - | - | - | - | - |
| 2013 | 51,158 | 8.9 | 5,507 | 13.9 | 56,975 | 9.2 | - | - | - | - | - | - |
| 2014 | 78,838 | 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** | 573,789 | 100.0 | 39,563 | 100.0 | 617,533 | 100.0 | 40,076 | 100.0 | 350,886 | 100.0 | 390,962 | 100.0 |

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

Table 2: Descriptive statistics

two systems separately, different patterns appear. Under the voluntary mechanism, very old houses and very new houses are less likely to have energy labels, probably because their sellers do not need a label to set themselves apart from the competition. In the mandatory system, labels are more common for newer houses, perhaps because the labels have such low cost that owners may fear that they send a bad signal if they have no label. Alternatively, newer houses might be more likely to be sold in general, and therefore their owners apply for labels more frequently.

In Appendix D, we examine the relationship between the Energy Performance Certificate and observable characteristics similarly, finding that the final label and a dwelling's characteristics are correlated. In subsection 6.1, we further examine the influence of those characteristics on the label that a dwelling receives.

## 5. Methodology

This section introduces our methodology. We first explore factors that drive the adoption of both voluntary and mandatory energy labels in subsection 5.1. Then, for both systems, we rely on a conventional hedonic pricing method, which is explained in subsection 5.2, to analyze to which extent the Dutch housing market values energy efficiency. In subsection 5.3, we describe a Regression Discontinuity Design to explicitly investigate the information values of labels. This approach builds on the continuous Energy Index (EI), which is used to calculate the discrete Energy Performance Certificate (EPC). Apparently, in the reformed mandatory labeling scheme, the EI is no longer calculated, so we cannot use our RDD approach for that period. To compensate, we use "artificial labels," checking whether there was already a premium for better-labeled houses before they actually received a label. Methodologically, this approach is identical to that portrayed in subsection 5.2.

### *5.1. Adoption*

What factors drive adoption of the energy labels? To better understand this process in voluntary and mandatory systems, respectively, we use fixed effects regressions. They help us to examine the factors that determine whether a transacted dwelling has an energy label and how these factors influence the resulting label in a sub-sample of labeled houses. These regressions proceed as follows:

$$\text{Label}_{int} = \alpha + \beta_i X_i + \delta_n + \theta_t + \epsilon_{int} \tag{1}$$

$$\text{LabelScale}_{int} = \alpha + \beta_i X_i + \delta_n + \theta_t + \epsilon_{int} \tag{2}$$

$\text{Label}_{int}$ is a binary variable with a value of one if a transacted dwelling $i$ in neighborhood[5] $n$ in period $t$ has an energy label and zero otherwise. $\text{LabelScale}_{int}$ is a categorical variable with values 1 to 7, indicating labels A to G. Hence, a negative coefficient means that the respective variable is associated with a better label. $X$ is a vector of dwelling specific characteristics, such as period of construction, dwelling type, size, or transaction price. $\delta_n$ and $\theta_t$ are location and month fixed effects, respectively. Finally, $\epsilon_{int}$ is a stochastic error term, assumed to be normally distributed with a mean of zero and variance of $\sigma^2$.

### *5.2. Valuation of Energy Efficiency*

Are energy-efficient dwellings valued in the residential housing market? Houses are sold as a bundle of many characteristics; energy efficiency is one of these. To isolate the value of a single item in such a bundle, a hedonic pricing method is commonly used, typically in the housing context, to measure how much utility-maximizing consumers are willing to pay for urban and environmental amenities (Rosen, 1974; Bishop et al., 2020). 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 price premiums. The benchmark specification is the following:

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

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) the electricity and gas use one year before the sale, or all three. As before, $X$ is a vector of house-specific characteristics, such as building year, dwelling type, and size. $\delta_n$ and $\theta_t$ are neighborhood and time fixed effects. Finally, $\epsilon_{int}$ is a stochastic error term, assumed to be normally distributed with a mean of zero and variance of $\sigma^2$. We estimate equation 3 for both labeling systems and also use it in subsection 6.3.2 to uncover the information value of mandatory labels.

[5]We measure the neighborhood on the Dutch 4-digit postcode level. These are small, homogeneous neighborhoods, where one would not expect large within-neighborhood variation in dwelling characteristics.

### 5.3. *Information Value*

Do (voluntary) energy labels have information value? To answer this question, we adopt a sharp Regression Discontinuity Design (RDD) 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 what becomes a treatment group. If observations close to the cutoff can be assumed to have similar characteristics besides this treatment assignment, the average treatment effect can be estimated by comparing the samples close to each side of the cutoff.

Since energy labels under the voluntary system are strictly determined based upon threshold values of the Energy Index (Table A.1), a continuous value we observe, our RDD model is constructed by comparing transaction prices of dwellings that are near the threshold criteria used to assign the label. We assume that these dwellings have similar characteristics besides the energy label. The main specification is as follows:

$$ln(P_i) = \alpha + \beta_i D_i^{\mathrm{Label}} + \gamma_i(\mathrm{EI}_i - \mathrm{c}) + \delta_i(\mathrm{EI}_i - \mathrm{c})D_i^{\mathrm{Label}} + \epsilon_i \tag{4}$$

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 a 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. $\beta_i$ 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 $i$. $\gamma_i$ is the coefficient of the running variable, and $\delta_i$ is the coefficient of the interaction term. $\epsilon_i$ is a stochastic error term, assumed to be normally distributed with a mean of zero and variance of $\sigma^2$.

We prefer a non-parametric estimation over parametric estimation as transacted dwellings are most similar around the cutoff points. To calculate the optimal bandwidth around the cutoff points, we follow Calonico et al. (2014). Furthermore, we estimate the model using local, linear and quadratic polynomials as estimators, since higher-order polynomials may be misleading (Gelman and Imbens, 2019). Finally, our RDD model includes an additional vector of covariates using a covariate-adjusted estimator, which could improve 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, repeating the estimation procedure for the other labels, as well.

## 6. Results

We report our results in three parts. First, we consider drivers of applying for an energy label in both systems (subsection 6.1). Then, we show the results for the period with voluntary labels (subsection 6.2), before turning to the results with mandatory labels (subsection 6.3).

### *6.1. Adoption*

Table 3 presents the results of fixed effects regressions based on equations 1 and 2. Columns (1) and (2) show how 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 under both systems.

As column (1) shows, under the voluntary system, a higher transaction price is associated with less likelihood that the house is labeled. This suggests owners of cheaper houses make greater use of energy labels. The influence of construction year appears to be inversely U-shaped: houses of medium age are more likely to be labeled by their owners than very old or very new ones. This makes sense, as the energy efficiency of medium-aged houses is most diffuse for potential buyers, while they can expect new houses to be well-insulated and old houses to be rather inefficient. Terraced and duplex houses are less likely to be labeled than apartments (with detached or semi-detached houses indistinguishable). Houses with a garden are on average more likely to be labeled. Finally, household and dwelling size are negatively associated with obtaining a label.

For the mandatory system, column (2) shows that labels are positively correlated with dwelling price: owners of a more expensive house are more likely to apply for a label before the sale. Also, the likelihood of obtaining a label seems more or less linearly related to building year, which stands at odds with the results for the voluntary system. The actual type of dwelling is insignificant. As under the voluntary system, the house's size reduces the likelihood of having a label. By contrast, however, the effect of household size is now positive under the mandatory scheme.

