Mandatory energy efficiency disclosure policies and house prices*

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Abstract

Mandatory energy efficiency disclosure policies are increasingly being used by governments around the world to reduce information-driven market failures. We exploit two policy changes in Flanders to study the causal effect of mandatory energy efficiency disclosure policies on house prices. We find that the introduction of mandatory energy performance certificates in 2008 that include an energy efficiency score did not affect the association between energy efficiency and sales prices, indicating that the policy change did not reduce information frictions. However, the introduction of EPC labels in 2019 affected the willingness to pay for energy efficiency.

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1 Introduction

Mandatory energy efficiency disclosure policies are increasingly being used by governments around the world.[1] Energy efficiency disclosure policies are often cited as a policy tool to reduce information-driven market frictions. If buyers cannot perfectly observe the energy efficieny of a house, they may be unwilling to pay for its true value (Gerarden et al., 2017). Imperfect information may thus lower the return from investments in energy efficiency and result in an energy efficiency gap: underinvestment in comparison to the optimal level. If the energy efficiency gap is mainly attributable to information-driven market frictions, then mandatory disclosure policies that provide information of the energy efficiency of buildings may yield substantial benefits. Indeed, mandatory energy performance certification for buildings is seen as a key policy instrument to reduce energy consumption (BPIE 2010).

In this paper we study the causal effect of the introduction of mandatory energy efficiency disclosure on house prices. If mandatory disclosure policies are able to reduce information-driven market frictions, we would indeed expect a causal effect on the association between energy efficiency and house prices.

To study the causal effect of energy efficiency disclosure policies we exploit two major policy changes. First, we study the introduction of mandatory EPCs in Flanders in November 2008. The EPCs contain a score that represents an estimate of the primary energy consumption in kWh/m^2/year. Second, since 2019, EPC labels were introduced in addition to the EPC score. Using rich transaction data from a large franchise network of real estate brokers, we study whether the introduction of the EPC score or label causally affected the association between house prices and an energy efficiency score. Therefore, we compare the association between house prices and energy efficiency immediately before and after the policy changes.

The results indicate that the introduction of mandatory EPCs in November 2008 did not affect the association between the EPC score and sales prices. Indeed, there was already a strong association between energy efficiency and sales prices before the introduction of mandatory EPCs and the policy change did not affect this association. Looking at

[1] In the European Union, all member states have a running system of energy performance certificates (EPCs) since 2009. In the US, at least ten states and dozens of municipalites have enacted mandatory residential energy efficiency audit and disclosure requirements (Myers et al., 2022).

the introduction of EPC labels in 2019, we see that the discount of having a label D or F (in comparison to label B) is larger than before the policy change. Therefore, the results indicate that the introduction of labels in addition to the EPC score decreases information frictions and ultimately affects the willingness to pay for energy efficiency.

We contribute to the existing literature in several ways. A first contribution is that we study the causal effect of the introduction of mandatory energy efficiency disclosure on real estate prices. The existing literature mainly focuses on the association between energy efficiency and sales prices as the association may affect investments in energy efficiency.[2] However, as significant resources are spent on energy efficiency disclosure, it is important to evaluate whether or not these policies have a causal impact.

The existing literature that studies the causal effects of mandatory energy efficiency disclosure policies is scarce and provides mixed evidence. Myers et al. (2022) study the causal effect of mandatory energy efficiency disclosure on the price capitalization of energy efficiency and energy-saving residential investments in Austin, Texas. Myers et al. find that the disclosure program had a positive effect on the capitalization of energy efficiency into home prices and on homeowners' decisions to invest in energy efficiency. Aydin et al. (2020) use data from the Netherlands to study whether or not the capitalization of energy efficiency differs between a set of homes that are labeled with an energy performance certificate and a control group that is not labeled. The findings do not provide evidence of a higher capitalization rate for homes that transacted with an energy performance certificate.

A second contribution is that we are able to exploit two policy changes in which first an EPC score was introduced and subsequently an EPC label (in addition to the EPC score). As the EPC label is based on the EPC score that was already available, one could expect that the EPC label has no added value if all decision makers act fully rational without biases. However, due to behavioral biases (Tversky and Kahneman, 1974) an EPC label may be easier to recall in comparison to an EPC score. Due to the two policy changes, our setting provides a unique opportunity to separately study the added value of energy

[2] See Brounen and Kok (2011); Fuerst et al. (2015); Fuerst, Oikarinen and Harjunen (2016); Hyland et al. (2013); Jensen et al. (2016); Hårsman et al. (2016); Olaussen et al. (2017); Fuerst, McAllister, Nanda and Wyatt (2016); de Ayala et al. (2016); Kahn and Kok (2014); Damen (2019) among others for the residential real estate market. Eichholtz et al. (2010, 2013) study the commercial real estate market. Most of the studies find a strong association between energy efficiency and sales prices.

efficiency disclosure and the EPC labelling.

A third contribution is that we study a setting with strong compliance in comparison to the existing literature. Indeed, 80% of the homes in the data from Aydin et al. has been transacted without an EPC and 40 percent of the targeted homes in the study by Myers et al. do not comply. If compliance is not random, the causal effect may be different in settings with higher compliance. As the compliance is much higher in Flanders, the potential influence of selection biases is much smaller in our setting. Indeed, 91% of the homes sold around the introduction of the EPC label have a valid EPC at the time of the listing.

The structure of the paper is as follows. We describe the policy change and background in Section 2. The methodology and data are described in Section 3 and 4. We present the results in Section 5. Finally, we provide a discussion in Section 6 and conclude in Section 7.

2 Background

In 2002, the European Parliament approved the first version of the Energy Performance of Buildings Directive. Article 7 of this directive required all member states to pass legislation that would make the disclosure of energy performance of buildings compulsory with a sale or rental of real estate. Since member states had a few years to design and implement the needed procedures, in Flanders these certificates became mandatory for sales of residential real estate on November 1st 2008. As of January 1st 2009, this also became mandatory for residential rentals. Wallonia followed in June 2010 (sales of single family housing) and in June 2011 (apartments and rentals), and Brussels Capital Region in May 2011 (sales) and November 2011 (rentals). [3]

In Flanders, EPCs became mandatory for almost all sales, except for those that transferred ownership without any public listings, so e.g. though an inheritance or gift. This share is likely to be very limited: around 2.5% of the households surveyed for the Flemish Housing Survey in 2008 and 2013 were living in a house transferred this way. Other exceptions are very limited: extraordinary objects like castles are also not required to

[3] Belgium consists of Flanders, Wallonia and Brussels Capital Region, each with their own government and legislative procedures.

obtain an EPC. In other cases, if the seller does not have an EPC, he risks a fine of 500 to 5000 euro's.

An EPC has to be estimated by an accredited specialist that follows the procedure drawn up by the Flemish government. They do this with an on-site visit and with software designed by the government. The estimation represents the predicted energy usage in kWh, per square meter, per year. This estimation costs around 250 euro.

On January 1st 2019, there was another policy change. From then on, the EPC score was not presented as a number, but as a label. These labels, represented as letters, represent 7 buckets of EPC scores. A building that required more than 500 kWh per square meter per year gets an F, up to A, for buildings that require less than 100 kWh. The 7th label, A+, is reserved for buildings that are energy neutral: those that do not use energy, or even produce it (which would correspond to an EPC of 0 or a negative EPC, respectively).

