Price Discrimination in the Residential Housing Sector:

Evidence from Green Buildings

Carolin Pommeranz* **Bertram I. Steininger***

January 15, 2017

Abstract

We analyze whether higher energy efficiency labels of residential apartments are associated with higher rental price premiums that landlords may use for price discrimination in the German rental housing market. Pricing strategies include (1) the self-selection of tenants by choosing the apartment with their preferred efficiency label and (2) the grouping of tenants according to local market segments. We use an extensive dataset including information on structural, neighborhood, and locational characteristics as well as maintenance costs. Results from spatial regression models indicate that rental price premiums are obtained for high efficient and discounts for less efficient apartments, but premiums are significantly larger in rather hot market segments. This indicates that property sellers are able to transfer more consumer surplus within hot market segments due to their empowered position.

JEL classification: Q48, Q51, R31

Keywords: energy efficiency, price discrimination, residential housing

*Carolin Pommeranz and Bertram I. Steininger are in the Institute of Real Estate Finance, RWTH Aachen University, Templergraben 64, 52056 Aachen, Germany. The authors can be contacted via e-mail: pommeranz@immo.rwth-aachen.de and steininger@immo.rwth-aachen.de.

Acknowledgements: The authors thank the Immobilien Scout GmbH, GfK Geomarketing, and Verivox GmbH for providing the dataset for this study and comments on results.

This research project is financed by the Ministry of Innovation, Science and Research (MIWF) of North Rhine-Westphalia as part of the competence center "Verbraucherforschung NRW" (KVF NRW). The KVF NRW is a cooperation project of the MIWF, the "Verbraucherzentrale Nordrhein-Westfalen e.V.", and the Ministry of Climate Protection, Environment, Agriculture, Conservation and Consumer Affairs (MKULNV) of North Rhine-Westphalia.

1. Introduction

Real estate literature has already shown that there is a significant price premium for energy-efficient buildings (Cajias and Piazolo, 2013; Chegut et al., 2013, Eichholtz et al., 2010; Kok and Jennen, 2012). Consumers are willing to pay a higher rental price for a higher energy efficiency, especially when they are environmentally aware. This premium can even be higher than the pure energy savings resulting from investment incentives that are not monetarily motivated. Fuerst et al. (2016) prove the existence of such a premium for energy efficiency that goes beyond the purely monetary consequences. They suggest that energy efficiency results in intangible and indirect benefits for consumers and green buildings have a 'signaling value'. Bond and Devine (2016) confirm the strength of the certification signal by identifying an additional premium over non-certified apartments. They argue that there are social status benefits from signaling to act environmentally aware. This is an additional incentive to invest into energy-efficient buildings for so-called 'green' consumers. However, the amount of this premium is not economically justified and varies on the individual awareness of each household. This can provide a significant incentive for landlords to take advantage of this varying willingness to pay in their pricing strategy.

When landlords rent out apartments regardless of the energy efficiency label at the same price, they restrict rental prices to a point where some tenants are willing to pay more for an increased efficiency quality.[1] However, landlords are interested in renting out their properties at the highest possible price and in order to increase their profits, they charge different rental price premiums for apartments with different energy efficiency labels.[2] This is called **price discrimination** and a well-known concept in microeconomics used to describe monopolistic pricing strategies mostly for consumer goods and services (e.g. Bergemann et al. (2015)). Transferred to the residential housing market, consumers experience heterogeneous utilities from energy efficiency labels and therefore have different price elasticities of demand. When potential tenants have different valuations for energy efficiency labels or when there are different groups of tenants with the same price elasticities, price discrimination allows landlords to exploit these differences by extracting consumer surplus and hence to raise their profits. The degree to which landlords can extract consumer surplus depends on the information available on tenants preferences. The extreme case being **first-degree price discrimination** in which landlords know the preferences regarding energy efficiency of each tenant and can extract the entire consumer surplus. However, this case of perfect price discrimination almost never occurs.

Landlords mostly know that they face potential tenants with a different willingness to pay for higher efficiency labels, but it is not always clear who is who. Having information on the individual willingness to pay of each tenant, landlords would be able to charge tenants, who are environmentally aware, a higher premium for a better energy efficiency label. In order to solve this problem, different

[1] Assuming that apartments are totally equal in their remaining characteristics. We ensure this by using a hedonic regression model.