For the sub-sample of labeled houses, we now turn to the effects of dwelling characteristics on the actual label, in columns (3) and (4). The higher the eventual transaction price, the better the average label of a house. In other words, those houses that are later sold for a higher price, are also, all else being equal, 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, under both systems, labels are in general better for newer houses, which is no surprise. One exceptional finding is that very old houses (1900–1929) appear to be better-labeled than houses built shortly thereafter, presumably because of better

| VARIABLES | (1)<br>Label (Dummy)<br>Voluntary System | (2)<br>Label (Dummy)<br>Mandatory System | (3)<br>Label (Categorical)<br>Voluntary System | (4)<br>Label (Categorical)<br>Mandatory System |
|---|---|---|---|---|
| Log price/m$^2$ | -0.0952*** | 0.111*** | -0.455*** | -0.582*** |
| | (0.00441) | (0.00360) | (0.0483) | (0.0160) |
| *Construction year* | | | | |
| 1900-1929 | – | – | – | – |
| 1930-1945 | 0.00192 | 0.00685* | 0.336*** | 0.101*** |
| | (0.00278) | (0.00312) | (0.0815) | (0.0148) |
| 1945-1959 | 0.0428*** | 0.00103** | 0.183* | -0.784*** |
| | (0.00366) | (0.00330) | (0.0729) | (0.0174) |
| 1960-1969 | 0.0287*** | 0.0210*** | -0.0406 | -1.370*** |
| | (0.00320) | (0.00310) | (0.0740) | (0.0183) |
| 1970-1979 | 0.0358*** | 0.0331*** | -0.491*** | -2.110*** |
| | (0.00315) | (0.00300) | (0.0746) | (0.0170) |
| 1980-1989 | 0.0368*** | 0.0430*** | -1.317*** | -2.571*** |
| | (0.00388) | (0.00300) | (0.0778) | (0.0162) |
| 1990-1999 | 0.174*** | 0.0358*** | -1.884*** | -3.271*** |
| | (0.00306) | (0.00301) | (0.0771) | (0.0172) |
| 2000- | -0.0128*** | 0.0568*** | -2.274*** | -4.056*** |
| | (0.00342) | (0.00306) | (0.116) | (0.0179) |
| *Dwelling type* | | | | |
| Apartment | – | – | – | – |
| Detached | -0.00803 | -0.0415** | 0.259* | 0.759*** |
| | (0.00636) | (0.0152) | (0.104) | (0.0510) |
| Duplex | -0.0154* | -0.00527 | 0.182* | 0.581*** |
| | (0.00628) | (0.0151) | (0.0899) | (0.0501) |
| Semi-Detached | -0.0003 | 0.00703 | 0.0776 | 0.483*** |
| | (0.00619) | (0.0150) | (0.0836) | (0.0500) |
| Terraced | -0.0184** | 0.0186 | -0.0292 | 0.206*** |
| | (0.00610) | (0.0150) | (0.0829) | (0.0496) |
| Multi-family home | -0.00874 | 0.0154 | 0.000430 | -0.0157 |
| | (0.00539) | (0.0143) | (0.0746) | (0.0459) |
| Garden | 0.0220*** | -0.00428 | -0.00951 | -0.328*** |
| | (0.00334) | (0.00346) | (0.0412) | (0.0234) |
| $\sqrt{\text{Household size}}$ | -0.00247** | 0.0662*** | -0.179*** | -0.267*** |
| | (0.000972) | (0.00137) | (0.0156) | (0.00521) |
| Log size | -0.0692*** | 0.00959*** | -0.116* | -0.372*** |
| | (0.00350) | (0.00297) | (0.0488) | (0.0135) |
| Constant | 1.023*** | -0.380*** | 9.164*** | 12.11*** |
| | (0.0451) | (0.0386) | (0.500) | (0.167) |
| Observations | 572,786 | 370,716 | 37,130 | 334,468 |
| R-squared | 0.0410 | 0.0596 | 0.237 | 0.602 |
| Transaction date FE | YES | YES | YES | YES |
| Postcode groups | 3,815 | 3,775 | 2,759 | 3,755 |

*Note:* 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 voluntary 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.

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

maintenance and differences in building quality between the pre- and post-war periods. A dwelling's type has no substantial influence on the actual label under the voluntary system. Under the mandatory system, meanwhile, apartments are labeled the best on average; the more detached a building, the worse is its label. This indicates that some unobserved characteristics might be correlated with both dwelling type and the final label under the mandatory system. Whether a house is a single- or multi-family home has no effect under both systems, while having a garden is associated with a better label under the mandatory system. Finally, larger houses and larger households, in general, have better labels.

### *6.2. Voluntary System*

For the voluntary labeling system, we use both the common hedonic pricing approach described in subsection 5.2 and the RDD outlined in subsection 5.3.

#### *6.2.1. Valuation of Energy Efficiency*

Table 4 reports the results of hedonic pricing models for the sub-sample of transactions with energy labels under the voluntary labeling system (2008-2014). Column (1) shows the baseline specification, controlling for postcode fixed effects. We find that better energy labels attract significant and large price premiums. Dwellings with energy label A transact at a 6.5% premium relative to D-labeled dwellings. Premiums for B- and C-labeled dwellings are 3.5% and 1.8%, respectively. F- and G-labeled dwellings transact at 2% and 5.8% discounts, respectively, relative to D-labeled 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 we properly control for neighborhood effects 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.

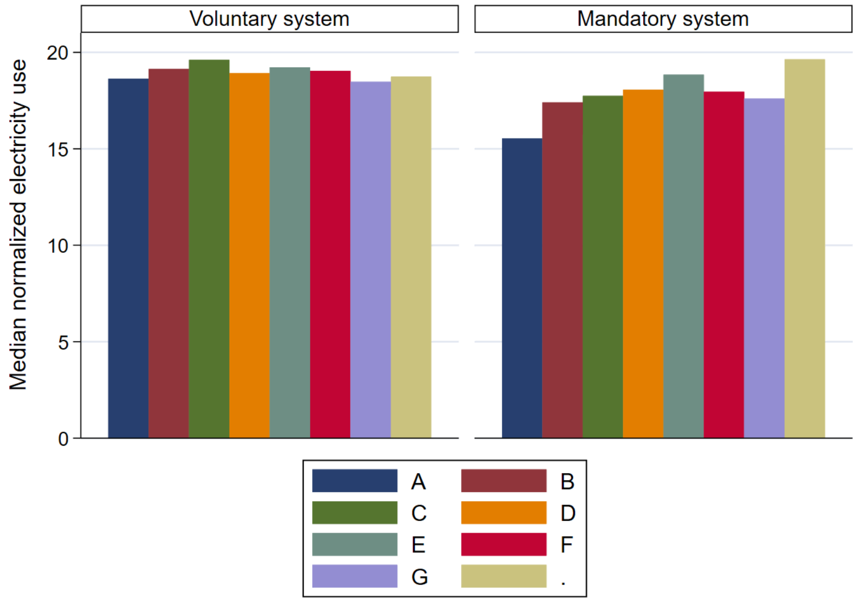
Energy labels may simply be a proxy for certain energy efficiency features of dwellings that are observable to homebuyers. In this respect, the high collinearity between the labels and energy efficiency measures poses difficulties in interpreting these price premiums. The left panel of Figure 2a barely shows a trend in median electricity use for worse labels. The left panel of Figure 2b shows a more pronounced linear relationship between gas use and label classes. Columns (2) and (3) 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 the effect of energy efficiency on transaction prices.