3 Methodology

The primary goal of EPCs is to reduce information asymmetry, increase the capitalization of energy efficiency in real estate prices, and thus ultimately increase the payoff of long-term investments in energy efficiency. It is thus expected that the implicit prices of energy efficiency will change around the implementation of these certificates. To assess this, we need a measure of energy efficiency that we can exploit both before and after the policy change, and a way to obtain the implicit price this measure of energy efficiency.

Hedonic pricing models are a commonly used tool in real estate literature to extract such implicit prices. These consider a house to be a bundle of measurable characteristics, like its size, location, building quality and number of bedrooms. All these characteristics together determine the maximum utility (hence hedonic) that the inhabitant will obtain from buying or renting the dwelling. By regressing these characteristics on the price of the house, we obtain the implicit prices for these characteristics. The coefficients of these characteristics can then be interpreted as the effect that these characteristics have on the price of the house, and thus as the conditional marginal average that people are willing to pay for it.

Just like, for example, the number of bed- and bathrooms, energy efficiency can also be considered a characteristic for which people are willing to pay. We could therefore use the same reasoning to determine the marginal impact of energy efficiency on the price. However, energy efficiency is of course not directly observable. It depends on a multitude of observable and unobservable characteristics.

So before we can do any meaningful analysis, we have to construct a measure of energy efficiency. Obviously, the EPC should reflect this energy efficiency as accurately as possible, but is unavoidably prone to measurement errors and other biases. A bigger obstacle, however, is that we cannot rely on the information provided by the EPC scores to evaluate the change in implicit pricing of energy efficiency, because we would lack a control group of houses that have been sold without an EPC. Most available data about energy efficiency generally stems from the EPC itself.

We, however, have access to a detailed transactions database which includes energy characteristics recorded independently of the EPC, and before November 1st 2008. This allows us to estimate an energy efficiency score for both houses with and without an EPC. We can then estimate the price of this energy efficiency score and test whether this is priced differently before and after the EPC implementation.

We split our sample in a sub-sample for which EPC scores are available, and a sub-sample for which energetic characteristics are available. We can subsequently estimate the relationship between the EPC scores and these energetic and other characteristics. To do so, we use the sub-sample with EPC scores to run a regression of the following form

$$\mathrm{EPC}_i = \alpha + \delta H_i + \gamma E_i + \theta L_i + \zeta M_i + \epsilon_i \tag{1}$$

in which α is a constant, H is a vector of housing characteristics, E a vector of energetic characteristics, L a vector of location dummies (on a municipal level), M a vector of dummies for the month that the property was listed as for sale, and ϵ as error term. We do not take the month sold here, because the EPC is determined before the property is listed, not at the time of sale. With this regression estimated with the recorded EPC scores, we can estimate EPC scores for observations without an EPC score, but for which we have (other) energetic characteristics available. Given the extensive list of dependent variables in the data set, this should give us a good pseudo-EPC. To make the comparison valid, we use this estimated EPC score both before and after the policy change (rather than the pseudo before and real EPC score after).

These estimations allow us to calculate the implicit prices for this energy efficiency measure just before and after the introduction of the EPC. As discussed above, we implement this measure into a classic hedonic pricing model of the following form:

$$P_i = \alpha + \beta_1 \text{ EPC estimate}_i + \beta_2 \text{ EPC estimate}_i \times \text{Post EPC dummy} + \delta H_i + \theta L_i + \zeta M_i + \epsilon_i \tag{2}$$

in which the dependent variable P_i is either the selling price or the initial asking price, H_i is (again) a vector of housing characteristics of house i, M_i is a vector of month dummies (either for month of sale or month of listing), L_i is a vector of location dummies (in this case on a district level due to the comparatively moderate number of observations), α is a constant and ϵ the error term. The coefficient of the interaction variable β_2 is the extent of which the implicit prices have changed after the introduction of the EPC.

For the switch to labels in 2019, we do not need to rely on our self constructed measure of energy efficiency that we obtained by estimating EPC scores. In this analysis, we can simply use the EPC score of the dwelling, since these were drawn up both before and after the change. So, in this case, our regression equation will be

$$P_i = \alpha + \beta_1 \text{ EPC score}_i + \beta_2 \text{ EPC score}_i \times \text{Post EPC labels dummy} + \delta H_i + \theta L_i + \zeta M_i + \epsilon_i \tag{3}$$

in which the symbols correspond with the ones used earlier. Since this score is converted into labels as of January 1st 2019, it seems logical to also look at results if we use dummies for the labels. We can of course easily determine which labels properties sold before 2019 would have gotten, since these categories are fixed. The regression for this analysis will be

$$P_i = \alpha + \beta \text{ Labels}_i + \eta \text{ Labels}_i \times \text{Post EPC labels dummy} + \delta H_i + \theta L_i + \zeta M_i + \epsilon_i \tag{4}$$

in which Labels is a vector of dummies which will equal to one if the EPC of house i falls into that label category. The rest of the symbols correspond with the definitions given earlier. Again, the coefficient of the interaction variable will be the change in price.

We will run the regressions (2), (3) and (4) with both selling price and initial offering price as a dependent variable. We will use the logarithmic transformation of both the dependent variable as the EPC estimate/score, so the coefficients can be interpreted as the percentage change. When controlling for time, we will use month dummies of the month in which the dwelling was sold in case of the selling price, and the month in which the dwelling was listed as for sale in case of the initial asking price. We do this to let the month dummy coincide with the month the decision regarding the price was made: at the listing, or at the time of sale.

Apart from the analysis on the prices, we preform the same analysis on days on market with regression

$$D_i = \alpha + \beta_1 \text{ EPC estimate}_i + \beta_2 \text{ EPC estimate}_i \times \text{Post EPC dummy} + \delta H_i + \theta L_i + \zeta M_i + \epsilon_i \tag{5}$$

for the policy change in 2008, and with regression

$$D_i = \alpha + \beta \text{ Labels}_i + \eta \text{ Labels}_i \times \text{Post EPC labels dummy} + \delta H_i + \theta L_i + \zeta M_i + \epsilon_i \tag{6}$$

for the policy change in 2019. In both equations, D_i is the logarithmic transformation of the number of days that property i was for sale before it was purchased.

For regressions (2), (3) and (4) we first regress the dependent variable (log of selling price, log of initial asking price or log of days on market) on just the EPC estimate/score, the interaction variable and a dummy that equals one if the policy change took effect (so either after November 1st 2008 or January 1st 2019). We then extent this regression with controls for housing characteristics, month dummies and location dummies respectively. We let the controls vary because the energy efficiency is unavoidably correlated with non-trivial housing characteristics like the size, type of building, age and condition. We use month dummies because e.g. technology can improve and the method of EPC estimation can slightly change. We include location dummies, because it is possible that location has an effect due to otherwise unobservable differences in e.g. environment, architectural styles and urban landscape.

4 Data

We received our data from real estate organisation ERA. ERA, short for Electronic Realty Associates, is a large international network of residential real estate agents. In Belgium, 134 real estate agencies are part of ERA. Most (107) are mainly active in Flanders. This data is transactional data: data that is recorded when an ERA office is involved in the sale, purchase or rental of a property. This type of data is commonly used in real estate studies.