[2] This is only possible because landlords have some degree of monopolistic power within housing markets and can set prices independently.

apartments with varying efficiency labels are offered in residential housing markets and tenants then self-select into different pricing categories by choosing the apartment with their preferred efficiency class. This is called **second-degree price discrimination** or **self-selection price discrimination**. With this pricing strategy, however, landlords are not able to extract the entire consumer surplus.

Furthermore, the willingness to pay for a higher energy efficiency label varies depending on the characteristics of the respective local housing market. In literature, housing market segments are separated to account for varying renting conditions since similar absolute cost savings or other benefits connected with higher energy efficiency may have a different relative impact on rental prices (Fuerst et al., 2015). Local market segments can either be identified by time, e.g. to account for periods with financial constraints, or by region to account for differences in urban and rural areas (Hyland et al., 2013), for differences in low and high pricing segments (Fuerst et al., 2015), and for differences in market liquidity measured by the time a building is offered on the market (Brounen and Kok, 2011). A common finding is that the importance of energy efficiency as a housing characteristic is higher in segments with difficult selling conditions and less competition. Thus, we distinguish between local housing markets in a rather hot or cold condition. Areas with hot housing markets are defined if a sufficient supply with affordable living space within a region or parts of a region cannot be guaranteed. This may particularly be the case if rents rise significantly faster than the national average, the average rent burden of households significantly exceeds the national average, the population is growing without necessary living space created by new construction activity or low vacancy rates are observed while demand is high (Chernobai and Hossain, 2012; Krainer, 2001; Novy-Marx, 2009). In hot housing markets, tenants are less price-sensitive and have a higher willingness to pay because the general demand for suitable living space is significantly higher. This makes their demand more inelastic and landlords can use this to charge a higher premium for energy efficiency labels. The price segregation based on grouping of tenants according to local market segments is referred to as **third-degree price discrimination**. With this pricing strategy, however, landlords are again not able to extract the entire consumer surplus.

This study analyzes whether higher energy efficiency labels are associated with higher rental price premiums that landlords may use for price discrimination in order to increase their profits. We use an extensive dataset containing information on neighborhood and structural characteristics as well as information on the energy costs that allows us to distinguish between energy cost savings and non-monetary benefits associated with the energy label. We assume that there are different pricing strategies of landlords including the self-selection of tenants by choosing the apartment with their preferred efficiency label and the grouping of tenants according to local market segments. Thus, we run hedonic regression models for the combined sample and for separated local market segments, respectively, to identify the specific rental price premiums for efficiency ratings. Price premiums can then be used to extract consumer surplus from environmentally aware consumers who ascribe a higher value to ‘being green’.

Energy efficiency labels of residential buildings provide optimal conditions for being used as differentiating criterions for price discrimination. Beside the environmental awareness of tenants, landlords make use of the fact that tenants are not always able to fully understand the energy certification and thus, partially overstate resulting monetary and indirect benefits.[3] Energy efficiency labels are a relatively new policy instrument to create higher transparency within residential housing markets with regard to energy characteristics of homes aiming to support the identification and exploitation of savings potentials within the housing sector. Brounen and Kok (2011) assume that landlords use energy labels as a strategic tool to reduce the issue of prevailing asymmetric information during the decision-making process of tenants and to accelerate the renting process. If landlords anticipate that the willingness to pay of tenants is based on an information criterion that is misunderstood or overstated, they take advantage of tenants' awareness and charge overpriced premiums for high efficiency labels and further extract consumer surplus. There is a potential risk of leaving no surplus to tenants that must be evaluated in order to determine measures to strengthen the position of tenants within the rental-process. If there is no surplus left to tenants, this can also result in a general loss of welfare effects.

Some studies conclude that incentives that are not related to energy cost savings might help to close the existing energy efficiency gap (Cajias et al., 2016; Fuerst et al., 2016). The building sector plays a key role in achieving energy goals. Within Germany, residential buildings account for approximately 35% of the total energy consumption and thus, provide a great energy savings potential. Around 70% of the approximately 18 million residential buildings were constructed before 1979 and thus, mostly lack current efficiency standards. Since a higher energy efficiency is assumed to be beneficial for the environment and the economy, policy makers recently focused on the implementation of regulations to decrease the emission of greenhouse gases from the building stock. Since 2008, the measurement of energy consumption has been mandatory in Germany due to the introduction of the EU Energy Performance of Buildings Directive (2010/31/EU). As an example for how policy changes can affect rental price premiums for the efficiency certificate, we analyze how the premiums for a high energy efficiency label changed after the introduction of obligation to disclose the energy efficiency information within property advertisements. Thus, we also provide insights in policy interventions and give recommendations on future policy changes in order to strengthen the position of tenants.