We find a strong, negative correlation between Energy Index and transaction prices. Hence, the market clearly values energy-efficient dwellings. A decrease in EI by one point on its 0 to 6.5 scale is associated

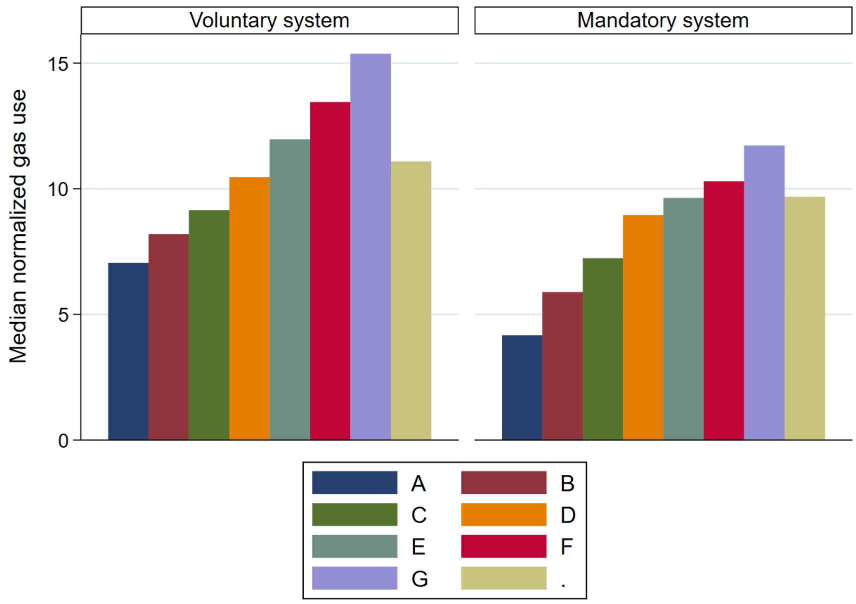
| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| MODELS | EPC | EI | Use | EPC & EI | EPC & Use | EPC, EI & Use |
| VARIABLES | $\log(p/m^2)$ | $\log(p/m^2)$ | $\log(p/m^2)$ | $\log(p/m^2)$ | $\log(p/m^2)$ | $\log(p/m^2)$ |
| *Energy Label* | | | | | | |
| A | 0.0651*** | | | 0.0368* | 0.0665*** | 0.0376* |
| | (0.0167) | | | (0.0185) | (0.0166) | (0.0185) |
| B | 0.0349*** | | | 0.0161 | 0.0360*** | 0.0168 |
| | (0.00663) | | | (0.00876) | (0.00657) | (0.00871) |
| C | 0.0175*** | | | 0.00672 | 0.0177*** | 0.00668 |
| | (0.00388) | | | (0.00517) | (0.00389) | (0.00517) |
| E | -0.00576 | | | 0.00797 | -0.00622 | 0.00782 |
| | (0.00412) | | | (0.00584) | (0.00409) | (0.00581) |
| F | -0.0199*** | | | 0.00881 | -0.0200*** | 0.00938 |
| | (0.00546) | | | (0.0101) | (0.00543) | (0.0100) |
| G | -0.0580*** | | | -0.00731 | -0.0577*** | -0.00577 |
| | (0.00823) | | | (0.0172) | (0.00819) | (0.0172) |
| Energy index | | -0.0398*** | | -0.0355** | | -0.0352** |
| | | (0.00392) | | (0.0109) | | (0.0109) |
| $\text{Log}\left(\frac{\text{Electricity use}}{\text{m}^2 * \sqrt{\text{household size}}}\right)$ | | | 0.0162*** | | 0.0145*** | 0.0144*** |
| | | | (0.00212) | | (0.00209) | (0.00208) |
| $\text{Log}\left(\frac{\text{Gas use}}{\text{m}^2 * \sqrt{\text{household size}}}\right)$ | | | -0.000327 | | 0.00308 | 0.00344 |
| | | | (0.00206) | | (0.00204) | (0.00204) |
| Constant | 9.179*** | 9.256*** | 9.081*** | 9.242*** | 9.084*** | 9.148*** |
| | (0.0608) | (0.0613) | (0.0612) | (0.0633) | (0.0606) | (0.0632) |
| Observations | 30230 | 30230 | 30230 | 30230 | 30230 | 30230 |
| R-squared | 0.318 | 0.318 | 0.315 | 0.318 | 0.320 | 0.321 |
| Dwelling controls | YES | YES | YES | YES | YES | YES |
| Transaction date FE | YES | YES | YES | YES | YES | YES |
| Postcode groups | 2661 | 2661 | 2661 | 2661 | 2661 | 2661 |

*Note:* 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. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table 4: Hedonic pricing model: Voluntary labeling system




(a) Median normalized electricity use in both systems: $\frac{\text{Electricity use}}{\text{m}^2 * \sqrt{\text{household size}}}$.




(b) Median normalized gas use in both systems: $\frac{\text{Gas use}}{\text{m}^2 * \sqrt{\text{household size}}}$.

Figure 2: Median normalized energy use for both the voluntary and the mandatory system.

with a mean increase in transaction prices by 4% in column (2). The effects of energy use move in different directions in column (3). A 1% increase in standardized electricity use (in kWh per $m^2$ and household size) leads on average to a 0.016% higher selling price.[6] A similar increase in normalized gas use (in $m^3$ per $m^2$ and household size) does not significantly affect the transaction price. This is in line 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[7].

Columns (4) and (5) further add energy labels into columns (2) and (3). Once we include EI to control for energy efficiency, the premiums attracted by energy labels become considerably smaller and mostly insignificant. The only exception is A-labeled houses, which sell, all else being equal, for a 3.7% price premium compared to D-labeled houses (significant at the 5%-level). Above that, the magnitudes are much smaller than those reported in column (1), suggesting that part of the premium energy labels attract can be explained by the correlation of energy labels with energy efficiency. When including energy use in column (5), no effect can be observed; the figures are basically identical to those in column (1).

Lastly, column (6) presents the most comprehensive specification, including EPCs, EI and energy use to estimate the effect on transaction prices. Here, too, the inclusion of energy use does not have meaningful effects and the results are very similar to column (4).

To summarize, we find significant and large price premiums at the time of sale for dwellings with better voluntary labels using hedonic pricing models, which aligns 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.[8] As a result, they can yield biased estimates that overestimate the premiums associated with energy labels.[9] We demonstrate that energy efficiency, as captured by the EI, appears to be capitalized in the market some extent, independent of voluntary labels. This is consistent with recent findings in the Dutch context (Aydin et al., 2020; Havlínová and Van Dijk, 2019). More importantly, the collinearity between energy efficiency and energy labels does not permit clear identification whether

[6]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.

[7]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.

[8]When we include only regional fixed effects or no location fixed effects at all, the models report much larger price premiums. This suggests 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.

[9]In appendix Appendix E, 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.

the latter have any additional effect on prices. Whether voluntary labels have information value remains unsettled.

*6.2.2. Information Value*

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 EI, a tiny change in EI can lead to assignment to a better or worse label category. If better energy labels are capitalized in the market, homeowners would have an incentive to manipulate EI to reach a better label category on just the better side of the cutoff point. The resulting so-called "bunching" effects around cutoffs have been found in studies in other contexts (e.g. Collins and Curtis, 2018). Although manipulation is unlikely in this case, as the EI is determined by an independent expert using a non-transparent software system, we nevertheless test whether there is evidence of potential manipulation around the EI cutoffs.

Figure 3 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.