As mentioned before, this data set is unique in the sense that it includes energetic characteristics that are obtained separately from the EPC. It includes data on, among other things, glass (single-, double- or triple-pane), heating technique (central heating or radiators), heating elements (e.g. underfloor heating or heaters), heating material (e.g. gas or electricity), and hot water equipment (e.g. storage geysers, instant water heaters). The original sample includes transactions from the beginning of this century, up until the last quarter of 2021, with a total number of observations of 76861. This includes both buy-sell and rental transactions, mostly in Flanders, but some in Wallonia and Brussels Capital Region as well.

Since this data was initially not recorded for the purpose of this study, it needs some cleaning. In line with previous research, we focused our analysis on single-family rather than multi-family housing (like apartments), since the factors determining the energy efficiency of the former will likely be different from those determining efficiency of the latter. We therefore exclude apartments from our sample. Since a relatively low number of transactions took place in Wallonia and Brussels Capital Region, we also delete those to prevent differences in policies influencing our results. Also in line with the literature, we focus on sales rather than rentals, since then the potential energy costs and savings are for the account of the new owner. We delete dwellings with a selling and/or asking price under €80,000 to exclude outliers, like transactions with symbolic amounts and houses in a terrible condition. Removing apartments, rentals, low priced houses, and transactions outside Flanders leaves us with 40288 observations.

With use of equation (1), an EPC score could be estimated for a total of 34728 observations. 2446 of these were sold before the EPC policy change. The summary statistics of the subset houses for which we have enough data to estimate an EPC score are in table 1 and 2. The summary statistics for the observations for which we had actual EPC scores are in table 7 and 8.

As mentioned, it is possible for a dwelling to obtain an A+ label if the EPC score is 0 or negative. We also see that in our initial sample. The distribution, however, suggest that most of these are incorrect. Of the 261 houses with an alleged A+ label, 243 were sold between 2009-2011, and only 1 in 2018-2020. We thus suspect that one or a few real estate agents filled in a 0 when there was no EPC available. Besides, the total number of observations is too low for any meaningful analysis, so we decided to delete all observations with an EPC score of 0 or lower, since these outliers can falsely skew the results. Of the remaining 27011 EPC observations, 8 have a score above 14,000, while all others are (mostly well) under 3721, so we also delete all observations with EPC scores above 4000.

If we compare transactions before and after a policy change, we need to check that the sample before and after are not of a different nature. These comparisons are in tables 3 to 6 for the subset of 2008-2009, and in table 9 to 12 for the subset of 2018-2019. If we compare the summary statistics for the remaining observations in the 6 months before and after the initial introduction of the EPC, the characteristics are very similar. The period before has a higher mean asking price, but this is probably mainly due to an outlier of 29 million (vs. a max of 3 million in the period after), because the median and 25th and 75th percentile are again very similar. The summary statistics of the data 6 months before and after the policy change in 2019, when the scores became labels, is even more similar, and also does not raise any concerns about the comparability of the sample around that date.

5 Results

First of all, we obtain our estimated pseudo-EPC for the observations around the November 1st 2008 policy change using equation (1) and OLS. The summary statistics of these estimates are in table 14, while the summary statistics of the actual EPC in our sample are in table 13. We can see that the summary statistics of the pseudo-EPCs generated by our estimation seem similar to the actual ones. The maximum of the estimated is quite a bit lower, but given that only 171 out of a 27003 actual EPCs were above that maximum estimated level of 1315.01, this does not raise any concerns.

We start the analysis of the relation between EPC and real estate prices with the first introduction of the EPC: November 1st 2008. As discussed, we regress the prices on the EPC, interaction variable and controls with a sample that includes 6 months before and after November 1st 2008. When we look at the results of the regressions in table 15 and 16, we can clearly see a negative relationship between the EPC score and the price. Since a higher EPC score corresponds to higher estimated energy usage, this was to be expected. Without any controls, a percentage change in estimated EPC score corresponds to a -0.426% change in the selling price and a -0.425% change in the initial asking price. When we control for housing characteristics and month of sale/listing (respectively), the coefficients decrease with more than half. It increases (in absolute terms) to -0.202 (selling price) and -0.212 (asking price) if we also control for location (on a district level).

The interaction variable, however, is not significant in any regression with selling price as a dependent variable. This interaction variable is significant in the regression with initial asking price as dependent variable and full controls at a 10% significance level. However, it is positive. This would suggest that a higher EPC decreases the initial asking price less after than before the introduction of the EPCs. This goes against our expectations. The estimated effect is also economically significant, as it implies a mitigation of the pre-EPC coefficient of 34.5%.

In the regression with days on market (table 17) as the dependent variable, no coefficient for either the estimated EPC score or the interaction variable is significant. This suggest that energy-efficiency of houses does not have a significant influence on the time in which they are sold. The policy change did not seem to influence that.

As discussed, from January 1st 2019, the EPC score became EPC labels in Flanders. To assess the impact this had on the capitalization of energy efficiency in the residential real estate prices, we regress our three dependent variables on the EPC score. Now, we can just use the EPC score rather than our estimate, since this score is also available for properties sold before January 1st 2019.

As shown in tables 18 and 19, the regression for the EPC itself has a negative effect on the selling price and initial asking price. Without controls, a 1% increase in EPC score is associated with a 0.289% decrease in selling price, and a 0.261% decrease in initial asking price. As a higher EPC is associated with less energy efficiency and more energy costs, this was to be expected. Controlled for housing characteristics, location and month of sale/listing, this decrease reduces to -0.108% and -0.087%. The larger number of observations allows us to correct for location effects on a municipal rather than district level here. The fact that all coefficients for the initial asking price are (in absolute terms) smaller than those for the selling price suggests that the importance of the EPC is underestimated in the process of determining the asking price. The interaction effects however, seem to be statistically insignificant. This suggest that the shift from an EPC score to EPC labels did not have any statistically significant effect.

When we look at the different labels however (table 21 and 22), this impression changes. When we use dummies for the EPC labels, we see a significant and negative coefficient for labels E and F, for both the selling and asking price. Again it seems that the negative effect of these two labels is underestimated in the asking price, since the coefficient for the selling price is larger (in absolute terms). Interestingly, the interaction effect of two labels, D and F, are also significant. This implies the negative effect that having a D or F label has on the price of a house has increase after the EPCs were expressed as labels rather than as a continuous score. It is worth noticing that the interaction variable of label E is not significant, but the regular coefficient is, while it is vice versa for label D.

When we look at the days on market rather than the price (table 20 and 23), we also witness quite a large and statistically significant coefficient for the EPC score. Controlled for housing characteristics, month of sale and location at a municipal level, a one percent higher EPC score is associated with a 0.221% more days on the market. This is interesting, since the housing characteristics control for e.g. houses being recently renovated. However, it seems that nothing changes after the switch from EPC score to labels, since all coefficients of the interaction effects are not significant.

After obtaining these results, it is natural to wonder whether the initial introduction of the EPC score also produced heterogeneous results. We checked for this by splitting up the EPC estimates into the corresponding labels, giving us an estimated label for the observations around November 2008. We ran the regression again, this time with dummies and interaction effect variables corresponding to the estimated labels. As shown in table 24, if we take the selling price as a dependent variable and do not control for any other variables, all coefficients of the interaction effects are positive and significant. Since B is the reference, this is not expected. But, as discussed, this EPC score correlates with many other housing characteristics. If we control for these, the significance of the effect disappears. This does not change if we also control for month of sale and location. Please note that the interaction variable of label A is missing because our estimation procedure did not result in pseudo-EPC scores under a 100 in the 6 months after November 1st 2008.