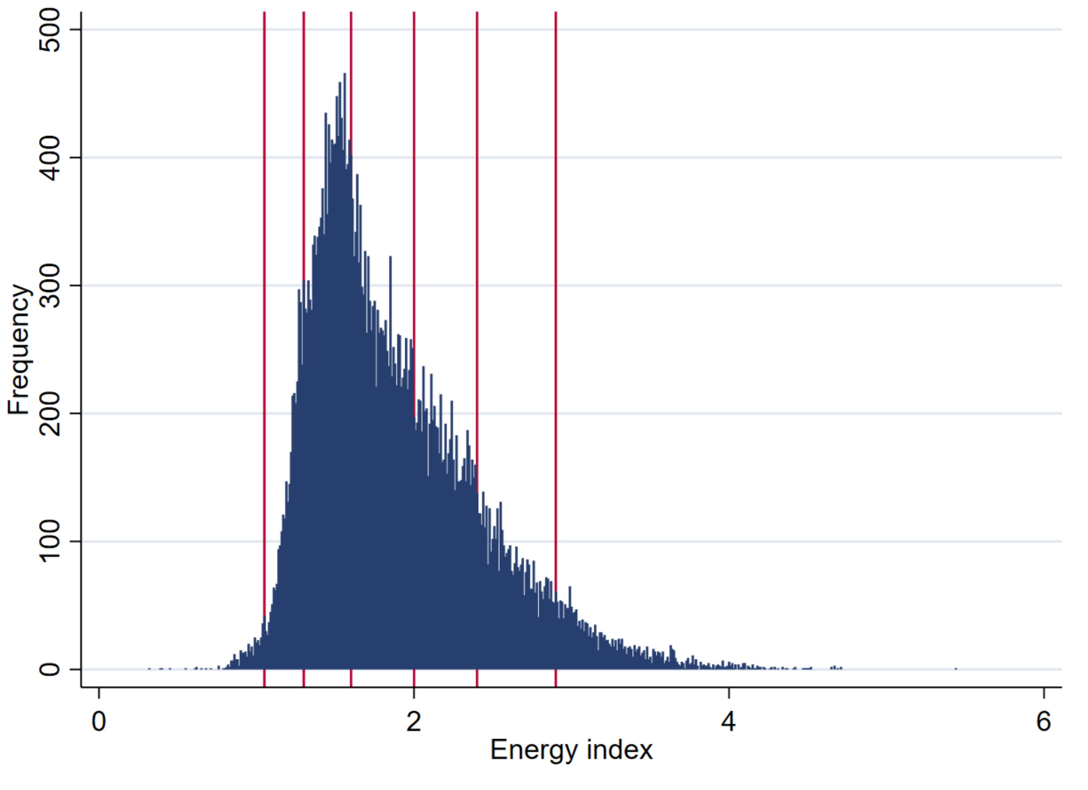



Figure 3: Distribution of the Energy Index in the Voluntary System. The higher the Energy Index, the worse the label.

To formally test whether the density of dwellings near the cutoffs is discontinuous, we employ a density manipulation test following Cattaneo et al. (2020), that uses the same bandwidth calculations as do 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. This approach demonstrably improves both size and power, under appropriate assumptions, relative to other approaches currently available in the literature Cattaneo et al. (2020). Table 5 shows the test results. We find that no discontinuities exist around any cutoffs except for D to E.

The density disparity at the D to E cutoff point could be explained in several ways. First, homeowners could have invested in energy efficiency just enough to obtain a D-labeled in preference to an E-label. Second, the independent experts might 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 the D-side of the D to E 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 own observations and uses non-transparent software to calculate the index, and because the frequency distribution is smooth at the other cutoff points, the last explanation appears to be most likely.

| | T | p-value |
|---|---|---|
| A-B | 0.2647 | 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 |

*Note:* The density manipulation test is performed according to Cattaneo et al. (2020).

Table 5: Density manipulation test

Before turning to the estimates, we show in Figure 4 the unconditional variation of the log of transaction prices per m$^2$ around each label cutoff point based on a linear fit. If energy labels have information value—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, these do not appear at most of the cutoffs.

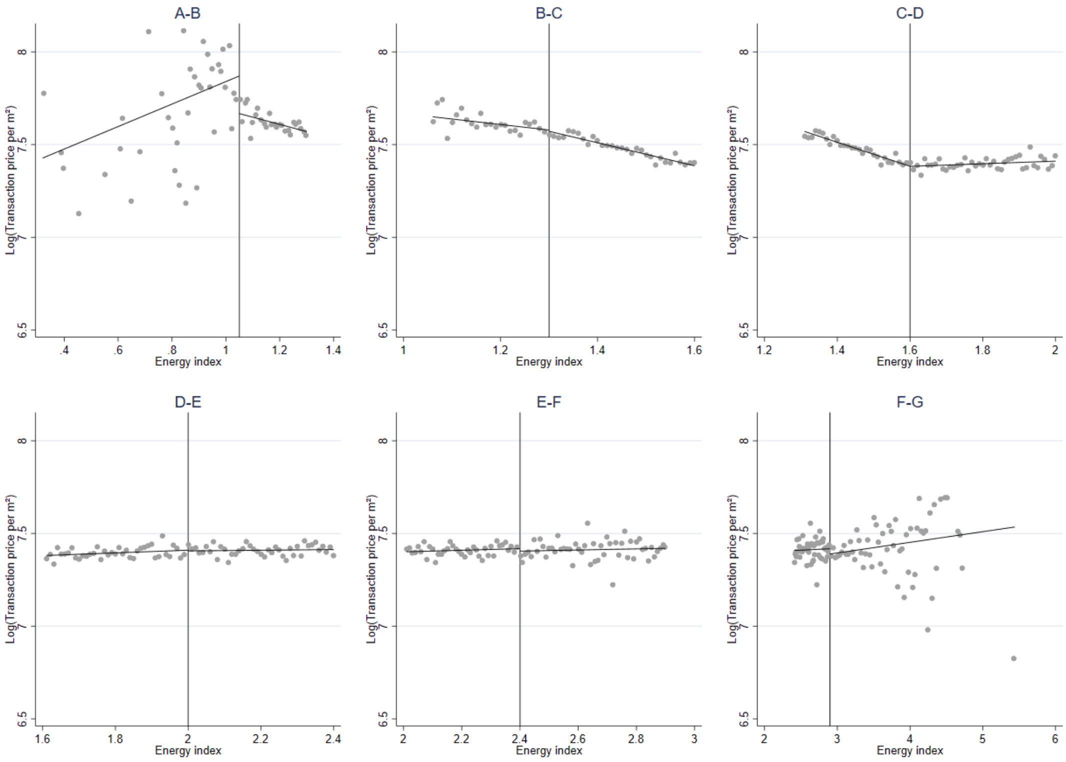



Figure 4: Transaction prices around the energy index cutoff points. The vertical axis depicts the natural logarithm of transaction prices per $m^2$. The horizontal axis depicts the energy index. Each dot represents a bin of about 1000 dwellings. The fitted line is a $1^{st}$-order polynomial fit.

Table 6 reports the coefficients of the baseline RDD model. The results of the estimation indicate that qualifying for a better label does not significantly affect transaction prices around most of the label cutoffs. For example, qualifying for an A label does not attract a significant price premium over a comparable B-label dwelling that is barely below the A-label threshold. Notably, we find some evidence of a D-label discount. An E-labeled dwelling is sold at a 5% premium compared to a D-labeled dwelling. As there appears to be potential manipulation around this cutoff, as indicated by the density test in Table 5, this coefficient estimate may be unreliable. Controlling for covariates (in Table F.3 in Appendix F), the E-label premium disappears.

We perform several robustness checks on the baseline RDD results in Table 6, which demonstrate that our results are insensitive to alternative model specifications, selection bias, time, and locational factors (see Appendix F). This suggests that the information value of voluntary labels (adopted from 2008 to 2014) is rather limited; at the margin, a better label did not yield a price premium in the Dutch residential housing market.

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

| | A-B | B-C | C-D | D-E | E-F | F-G |
|---|---|---|---|---|---|---|
| $D^{label}$=1 | 0.0613 | 0.0264 | -0.0190 | 0.0504* | -0.0480 | 0.00996 |
| | (0.102) | (0.0466) | (0.0179) | (0.0254) | (0.0332) | (0.0470) |
| Observations | 3,888 | 14,763 | 22,197 | 18,051 | 11,397 | 6,358 |

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

Table 6: RDD: main specification

### *6.3. Mandatory System*

For the analysis of the mandatory system we use the hedonic pricing approach of section 5.2 both in the common way and in an "artificial" way.

#### *6.3.1. Energy Efficiency*

The results of hedonic pricing models for the mandatory labeling system are presented in Table 7. Column (1) shows the baseline results. Results including neighborhood fixed effects are similar to those found in the voluntary labeling system—column (1) in Table 4. Again we uncover significant price premiums for each step increase in energy labels with the sole exception of the A category, which has a lower price premium than the B category. The magnitude of the other estimated premiums is somewhat larger than those found in the voluntary labeling system. As labels in the mandatory system do not require the EI, we cannot directly control for energy efficiency, as we did above (Table 4). Rather, columns (2) and (3) adopt electricity and gas use as proxies for energy efficiency. Both types of energy use have the same signs as in the results for the voluntary system, and the results suggest that actual energy use does not explain the label premiums, because the estimated premiums in column (3) are rather similar to those in column (1).