In the regression for the initial asking price (table 25), there is also a significant and positive effect for worse EPC labels than the reference category B, but in this regression it stays limited to just 2, C and F. Again, these results disappear when we control for other housing characteristics, month of listing and location. In the days on market regression (table 26), there is one coefficient significant after adding any or all controls: the interaction coefficient of label C. Referenced to label B, houses with an estimated C label get sold around 1% more quickly after the policy change.

6 Discussion

Before drawing final conclusions, it is important to note some limitations to the results presented above. An important one is that our estimated EPC score is not a perfect match for either the EPC score or energy efficiency. Our regression (1) of the EPC score on the energy and housing characteristics and month and location dummies has an R-squared of 57%. Ideally, this would be higher. However, it is already quite a bit higher than the R-squared we obtain when we omit the energy characteristics: it then drops to 45%.

Another potential limitation are measurement and data entry errors. As discussed before, the distribution of A+ labels over the years was very weird. It seemed that at least 243 of the 261 properties in the database with an A+ label did not actually have one, but that the real estate agent just filled in a 0 because the EPC was not available. This error is harder to check for other variables, and impossible to rule out. With manual data entry, such mistakes are always possible. However, since this type of data is commonly used in the real estate literature, this potential bias concerns most other studies as well, and its is likely to be random and limited. Besides, most variables are dummies, for which such mistakes are less plausible.

It is also possible that compulsory disclosure of EPCs takes longer than a year to take effect. In this case, we would not capture a sudden shift, but a more gradual one. Our current research setting does not allow us to rule out this possibility, so we are currently looking for ways to do so.

It is also possible that the effect is heterogeneous, as we have seen with the conversion to labels in 2019. We check for heterogeneity on an EPC estimate level, but it is possible that for example EPCs of detached and semi-detached housing have had a different effect on the price. We also plan to extent this research with various checks for that.

As mentioned, any measure of energy efficiency will unavoidably be correlated with other important characteristics, both observable, like the age of the house, and unobservable, like the number of windows. This is also the case for our pseudo-EPC. It is thus possible that prices differences of other characteristics (partly) contaminate our results.

As a robustness check, we can compare the implicit prices for individual characteristics that influence energy efficiency. We have selected the 8 that had the largest effect on EPC according to our estimation of equation (1) and look at their implicit prices, again 6 months before and after the introduction of the EPC. We have done this analysis in the same way as before: a classic hedonic pricing model, with differing controls. For sake of brevity, we only show the model with none (model (1)) controls, or all controls (model (4)). The results are in table 27. Also in this case, we do not see any logical pattern that would emerge if the implicit prices of energy efficiency would have increased. On the contrary, roof insulation has become a bit cheaper after November 1st 2008.

7 Conclusion

In this paper, we assessed the effect that mandatory energy performance certificates had on the capitalization of energy efficiency in Flanders, exploiting policy changes in 2008 and 2019. In November 2008, disclosing an energy performance certificate became mandatory for (almost) all sales of residential real estate in Flanders. From then on, sellers were obliged let an expert estimate an EPC score before listing the house, and disclosing that information in all public advertisements. In January 2019, this EPC score became an EPC label, and was henceforth represented as a letter (F to A+), rather than as a number.

We exploit a novel data set to assess the changes in prices and days on market after these two policy changes. Most available data on energy characteristics stems from the EPC, which makes it impossible to assess the effect of energy efficiency on prices and days on market. Our data set solves that issue since it contains variables that have been recorded both before and after the implementation of the EPC. This allows us to use EPC scores to estimate EPC scores for dwellings without one.

We implement this estimated EPC score into a classic hedonic pricing model, together with other housing characteristics and location and month dummies, to obtain the implicit prices for (our measure of) energy efficiency. Our results do not show any significant change in the implicit selling price for energy efficiency after the EPCs became mandatory. Our results even suggest that energy inefficiency had a less negative on the initial asking price after November 1st 2008. This could indicate that sellers are less optimistic about the worth of their energy efficiency. For days on market, we find no change with the introduction of EPCs.

For the policy change in 2019, when the EPC score became EPC labels, we were able to just use the EPC scores, since this is available for transactions both before and after January 2019. We do not see any change in the implicit prices of the EPC score itself, in either the selling price or initial asking price. However, when we transform the continuous EPC score into dummy variables corresponding to the labels, we witness that the discount of having a label D or F is larger than before. This implies that the switch from an EPC score to EPC labels had a positive effect on the price of energy efficiency, though limited and heterogeneous. The effect is also present on the initial asking price for precisely these labels. For the days on market, we again find no change in effect. Extending our initial 2008 analysis with these label dummies does not produce significant results.

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Table 1: Houses sold, with estimated EPC

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Selling price	34,679	243,654.40	102,665.10	80,500	170,000	225,000	295,000	810,000
Initial asking price	34,679	265,802.80	247,600.20	80,500	185,000	242,000	319,000	29,001,000
Liveable area (m2)	34,679	185.26	69.76	40.00	140.00	170.00	215.00	600.00
Number of bedrooms	34,679	3.14	0.93	0	3	3	4	6
Number of bathrooms	34,679	1.15	0.45	0	1	1	1	4
Estimated EPC score	34,679	482.78	179.15	0.35	356.33	483.35	605.93	1,315.01
Age	34,679	56.99	31.77	0	35	53	72	121

Table 2: Houses sold, with estimated EPC

Statistic	N	Mean	St. Dev.
Detached building	34,679	0.42	0.49
Semi-detached building	34,679	0.26	0.44
Garden available	34,679	0.85	0.36
Roof insulation	34,679	0.47	0.50
Cavity insulation	34,679	0.13	0.33
Single-pane glass	34,679	0.33	0.47
Gas (as heating material)	34,679	0.62	0.49
Estimated EPC label A+	34,679	0.00	0.00
Estimated EPC label A	34,679	0.01	0.11
Estimated EPC label B	34,679	0.05	0.21
Estimated EPC label C	34,679	0.10	0.30
Estimated EPC label D	34,679	0.17	0.38
Estimated EPC label E	34,679	0.20	0.40
Estimated EPC label F	34,679	0.47	0.50
Sold in 2006	34,679	0.03	0.18
Sold in 2007	34,679	0.04	0.19
Sold in 2008	34,679	0.04	0.20
Sold in 2009	34,679	0.05	0.22
Sold in 2010	34,679	0.06	0.23
Sold in 2011	34,679	0.06	0.24
Sold in 2012	34,679	0.06	0.25
Sold in 2013	34,679	0.07	0.25
Sold in 2014	34,679	0.08	0.26
Sold in 2015	34,679	0.07	0.26
Sold in 2016	34,679	0.07	0.26
Sold in 2017	34,679	0.06	0.24
Sold in 2018	34,679	0.06	0.24
Sold in 2019	34,679	0.07	0.25
Sold in 2020	34,679	0.06	0.24