#### *6.3.2. Information Value*

As a further check of the labels' information value using hedonic pricing models, we investigate whether better-labeled houses already enjoyed a price premium before their owners applied for labels, following the

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| MODELS | EPC | Use | EPC & Use | Artificial labels (2000-2017) |
| VARIABLES | $\log(p/m^2)$ | $\log(p/m^2)$ | $\log(p/m^2)$ | $\log(p/m^2)$ |
| *Energy Label* | | | | |
| A | 0.0497*** | | 0.0630*** | 0.0179*** |
| | (0.00309) | | (0.00309) | (0.00354) |
| B | 0.0624*** | | 0.0676*** | 0.0303*** |
| | (0.00208) | | (0.00208) | (0.00261) |
| C | 0.0322*** | | 0.0343*** | 0.0124*** |
| | (0.00146) | | (0.00146) | (0.00180) |
| E | -0.0165*** | | -0.0182*** | 0.00456* |
| | (0.00187) | | (0.00184) | (0.00192) |
| F | -0.0439*** | | -0.0462*** | 0.000577 |
| | (0.00241) | | (0.00238) | (0.00263) |
| G | -0.122*** | | -0.125*** | -0.0321*** |
| | (0.00304) | | (0.00298) | (0.00347) |
| $\text{Log}\left(\frac{\text{Electricity use}}{\text{m}^2 * \sqrt{\text{household size}}}\right)$ | | 0.493*** | 0.0253*** | |
| | | (0.00123) | (0.00108) | |
| $\text{Log}\left(\frac{\text{Gas use}}{\text{m}^2 * \sqrt{\text{household size}}}\right)$ | | 0.00819*** | -0.0123*** | |
| | | (0.00121) | (0.00107) | |
| Constant | 9.090*** | 8.776*** | 9.000*** | 9.127*** |
| | (0.0366) | (0.0339) | (0.0358) | (0.0374) |
| Observations | 294654 | 294654 | 294654 | 205949 |
| R-squared | 0.329 | 0.341 | 0.332 | 0.300 |
| Dwelling controls | YES | YES | YES | YES |
| Transaction date FE | YES | YES | YES | YES |
| Postcode groups | 3695 | 3695 | 3695 | 3521 |

*Note:* 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.

Table 7: Hedonic pricing model: Mandatory labeling system

reasoning of Olaussen et al. (2017). To do so, we look at houses that did not have a label at the time of their transaction but later received one, which we term an "artificial" label. For the mandatory system, we then check whether "artificial" labels can explain the described price premiums. Column (4) of Table 7 re-estimates column (1) using all transacted dwellings that did not have a label at the time of the sale but later received one. For the better-labeled houses, about one-third to one-half of the premium was already present before the owner applied for the EPC. We infer that buyers can gauge energy efficiency to some degree without an actual Energy Performance Certificate. This indicates that dwelling characteristics, that buyers (but not researchers) can observe, partially explain the price premiums—as estimated by hedonic pricing models—that energy labels command in the mandatory system.[10]

## 7. Conclusion and Policy Implications

This paper examined the information value of energy labels. We asked whether energy labels contain unobserved information that is unavailable to the market (that is, information that cannot readily be observed by the buyer) and whether a voluntary compared to a mandatory design for a label system matters for its information value. To do so, we estimated the effect of energy labels on transaction prices using administrative data on all residential property transactions in the Netherlands from 2000 to 2017, employing several methodologies to address shortcomings in the literature.

We found robust evidence that voluntary labels (from 2008 to 2014) had limited information value in the Dutch residential housing market. In particular, RDD analysis suggests that a better label is not associated 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 into the market. This may arise due to limitations in the policy design and execution of voluntary labels and the subsequently low adoption rate in the market.

The information value of mandatory labels is less obvious. While the RDD analysis we performed for voluntary labels relies critically on the availability of the underlying Energy Index (EI), the EI is not part of the mandatory system, so we could not perform a similar analysis. As a result, whether the findings hold for the mandatory labeling system remains unclear. On the one hand, mandatory labels have much less information content than voluntary labels, which are determined in a relatively rigorous manner by an independent expert, based on more than 150 dwelling characteristics. Mandatory labels, based on 10

[10] For the voluntary system, we do not find such effects of "artificial" labels. This suggests that while the voluntary 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 (but not at the margin, as subsection 6.2.2 showed).

characteristics, are still less likely to contain more information value than what potential homebuyers can easily observe. On the other hand, mandatory labels are more salient to homebuyers because of their high adoption rate and their use in determining the ranking on the largest real estate website in the Dutch market, Funda.nl. Nevertheless, we showed that significant price premiums were present for transacted dwellings before they obtained energy labels, implying that at least part of the price premium cannot be attributed to the energy labels.

Notably, this paper defined the information value of energy labels based on transaction prices. To what extent energy labels have any impact on investments in insulation and the associated value created by potential buyers was not considered here. The presence of energy labels might make it easier for buyers to invest in insulation or to easily assess the value of such insulation. This presents an avenue for future research to obtain a broader understanding of the information value of energy labels in the housing market.

Acknowledging that labels might play a role in providing energy-related information to buyers, and that labels can function as an educational tool, labeling should be neither the sole vehicle for educating the public on energy efficiency nor the government's only tool for influencing behavior. In short, labeling should be only part of a larger system to deliver information about energy efficiency to the public. In the design of the system, labeling with a more thorough assessment process has greater potential to provide additional information to homebuyers. In this regard, the latest reform of the Dutch system has promise to improve the information function of the energy labels.

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## Appendix A. Labeling process in the voluntary system

The input menu of the EPA-W software in Figure A.1 shows the level of details of the input characteristics. For each room in a dwelling, the length, width, and height are inserted. Furthermore, for every individual surface of the room, the expert inputs 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 are included. Moreover, the characteristics of doors, such as material, insulation, and size, are included in the system. Each of these factors has some weight in determining the Energy Index, which is converted to the Energy Performance Certificate based on Table A.1.

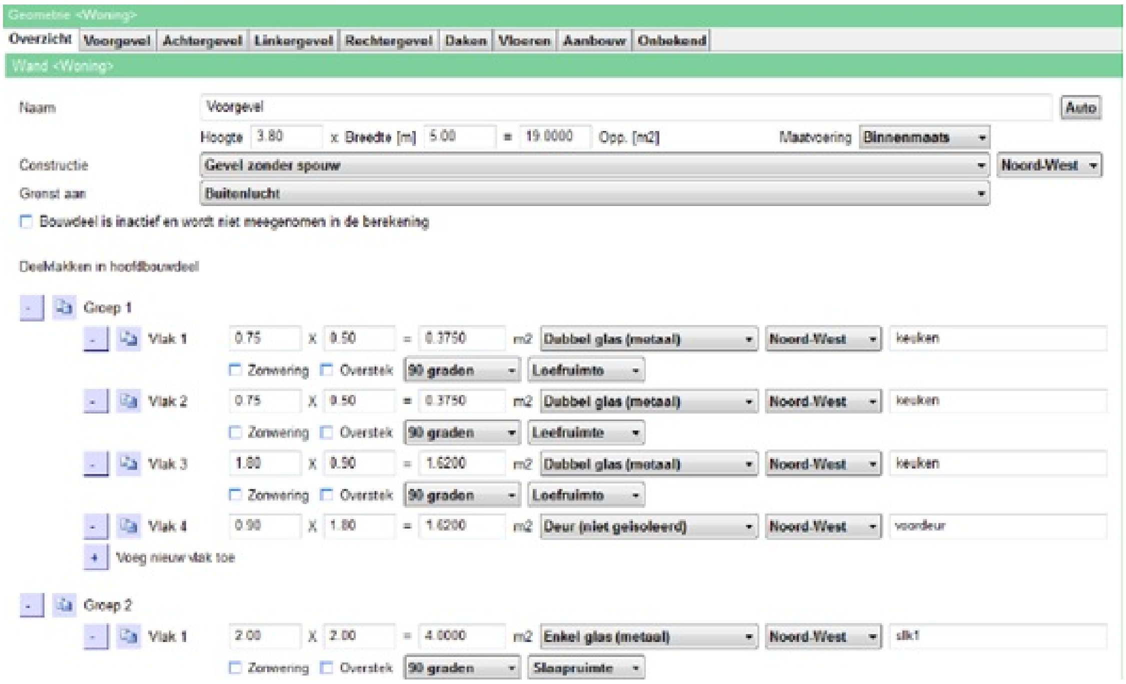


Figure A.1: Example input menu EPA-W software.

| 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 | – | |

Table A.1: Energy labels and energy index values in the voluntary system

## Appendix B. Sample Construction: Further Details

Of dwellings in the database of transactions when the voluntary system was active, 12,896 were built before the 20$^{\text{th}}$ century, and 489 (4%) had a voluntary energy label. Furthermore, 40,991 dwellings are ten years or younger at the time of sale, and 607 of those (1.5%) had an EPC. Concerning the mandatory system, we excluded 7,446 buildings from before 1900, of which 1,710 (23%) were unlabeled. Excluding those observations did not meaningfully affect the sample composition, as the fractions in Table 2 do not change by more than one percentage point. The only difference concerns the labels: there are now on average fewer well-labeled houses in the voluntary system and fewer badly-labeled houses in the mandatory system. The results of all analyses are not notably altered (that is, coefficients and standard errors are very similar overall).