Table 3: Houses sold, with estimated EPC
Sold 6 months before EPC introduction

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Selling price	781	219,222.20	87,510.64	82,500	160,000	205,000	260,000	760,000
Initial asking price	781	288,813.70	1,044,382.00	82,500	175,000	220,000	295,000	29,001,000
Liveable area (m2)	781	182.29	63.45	60.00	140.00	170.00	208.00	600.00
Number of bedrooms	781	3.10	0.86	0	3	3	4	6
Number of bathrooms	781	1.15	0.47	0	1	1	1	4
Estimated EPC score	781	557.59	173.55	115.56	435.34	558.75	671.38	1,249.05
Age	781	54.12	30.56	1	33	48	70	108

Table 4: Houses sold, with estimated EPC
Sold 6 months before EPC introduction

Statistic	N	Mean	St. Dev.
Detached building	781	0.44	0.50
Semi-detached building	781	0.25	0.43
Garden available	781	0.92	0.27
Roof insulation	781	0.47	0.50
Cavity insulation	781	0.14	0.35
Single-pane glass	781	0.39	0.49
Gas (as heating material)	781	0.56	0.50
Estimated EPC label A+	781	0.00	0.00
Estimated EPC label A	781	0.00	0.00
Estimated EPC label B	781	0.01	0.10
Estimated EPC label C	781	0.06	0.24
Estimated EPC label D	781	0.10	0.31
Estimated EPC label E	781	0.20	0.40
Estimated EPC label F	781	0.62	0.48
Sold in 2008	781	1.00	0.00

Table 5: Houses sold, with estimated EPC
Sold 6 months after EPC introduction

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Selling price	737	217,922.60	77,396.68	85,000	165,000	205,000	258,000	565,000
Initial asking price	737	245,828.30	133,839.10	85,000	180,000	225,000	285,000	3,000,000
Liveable area (m2)	737	187.58	69.43	50.00	145.00	170.00	220.00	595.00
Number of bedrooms	737	3.14	0.86	0	3	3	4	6
Number of bathrooms	737	1.15	0.44	1	1	1	1	4
Estimated EPC score	737	544.06	164.55	90.68	436.88	543.27	654.64	1,101.98
Age	737	54.00	30.02	0	34	49	69	109

Table 6: Houses sold, with estimated EPC
Sold 6 months after EPC introduction

Statistic	N	Mean	St. Dev.
Detached building	737	0.39	0.49
Semi-detached building	737	0.27	0.44
Garden available	737	0.93	0.26
Roof insulation	737	0.42	0.49
Cavity insulation	737	0.13	0.34
Single-pane glass	737	0.39	0.49
Gas (as heating material)	737	0.55	0.50
Estimated EPC label A+	737	0.00	0.00
Estimated EPC label A	737	0.001	0.04
Estimated EPC label B	737	0.02	0.14
Estimated EPC label C	737	0.05	0.21
Estimated EPC label D	737	0.12	0.32
Estimated EPC label E	737	0.21	0.41
Estimated EPC label F	737	0.60	0.49
Sold in 2008	737	0.23	0.42
Sold in 2009	737	0.77	0.42

Table 7: Houses sold, with available EPC score

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Selling price	27,003	255,592.90	107,296.40	80,500	180,000	235,000	310,000	810,000
Initial asking price	27,003	275,021.90	116,497.60	82,000	195,000	250,000	329,000	2,100,000
Liveable area (m2)	26,597	184.12	69.68	42.00	140.00	170.00	213.00	600.00
Number of bedrooms	27,003	3.13	0.96	0	3	3	4	6
Number of bathrooms	27,003	1.13	0.48	0	1	1	1	4
EPC score	27,003	475.69	238.78	1	300	441	604	3,721
Age	25,293	58.86	31.81	0	38	54	75	121

Table 8: Houses sold, with available EPC score

Statistic	N	Mean	St. Dev.
Detached housing	27,001	0.42	0.49
Semi-detached housing	27,001	0.26	0.44
Garden available	27,003	0.82	0.38
Roof insulation	26,991	0.48	0.50
Cavity insulation	26,991	0.12	0.33
Single-pane glass	26,997	0.32	0.47
Gas (as heating material)	26,995	0.64	0.48
Label A+	27,003	0.00	0.00
Label A	27,003	0.01	0.09
Label B	27,003	0.08	0.28
Label C	27,003	0.16	0.37
Label D	27,003	0.18	0.39
Label E	27,003	0.17	0.37
Label F	27,003	0.40	0.49
Sold in 2006	27,003	0.0005	0.02
Sold in 2007	27,003	0.0003	0.02
Sold in 2008	27,003	0.001	0.03
Sold in 2009	27,003	0.02	0.14
Sold in 2010	27,003	0.05	0.21
Sold in 2011	27,003	0.05	0.23
Sold in 2012	27,003	0.08	0.27
Sold in 2013	27,003	0.09	0.28
Sold in 2014	27,003	0.09	0.29
Sold in 2015	27,003	0.09	0.28
Sold in 2016	27,003	0.09	0.29
Sold in 2017	27,003	0.09	0.28
Sold in 2018	27,003	0.09	0.29
Sold in 2019	27,003	0.10	0.30
Sold in 2020	27,003	0.09	0.29

Table 9: Houses sold, with available EPC score
Sold 6 months before labels introduction

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Selling price	1,224	264,039.10	105,491.10	81,000	190,000	248,500	320,500	750,000
Initial asking price	1,224	284,040.90	114,565.20	88,000	199,000	265,000	337,875	975,000
Liveable area (m2)	1,213	183.50	71.87	47.25	135.00	170.00	212.00	550.00
Number of bedrooms	1,224	3.06	1.05	0	3	3	4	6
Number of bathrooms	1,224	1.09	0.48	0	1	1	1	4
EPC score	1,224	463.07	243.99	26	285.5	424	591.2	1,678
Age	1,042	58.25	31.15	0	38	54	71	118

Table 10: Houses sold, with available EPC score
Sold 6 months before labels introduction

Statistic	N	Mean	St. Dev.
Detached building	1,224	0.41	0.49
Semi-detached building	1,224	0.30	0.46
Garden available	1,224	0.69	0.46
Roof insulation	1,224	0.50	0.50
Cavity insulation	1,224	0.13	0.34
Single-pane glass	1,224	0.27	0.45
Gas (as heating material)	1,224	0.66	0.47
Label A+	1,224	0.00	0.00
Label A	1,224	0.01	0.09
Label B	1,224	0.11	0.31
Label C	1,224	0.17	0.37
Label D	1,224	0.18	0.38
Label E	1,224	0.16	0.37
Label F	1,224	0.38	0.48
Sold in 2018	1,224	1.00	0.00

Table 11: Houses sold, with available EPC score
6 months after labels introduction

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Selling price	1,310	267,665.10	114,876.00	80,800	190,000	244,500	320,000	810,000
Initial asking price	1,310	287,178.10	124,914.30	85,000	199,500	260,000	348,000	950,000
Liveable area (m2)	1,301	182.87	69.99	50.00	138.00	169.00	211.00	590.00
Number of bedrooms	1,310	3.01	1.08	0	3	3	4	6
Number of bathrooms	1,310	1.08	0.48	0	1	1	1	4
EPC score	1,310	456.07	245.43	6	282	414	583	2,039
Age	1,101	59.97	32.42	0	40	55	73	119

Table 12: Houses sold, with available EPC score
6 months after labels introduction

Statistic	N	Mean	St. Dev.
Detached building	1,310	0.39	0.49
Semi-detached building	1,310	0.28	0.45
Garden available	1,310	0.69	0.46
Roof insulation	1,308	0.50	0.50
Cavity insulation	1,308	0.11	0.32
Single-pane glass	1,309	0.29	0.45
Gas (as heating material)	1,309	0.67	0.47
Label A+	1,310	0.00	0.00
Label A	1,310	0.01	0.11
Label B	1,310	0.11	0.31
Label C	1,310	0.16	0.37
Label D	1,310	0.18	0.39
Label E	1,310	0.16	0.37
Label F	1,310	0.37	0.48
Sold in 2019	1,310	1.00	0.00

Table 13: Summary statistics of the EPC scores

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
EPC score	27,003	475.69	238.78	1	300	441	604	3,721

Table 14: Summary statistics of the estimated EPC scores

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Estimated EPC score	34,679	482.78	179.15	0.35	356.33	483.35	605.93	1,315.01

Table 15: Regression discontinuity, 1 november 2008
window of 6 months

	Dependent variable:			
	Selling price (log)			
	(1)	(2)	(3)	(4)
Epc estimate (log)	-0.426^{***}	-0.188^{***}	-0.185^{***}	-0.202^{***}
	(0.035)	(0.031)	(0.031)	(0.026)
Epc estimate (log) × epc implementation dummy	0.085^{*}	0.020	0.019	0.019
	(0.050)	(0.032)	(0.032)	(0.027)
Constant	14.899^{***}	8.449^{***}	8.317^{***}	10.875^{***}
	(0.219)	(0.496)	(0.503)	(0.452)
Post 01 Nov 2008 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	1,518	1,518	1,518	1,518
R^2	0.137	0.684	0.685	0.789
Adjusted R^2	0.135	0.668	0.667	0.773
Residual Std. Error	0.336 (df = 1514)	0.208 (df = 1445)	0.209 (df = 1435)	0.172 (df = 1414)
F Statistic	80.145^{***} (df = 3; 1514)	43.348^{***} (df = 72; 1445)	37.982^{***} (df = 82; 1435)	51.200^{***} (df = 103; 1414)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 16: Regression discontinuity, 1 november 2008
window of 6 months

	Dependent variable:			
	Initial asking price (log)			
	(1)	(2)	(3)	(4)
Epc estimate (log)	-0.425^{***}	-0.171^{***}	-0.176^{***}	-0.212^{***}
	(0.040)	(0.039)	(0.040)	(0.038)
Epc estimate (log) $\times$ epc implementation dummy	0.126^{**}	0.069^{*}	0.072^{*}	0.073^{*}
	(0.057)	(0.041)	(0.041)	(0.039)
Constant	15.001^{***}	9.308^{***}	8.915^{***}	10.988^{***}
	(0.251)	(0.637)	(0.646)	(0.654)
Post 01 Nov 2008 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	1,518	1,518	1,518	1,518
R^2	0.099	0.583	0.584	0.645
Adjusted R^2	0.097	0.562	0.560	0.619
Residual Std. Error	0.384 (df = 1514)	0.267 (df = 1445)	0.268 (df = 1435)	0.249 (df = 1414)
F Statistic	55.604^{***} (df = 3; 1514)	28.038^{***} (df = 72; 1445)	24.535^{***} (df = 82; 1435)	24.974^{***} (df = 103; 1414)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 17: Regression discontinuity, 1 november 2008
window of 6 months

	Dependent variable:			
	Days on market (log)			
	(1)	(2)	(3)	(4)
Epc estimate (log)	−0.029	0.185	0.164	0.242
	(0.108)	(0.150)	(0.152)	(0.154)
Epc estimate (log) × epc implementation dummy	0.194	0.214	0.196	0.199
	(0.155)	(0.157)	(0.158)	(0.157)
Constant	4.226***	7.421***	6.000**	7.520***
	(0.680)	(2.444)	(2.464)	(2.661)
Post 01 Nov 2008 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	1,514	1,514	1,514	1,514
R^2	0.008	0.082	0.094	0.123
Adjusted R^2	0.006	0.036	0.042	0.059
Residual Std. Error	1.041 (df = 1510)	1.025 (df = 1441)	1.022 (df = 1431)	1.013 (df = 1410)
F Statistic	3.955*** (df = 3; 1510)	1.790*** (df = 72; 1441)	1.812*** (df = 82; 1431)	1.926*** (df = 103; 1410)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: Regression discontinuity, 1 january 2019
window of 6 months

	Dependent variable:			
	Selling price (log)			
	(1)	(2)	(3)	(4)
Epc (log)	-0.289^{***}	-0.124^{***}	-0.124^{***}	-0.108^{***}
	(0.019)	(0.016)	(0.016)	(0.013)
Epc score (log) × label implementation dummy	-0.019	-0.021	-0.019	-0.016
	(0.026)	(0.018)	(0.018)	(0.014)
Constant	14.141^{***}	6.917^{***}	7.067^{***}	11.002^{***}
	(0.116)	(0.463)	(0.468)	(0.432)
Post 01/01/2019 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	2,534	2,035	2,035	2,035
R^2	0.172	0.687	0.689	0.859
Adjusted R^2	0.171	0.675	0.675	0.832
Residual Std. Error	0.366 (df = 2530)	0.221 (df = 1960)	0.221 (df = 1950)	0.159 (df = 1703)
F Statistic	175.691^{***} (df = 3; 2530)	58.014^{***} (df = 74; 1960)	51.402^{***} (df = 84; 1950)	31.379^{***} (df = 331; 1703)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 19: Regression discontinuity, 1 january 2019
window of 6 months

	Dependent variable:			
	Initial asking price (log)			
	(1)	(2)	(3)	(4)
Epc (log)	-0.261^{***}	-0.099^{***}	-0.099^{***}	-0.087^{***}
	(0.019)	(0.016)	(0.016)	(0.013)
Epc score (log) × label implementation dummy	-0.017	-0.027	-0.025	-0.024
	(0.026)	(0.018)	(0.018)	(0.014)
Constant	14.046^{***}	7.042^{***}	7.240^{***}	10.991^{***}
	(0.115)	(0.459)	(0.464)	(0.445)
Post 01/01/2019 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	2,534	2,035	2,035	2,035
R^2	0.147	0.684	0.685	0.846
Adjusted R^2	0.146	0.672	0.672	0.816
Residual Std. Error	0.364 (df = 2530)	0.219 (df = 1960)	0.219 (df = 1950)	0.164 (df = 1703)
F Statistic	144.877^{***} (df = 3; 2530)	57.263^{***} (df = 74; 1960)	50.594^{***} (df = 84; 1950)	28.319^{***} (df = 331; 1703)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 20: Regression discontinuity, 1 january 2019
window of 6 months

	Dependent variable:			
	Days on market			
	(1)	(2)	(3)	(4)
Epc (log)	0.155***	0.280***	0.278***	0.221***
	(0.048)	(0.065)	(0.065)	(0.068)
Epc score (log) × label implementation dummy	−0.054	−0.067	−0.073	−0.053
	(0.065)	(0.072)	(0.072)	(0.075)
Constant	3.294***	3.705**	4.189**	5.420**
	(0.288)	(1.830)	(1.851)	(2.304)
Post 01/01/2019 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	2,526	2,027	2,027	2,027
R^2	0.006	0.099	0.105	0.265
Adjusted R^2	0.005	0.065	0.066	0.122
Residual Std. Error	0.911 (df = 2522)	0.871 (df = 1952)	0.871 (df = 1942)	0.844 (df = 1695)
F Statistic	5.230*** (df = 3; 2522)	2.908*** (df = 74; 1952)	2.700*** (df = 84; 1942)	1.850*** (df = 331; 1695)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: Regression discontinuity, 1 january 2019, window of 6 months