## Appendix C. Histograms

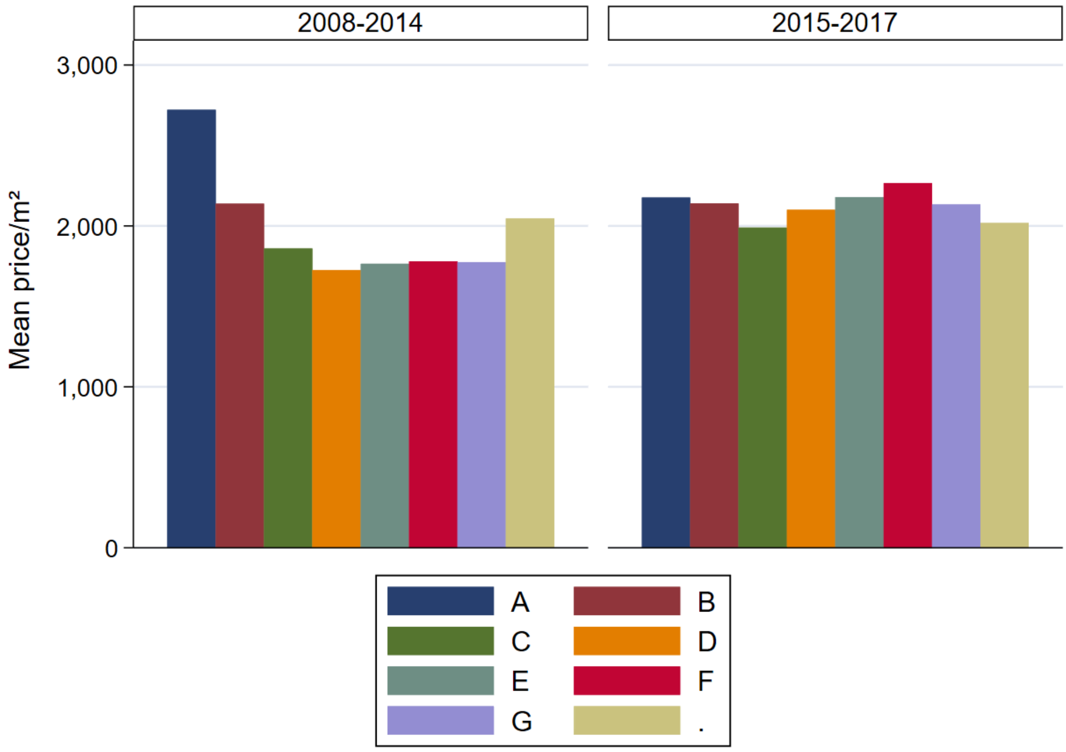


Figure C.1: Transaction price of dwellings in the voluntary (left) and mandatory (right) system.

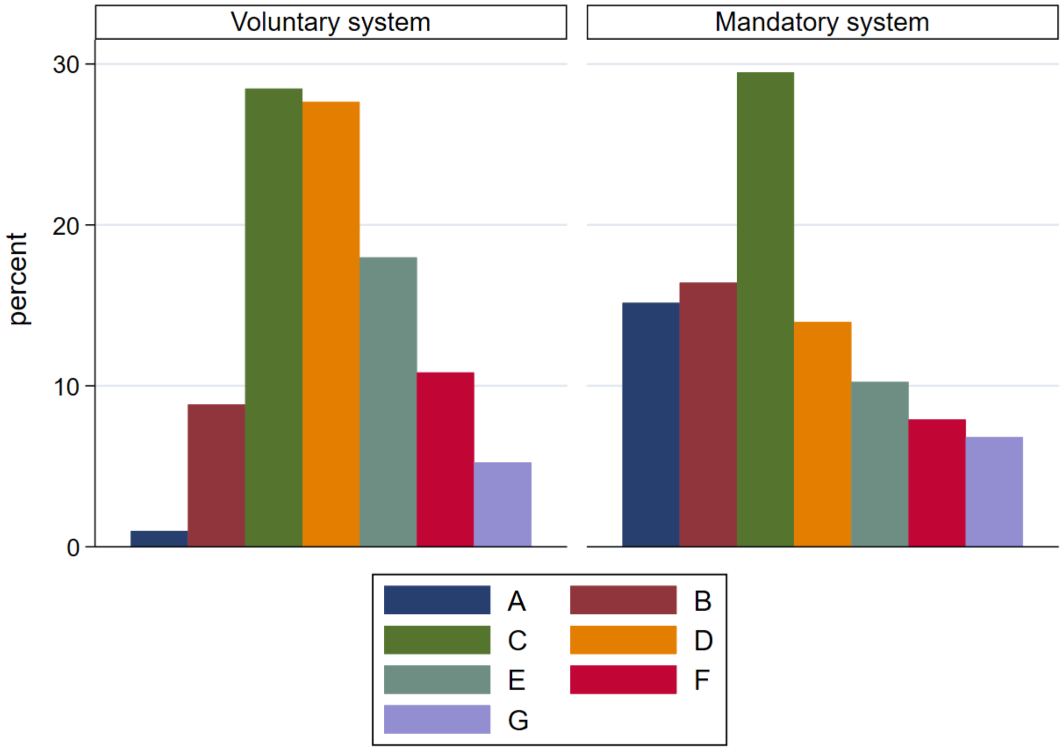


Figure C.2: Labels of transacted dwellings in the voluntary (left) and mandatory (right) system.

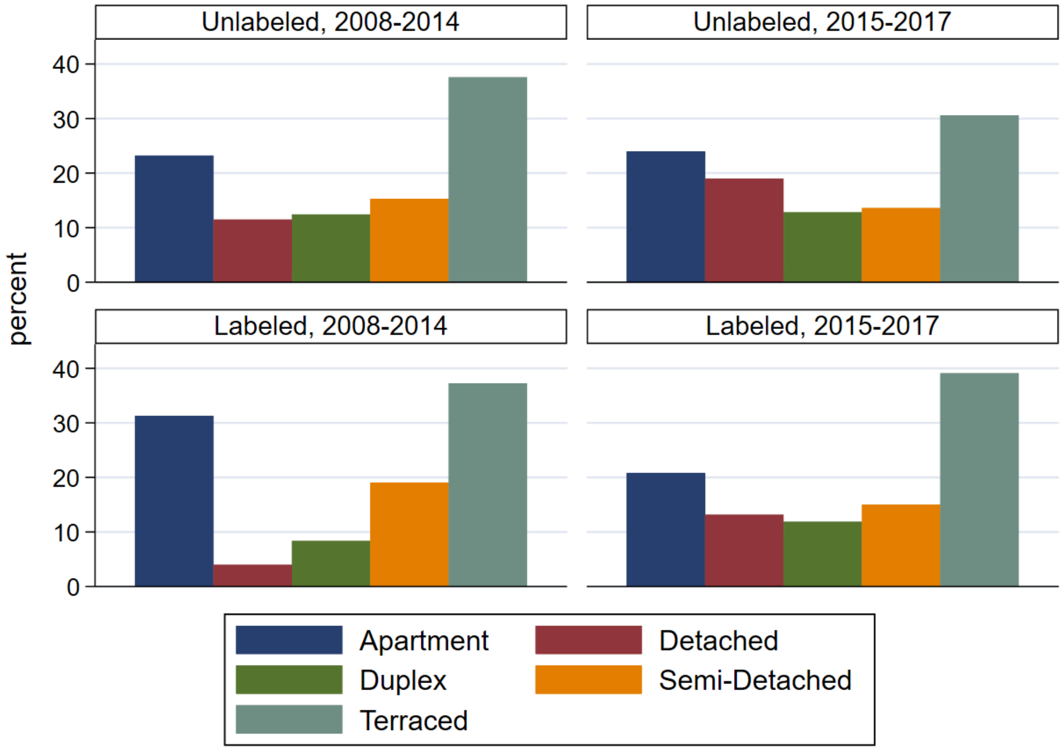


Figure C.3: Type of transacted dwellings in the voluntary (left) and mandatory (right) system, differentiated by labeling status.