	Dependent variable:			
	Selling price (log)			
	(1)	(2)	(3)	(4)
Label A	0.066	0.072	0.070	0.077
	(0.115)	(0.083)	(0.083)	(0.070)
Label C	−0.074*	−0.002	−0.003	−0.003
	(0.041)	(0.029)	(0.029)	(0.022)
Label D	−0.121***	−0.014	−0.016	−0.024
	(0.040)	(0.029)	(0.029)	(0.023)
Label E	−0.232***	−0.090***	−0.090***	−0.097***
	(0.041)	(0.030)	(0.030)	(0.023)
Label F	−0.426***	−0.141***	−0.143***	−0.129***
	(0.036)	(0.029)	(0.029)	(0.022)
Label A × label implementation dummy	0.186	−0.030	−0.033	0.010
	(0.148)	(0.104)	(0.104)	(0.086)
Label C × label implementation dummy	0.029	−0.006	−0.001	−0.039
	(0.057)	(0.038)	(0.038)	(0.029)
Label D × label implementation dummy	−0.120**	−0.048	−0.043	−0.066**
	(0.056)	(0.038)	(0.038)	(0.029)
Label E × label implementation dummy	−0.079	−0.034	−0.029	−0.018
	(0.057)	(0.039)	(0.039)	(0.030)
Label F × label implementation dummy	−0.008	−0.047	−0.041	−0.050*
	(0.050)	(0.034)	(0.034)	(0.026)
Constant	12.638***	6.338***	6.410***	10.375***
	(0.032)	(0.456)	(0.456)	(0.425)
Post 01 Jan 2019 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	2,534	2,035	2,035	2,035
R^2	0.176	0.688	0.690	0.860
Adjusted R^2	0.172	0.675	0.676	0.832
Residual Std. Error	0.366 (df = 2522)	0.221 (df = 1952)	0.221 (df = 1942)	0.159 (df = 1695)
F Statistic	48.986*** (df = 11; 2522)	52.443*** (df = 82; 1952)	47.048*** (df = 92; 1942)	30.715*** (df = 339; 1695)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 22: Regression discontinuity, 1 january 2019, window of 6 months

	Dependent variable:			
	Initial asking price (log)			
	(1)	(2)	(3)	(4)
Label A	0.023	0.071	0.068	0.077
	(0.114)	(0.082)	(0.082)	(0.072)
Label C	−0.079*	−0.006	−0.005	−0.008
	(0.041)	(0.028)	(0.028)	(0.023)
Label D	−0.109***	−0.002	−0.002	−0.010
	(0.040)	(0.029)	(0.029)	(0.023)
Label E	−0.219***	−0.071**	−0.069**	−0.080***
	(0.041)	(0.030)	(0.030)	(0.024)
Label F	−0.394***	−0.110***	−0.111***	−0.102***
	(0.036)	(0.029)	(0.029)	(0.023)
Label A × label implementation dummy	0.176	−0.078	−0.084	−0.039
	(0.147)	(0.103)	(0.103)	(0.089)
Label C × label implementation dummy	0.046	0.001	0.003	−0.029
	(0.056)	(0.038)	(0.038)	(0.030)
Label D × label implementation dummy	−0.118**	−0.056	−0.051	−0.074**
	(0.055)	(0.037)	(0.037)	(0.030)
Label E × label implementation dummy	−0.060	−0.034	−0.032	−0.020
	(0.057)	(0.038)	(0.038)	(0.031)
Label F × label implementation dummy	0.006	−0.052	−0.049	−0.057**
	(0.050)	(0.034)	(0.034)	(0.027)
Constant	12.698***	6.584***	6.668***	10.428***
	(0.032)	(0.451)	(0.452)	(0.438)
Post 01 Jan 2019 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	2,534	2,035	2,035	2,035
R^2	0.151	0.685	0.687	0.847
Adjusted R^2	0.148	0.671	0.672	0.816
Residual Std. Error	0.364 (df = 2522)	0.219 (df = 1952)	0.219 (df = 1942)	0.164 (df = 1695)
F Statistic	40.851*** (df = 11; 2522)	51.699*** (df = 82; 1952)	46.263*** (df = 92; 1942)	27.636*** (df = 339; 1695)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 23: Regression discontinuity, 1 january 2019, window of 6 months

	Dependent variable:			
	Days on market (log)			
	(1)	(2)	(3)	(4)
Label A	−0.106	0.010	0.003	0.055
	(0.286)	(0.327)	(0.328)	(0.371)
Label C	0.019	0.041	0.058	0.061
	(0.102)	(0.113)	(0.114)	(0.118)
Label D	0.179*	0.236**	0.240**	0.270**
	(0.100)	(0.115)	(0.116)	(0.120)
Label E	0.157	0.296**	0.305**	0.224*
	(0.102)	(0.120)	(0.120)	(0.125)
Label F	0.198**	0.359***	0.362***	0.309***
	(0.090)	(0.114)	(0.114)	(0.119)
Label A × label implementation dummy	−0.032	−0.112	−0.117	−0.174
	(0.370)	(0.411)	(0.412)	(0.459)
Label C × label implementation dummy	0.041	0.004	−0.009	−0.029
	(0.142)	(0.150)	(0.151)	(0.157)
Label D × label implementation dummy	−0.171	−0.162	−0.171	−0.240
	(0.139)	(0.149)	(0.150)	(0.155)
Label E × label implementation dummy	−0.023	−0.054	−0.078	−0.027
	(0.143)	(0.153)	(0.154)	(0.159)
Label F × label implementation dummy	−0.052	−0.105	−0.119	−0.105
	(0.126)	(0.135)	(0.136)	(0.140)
Constant	4.089***	5.175***	5.284***	6.411***
	(0.079)	(1.802)	(1.808)	(2.268)
Post 01 Jan 2019 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	2,526	2,027	2,027	2,027
R^2	0.007	0.099	0.104	0.266
Adjusted R^2	0.002	0.061	0.061	0.119
Residual Std. Error	0.912 (df = 2514)	0.873 (df = 1944)	0.873 (df = 1934)	0.846 (df = 1687)
F Statistic	1.509 (df = 11; 2514)	2.605*** (df = 82; 1944)	2.438*** (df = 92; 1934)	1.807*** (df = 339; 1687)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 24: Regression discontinuity, 1 november 2008
window of 6 months