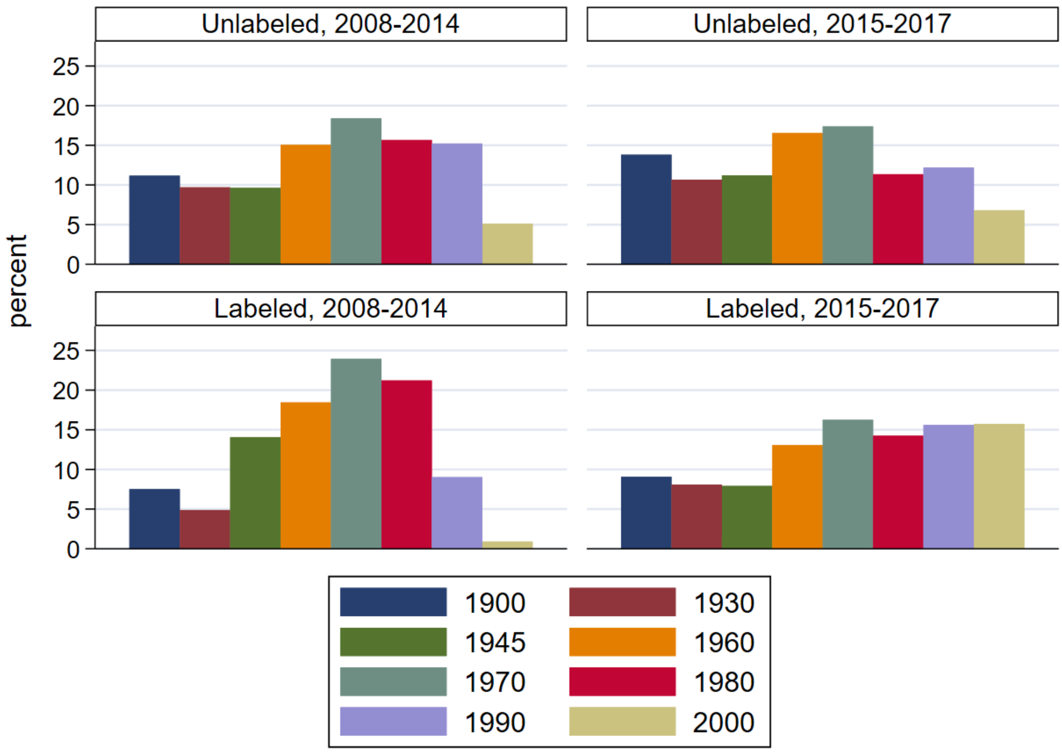


Figure C.4: Building year of transacted dwellings in the voluntary (left) and mandatory (right) system, differentiated by labeling status.

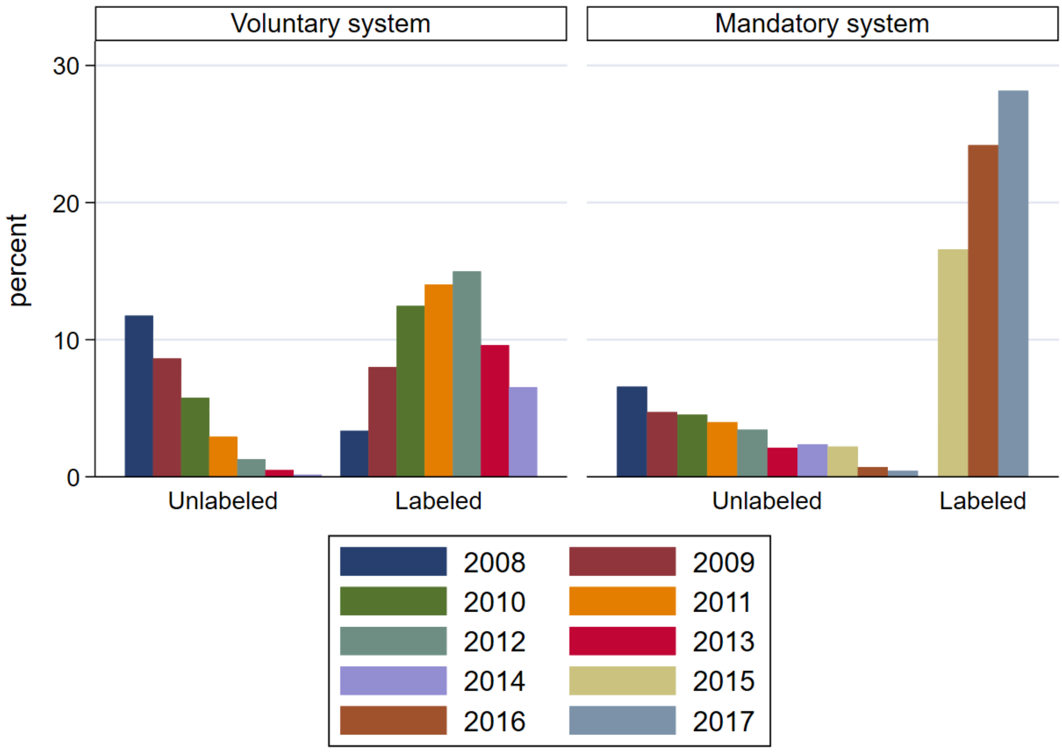


Figure C.5: Transaction year of dwellings in the voluntary (left) and mandatory (right) system.

## Appendix D. Further Summary Statistics: Sample Overview by Label Groups

Furthermore, between energy label groups, dwellings vary in all of their observed characteristics (Table D.1 and Table D.2). In the voluntary system, A-labeled dwellings, for example, comprise 51% of apartments, compared to 30% for G-labeled dwellings. Moreover, A-labeled dwellings are either relatively old, with more having a construction year of 1900 to 1929, or relatively new, with more having a construction year of 1990 and later. G-labeled dwellings are relatively old. Moreover, energy-efficient dwellings are transacted relatively often in later years; 88% of A-labeled dwellings were transacted in 2011 or later, while only 57% of G-labeled dwellings were transacted since that time.

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

| | 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 |

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

Table D.1: Characteristics per label group in the voluntary 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 |

*Note:* Dwellings with a construction year before 1900 are omitted.

Table D.2: Characteristics per label group in the mandatory system

## Appendix E. Matching

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

The matching results for the voluntary system are shown in Table E.1. Here we see that significant price premiums only appear for the medium labels, and these are relatively small in magnitude. This suggests that the actual price premiums (almost) disappear once we control for the different propensities of owners to actually apply 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 E.2 depicts the corresponding matching results for the mandatory system. For all label improvements excluding A to B, we now find significant premiums on transaction price. The results are very similar to what we found using the regular hedonic pricing model in column (5) of Table 7. This should be unsurprising because, in the mandatory system, the majority of houses are labeled; hence, the decision to apply for an EPC is less relevant compared to our analysis of the voluntary system.

| | A-B | B-C | C-D | D-E | E-F | 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 |

*Note:* 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.

Table E.1: Matching results: voluntary system

| | A-B | B-C | C-D | D-E | E-F | 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 |

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

Table E.2: Matching results: mandatory system

## Appendix F. Further RDD Results

### *Appendix F.1. Robustness checks*

To check the robustness of our results, we test whether the covariates are balanced across the cutoffs—more specifically whether across the cutoffs dwellings are similar in terms of construction year and type. We estimate a series of RDD models in which construction year and type variables are used as outcome variables, and we test the null hypothesis that there are no discontinuities in these characteristics around the cutoffs. Tables F.1 and F.2 report the results of a total of 72 RDD estimates, most of which 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-labeled dwellings built between 1945 and 1959 have a 9.7 percentage point larger fraction than E-labeled ones of the same period. By contrast, D-labeled dwellings built between 1960 and 1969 have an 8.2 percentage point smaller fraction than E-labeled ones of the same period. This fact may explain the counter-intuitive premium between labels D and E: the sample is relatively non-random around the threshold.

Furthermore, as robustness checks, we include the period of construction and type variables on the right-hand side of our baseline RDD model, with results, as reported in Table F.3, that are very similar to those reported in Table 6. We find no significant premiums at five out of the six label cut-offs, but a significant

|  | (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 | 0.216 | -0.086 | 0.106 | 0.026 | -0.122 | 0.020 | -0.111 | -0.048 | 3,877 |
|  | (0.122) | (0.060) | (0.055) | (0.029) | (0.085) | (0.031) | (0.112) | (0.112) |  |
| B-C | -0.043 | 0.002 | 0.057** | -0.013 | -0.060 | -0.025 | 0.076 | 0.019 | 14,753 |
|  | (0.027) | (0.009) | (0.020) | (0.033) | (0.032) | (0.044) | (0.051) | (0.017) |  |
| C-D | -0.020 | 0.006 | -0.015 | 0.044 | -0.007 | 0.082 | -0.048 | -0.001 | 22,184 |
|  | (0.011) | (0.010) | (0.019) | (0.023) | (0.034) | (0.044) | (0.026) | (0.001) |  |
| D-E | -0.031 | -0.013 | 0.098** | -0.093** | 0.049 | 0.006 | -0.010 | 0.000 | 18,031 |
|  | (0.018) | (0.017) | (0.030) | (0.029) | (0.030) | (0.017) | (0.007) | (0.001) |  |
| E-F | -0.007 | 0.009 | 0.008 | 0.050 | -0.104* | 0.009 | 0.003 | -0.004 | 11,384 |
|  | (0.025) | (0.023) | (0.032) | (0.041) | (0.050) | (0.009) | (0.004) | (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) |  |

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

Table F.1: RDD: estimates of construction year dummies

|  | (1) Apartment | (2) Detached | (3) Duplex | (4) Semi-Detached | (5) Terraced | N |
|---|---|---|---|---|---|---|
| A-B | 0.091 | -0.043 | -0.009 | 0.105 | -0.096 | 3,888 |
|  | (0.112) | (0.064) | (0.065) | (0.063) | (0.092) |  |
| B-C | -0.076 | 0.010 | 0.066** | 0.002 | 0.018 | 14,763 |
|  | (0.042) | (0.021) | (0.020) | (0.042) | (0.036) |  |
| C-D | 0.026 | -0.008 | -0.046* | -0.042 | 0.053 | 22,197 |
|  | (0.024) | (0.010) | (0.020) | (0.027) | (0.034) |  |
| D-E | 0.001 | 0.012 | -0.012 | 0.012 | 0.005 | 18,051 |
|  | (0.031) | (0.011) | (0.019) | (0.027) | (0.031) |  |
| E-F | -0.156** | 0.020 | 0.075* | 0.016 | 0.046 | 11,397 |
|  | (0.049) | (0.017) | (0.034) | (0.032) | (0.044) |  |
| F-G | 0.069 | 0.025 | -0.061 | -0.019 | -0.014 | 6,358 |
|  | (0.055) | (0.034) | (0.045) | (0.051) | (0.056) |  |

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

Table F.2: RDD: estimates of dwelling type dummies

D-labeled discount remains. Overall, our results do not seem to be driven by the inclusion of additional control variables.

| | A-B | B-C | C-D | D-E | E-F | F-G |
|---|---|---|---|---|---|---|
| $D^{label}$=1 | - | -0.0125 | -0.0190 | 0.0447 | -0.0566 | -0.00104 |
| | - | (0.0409) | (0.0231) | (0.0291) | (0.0348) | (0.0521) |
| Observations | - | 14,629 | 22,074 | 17,969 | 11,340 | 6,327 |

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

Table F.3: RDD: including covariates

Next, we test whether our RDD results are robust to a quadratic polynomial specification. Results, reported in Table F.4, are again quantitatively similar. Hence, the main results in Table 6 are unlikely to be driven by model specifications.

| | A-B | B-C | C-D | D-E | E-F | F-G |
|---|---|---|---|---|---|---|
| $D^{label}$=1 | 0.110 | 0.0503 | -0.0113 | 0.0559 | -0.0328 | 0.00883 |
| | (0.140) | (0.0603) | (0.0264) | (0.0336) | (0.0451) | (0.0596) |
| Observations | 3,888 | 14,763 | 22,197 | 18,051 | 11,397 | 6,358 |

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

Table F.4: RDD: using quadratic local polynomials

One potential source of bias is selection; 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 bias our estimates regarding the effects of energy labels. To alleviate this concern, we re-estimate the RDD model using non-transactional data; instead of transaction prices, we use the so-called WOZ values of dwellings, which are determined every year by local municipalities and to levy property tax. WOZ values are rather accurate compared to the transaction prices (Smeitink, 2019). The results reported in Table F.5 are overall similar to those in Table 6. Therefore, selection bias is unlikely to influence our results.

Another potential bias may arise from the equal treatment of houses in regions with very different housing market conditions. Olaussen et al. (2017) argued that potential buyers in Norway may not care about energy ratings when they buy a home, as other factors play much bigger roles in Norway's market, which has fast bidding rounds. To further investigate the effect of housing market conditions on energy labels' price premiums, we construct two sub-samples, one including houses in a region with relatively high housing demand compared to supply (the province of Zuid-Holland) and the other including houses in a

| | A-B | B-C | C-D | D-E | E-F | F-G |
|---|---|---|---|---|---|---|
| $D^{label}$=1 | -0.0471 | -0.0122 | -0.0251 | 0.0359 | -0.0336 | 0.0317 |
| | (0.0831) | (0.0350) | (0.0212) | (0.0264) | (0.0332) | (0.0462) |
| Observations | 3,784 | 14,558 | 21,969 | 17,864 | 11,271 | 6,289 |

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

Table F.5: RDD: using WOZ value

region where housing demand is low (the province of Gelderland). The results are shown in Tables F.6 and F.7. We find very similar estimated coefficients using either of these two sub-samples, which means that the main results presented in Table 6 can not be attributed to different housing market conditions.[11].

| | A-B | B-C | C-D | D-E | E-F | F-G |
|---|---|---|---|---|---|---|
| $D^{label}$=1 | - | -0.0428 | -0.0545 | 0.111* | 0.00511 | -0.0162 |
| | - | (0.0534) | (0.0535) | (0.0506) | (0.0613) | (0.0708) |
| Observations | - | 2,338 | 3,783 | 3,342 | 2,403 | 1,409 |

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

Table F.6: RDD: South-Holland

| | A-B | B-C | C-D | D-E | E-F | F-G |
|---|---|---|---|---|---|---|
| $D^{label}$=1 | - | 0.0380 | 0.0658 | -0.0763 | 0.0515 | 0.0552 |
| | - | (0.0937) | (0.0630) | (0.0735) | (0.0829) | (0.103) |
| Observations | 1,407 | 2,436 | 2,047 | 1,155 | 590 | |

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

Table F.7: RDD: Gelderland

[11]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).