	Dependent variable:			
	Selling price (log)			
	(1)	(2)	(3)	(4)
Estimated label A	0.115	0.139	0.135	0.162
	(0.351)	(0.221)	(0.221)	(0.184)
Estimated label C	−0.411***	−0.102	−0.100	−0.117*
	(0.130)	(0.083)	(0.083)	(0.069)
Estimated label D	−0.321**	−0.038	−0.037	−0.077
	(0.126)	(0.081)	(0.081)	(0.068)
Estimated label E	−0.470***	−0.048	−0.044	−0.088
	(0.123)	(0.080)	(0.080)	(0.067)
Estimated label F	−0.685***	−0.166**	−0.161**	−0.199***
	(0.121)	(0.080)	(0.080)	(0.067)
Estimated label A × epc implementation dummy				
Estimated label C × epc implementation dummy	0.412**	−0.012	−0.012	−0.022
	(0.167)	(0.107)	(0.107)	(0.089)
Estimated label D × epc implementation dummy	0.290*	0.019	0.018	0.042
	(0.158)	(0.100)	(0.100)	(0.083)
Estimated label E × epc implementation dummy	0.300*	−0.070	−0.071	−0.043
	(0.154)	(0.097)	(0.098)	(0.081)
Estimated label F × epc implementation dummy	0.414***	0.041	0.040	0.047
	(0.151)	(0.095)	(0.096)	(0.079)
Constant	12.806***	7.403***	7.385***	9.833***
	(0.120)	(0.470)	(0.468)	(0.426)
Post 01 Nov 2008 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	1,518	1,518	1,518	1,518
R^2	0.120	0.686	0.687	0.789
Adjusted R^2	0.114	0.668	0.667	0.773
Residual Std. Error	0.340 (df = 1507)	0.208 (df = 1438)	0.208 (df = 1428)	0.172 (df = 1407)
F Statistic	20.570*** (df = 10; 1507)	39.711*** (df = 79; 1438)	35.177*** (df = 89; 1428)	47.901*** (df = 110; 1407)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 25: Regression discontinuity, 1 november 2008
window of 6 months

	Dependent variable:			
	Initial asking price (log)			
	(1)	(2)	(3)	(4)
Estimated label A	0.086	0.149	0.142	0.161
	(0.398)	(0.282)	(0.283)	(0.264)
Estimated label C	-0.366^{**}	-0.053	-0.050	-0.079
	(0.147)	(0.105)	(0.106)	(0.099)
Estimated label D	-0.258^{*}	0.028	0.028	-0.024
	(0.143)	(0.103)	(0.104)	(0.097)
Estimated label E	-0.418^{***}	0.010	0.010	-0.054
	(0.140)	(0.102)	(0.103)	(0.096)
Estimated label F	-0.649^{***}	-0.133	-0.135	-0.198^{**}
	(0.137)	(0.102)	(0.103)	(0.096)
Estimated label A $\times$ epc implementation dummy				
Estimated label C $\times$ epc implementation dummy	0.367^{*}	-0.084	-0.080	-0.085
	(0.189)	(0.136)	(0.137)	(0.128)
Estimated label D $\times$ epc implementation dummy	0.243	-0.049	-0.046	-0.031
	(0.179)	(0.128)	(0.128)	(0.120)
Estimated label E $\times$ epc implementation dummy	0.276	-0.115	-0.111	-0.087
	(0.174)	(0.124)	(0.125)	(0.117)
Estimated label F $\times$ epc implementation dummy	0.418^{**}	0.034	0.039	0.049
	(0.171)	(0.122)	(0.122)	(0.114)
Constant	12.877^{***}	8.320^{***}	8.354^{***}	10.212^{***}
	(0.136)	(0.600)	(0.598)	(0.612)
Post 01 Nov 2008 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	1,518	1,518	1,518	1,518
R^2	0.096	0.590	0.591	0.651
Adjusted R^2	0.090	0.568	0.566	0.624
Residual Std. Error	0.386 (df = 1507)	0.266 (df = 1438)	0.266 (df = 1428)	0.248 (df = 1407)
F Statistic	15.926^{***} (df = 10; 1507)	26.247^{***} (df = 79; 1438)	23.199^{***} (df = 89; 1428)	23.863^{***} (df = 110; 1407)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 26: Regression discontinuity, 1 november 2008
window of 6 months

	Dependent variable:			
	Days on market (log)			
	(1)	(2)	(3)	(4)
Estimated label A	−0.018	0.480	0.478	0.385
	(1.072)	(1.084)	(1.083)	(1.077)
Estimated label C	−0.180	0.046	0.011	0.042
	(0.395)	(0.406)	(0.405)	(0.404)
Estimated label D	−0.208	−0.032	−0.085	−0.042
	(0.385)	(0.398)	(0.397)	(0.396)
Estimated label E	−0.129	0.065	0.0001	0.068
	(0.376)	(0.394)	(0.393)	(0.393)
Estimated label F	−0.186	0.060	−0.008	0.073
	(0.370)	(0.393)	(0.393)	(0.393)
Estimated label A × epc implementation dummy				
Estimated label C × epc implementation dummy	−0.666	-0.999^{*}	-0.998^{*}	-1.035^{**}
	(0.509)	(0.524)	(0.523)	(0.522)
Estimated label D × epc implementation dummy	−0.289	−0.552	−0.516	−0.528
	(0.482)	(0.491)	(0.490)	(0.488)
Estimated label E × epc implementation dummy	−0.032	−0.245	−0.255	−0.307
	(0.470)	(0.478)	(0.478)	(0.476)
Estimated label F × epc implementation dummy	−0.127	−0.341	−0.331	−0.357
	(0.460)	(0.469)	(0.468)	(0.466)
Constant	4.216^{***}	8.727^{***}	8.821^{***}	10.723^{***}
	(0.367)	(2.313)	(2.292)	(2.502)
Post 01 Nov 2008 dummy	X	X		
Housing characteristics		X	X	X
Month dummies			X	X
Location dummies				X
Observations	1,514	1,514	1,514	1,514
R^2	0.018	0.091	0.103	0.131
Adjusted R^2	0.011	0.041	0.047	0.062
Residual Std. Error	1.038 (df = 1503)	1.022 (df = 1434)	1.019 (df = 1424)	1.011 (df = 1403)
F Statistic	2.699^{***} (df = 10; 1503)	1.825^{***} (df = 79; 1434)	1.834^{***} (df = 89; 1424)	1.917^{***} (df = 110; 1403)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 27: Regression discontinuity, 1 november 2008
window of 6 months

	Dependent variable:	
	Selling price (log)	
	(1)	(4)
Semi-detached housing	−0.038	0.046
	(0.044)	(0.028)
Interaction variable	−0.004	0.007
	(0.064)	(0.035)
Detached housing	0.313^{***}	0.121^{***}
	(0.036)	(0.033)
Interaction variable	−0.032	0.010
	(0.052)	(0.031)
Liveable area (log m2)	0.712^{***}	0.298^{***}
	(0.047)	(0.041)
Interaction variable	-0.157^{**}	−0.040
	(0.064)	(0.045)
Single-pane glass	-0.241^{***}	−0.031
	(0.038)	(0.023)
Interaction variable	0.0245	−0.003
	(0.054)	(0.030)
Roof insulation	0.236^{***}	0.025
	(0.038)	(0.022)
Interaction variable	-0.130^{**}	-0.050^{*}
	(0.054)	(0.030)
Central heating	0.377^{***}	0.086^{***}
	(0.041)	(0.025)
Interaction variable	−0.089	0.008
	(0.061)	(0.033)
Gas (as heating material)	−0.061	0.050^{**}
	(0.039)	(0.023)
Interaction variable	−0.046	−0.046
	(0.055)	(0.030)
Electricity (as heating material)	−0.035	−0.073
	(0.081)	(0.047)
Interaction variable	0.021	0.039
	(0.105)	(0.060)
Post 01 Nov 2008 dummy	X	
Housing characteristics		X
Month dummies		X
Location dummies		X
Observations	639	639
Note:	*p<0.1; **p<0.05; ***p<0.01	