This study is structured as follows: The second section theoretically discusses potential forms of price discrimination related to the green efficiency labels in the residential housing market. Thereafter, a detailed description of the dataset and descriptive statistics is given followed by an introduction of the empirical model in the fourth section. Results are discussed in the fifth section and a robustness check including a liquidity model is presented in section six. Finally, we conclude by giving recommendations for future policy adaption regarding energy certification in the residential housing market.

[3] The individual perception of environmental awareness must be evaluated using survey techniques that are not part of this study.

2. A Conceptual Model for Price Discrimination and Green Buildings

Price discrimination is defined as the pricing strategy to charge different prices for equivalent consumer goods or services. This concept is based on microeconomics and used to describe the pricing strategies of monopolistic firms, e.g. in the car market (Goldberg and Verboven, 2001; Verboven, 1996). We transfer this pricing strategy to the residential housing market and analyze whether there are rental price premiums for energy efficiency labels occurring that landlords use for extracting consumer surplus.

Price discrimination is based on the assumption that consumers experience heterogeneous benefits from the difference in energy efficiency labels and have different price elasticities of demand. If this is the case, profits from separating the markets are greater than profits from keeping the markets combined. By separating the housing market into different segments according to the price elasticities of tenants, landlords can extract consumer surplus and hence raise their profits. Consumers with a relatively inelastic demand are charged a higher price, whereas those with a relatively elastic demand are charged a lower price. Landlords must have some degree of monopolistic power within residential housing markets in order to make price discrimination more effective and they must be able to control the renting process; by separating tenants into distinct markets, e.g. based on their willingness to pay or on regional housing market conditions, they must prevent the re-renting of the apartments from consumers with an elastic demand in one market to those with an inelastic demand in another market.

Within the residential housing market, we assume that there are two different forms of price discrimination related to energy efficiency occurring. Both relate to the pure price effect of the energy label that is not economically justified by energy cost savings. First, we assume that landlords price-discriminate potential tenants by offering apartments with different efficiency ratings since they anticipate a variation in the willingness to pay for green labels based on individual green awareness. Second, landlords group consumers according to local housing market conditions since the price sensitivity of potential tenants varies with the demand for affordable living space in the specific market segment.

2.1. Second-Degree Price Discrimination: Self-Selection of Tenants

Landlords are interested in renting out their apartments at the highest possible price. The optimal pricing policy for landlords dealing with different groups of consumers is to offer a high quality apartment to the high-willingness-to-pay market at a high price and a reduced quality apartment to the consumers with a lower willingness to pay. Thus, the landlord needs to know the demand curves and the exact willingness to pay of each tenant. Even if the landlord is aware of the statistical distribution of the willingness to pay within the market, individuals may pretend to have a lower willingness to pay than they really have as they anticipate a price discount. Thus, there is no effective way to tell different consumer groups apart. However, landlords can offer different price-quality packages in the market, whereas one package is targeted to the high-end consumer and the other to the low-end consumer and thus, give the consumer an incentive to self-select. While landlords specifically encourage self-selection by adjusting the quality of their buildings, separation based on quality characteristics is brought into the market by differentiating between the energy efficiency labels. When landlords discriminate potential consumers by separating consumer groups with different demand elasticities and adapting the quality of the offered apartment to consumers' individual preferred attributes, this is known as **the second-degree** or **self-selection price discrimination**. Second-degree price discrimination is typically used to explain differences in airfares between business and tourist travelers within the airline market (Giaume and Guillou, 2004; Stavins, 2001).

Figure 1 illustrates second-degree price discrimination for apartments with different energy labels assuming constant marginal costs.[4] If a single rental price premium is charged, it would be p_0 and the offered quantity of energy efficient buildings would be q_0. Instead, three different premiums are charged based on the energy efficiency label of the respective apartment assuming all other attributes to be identical. The first block includes apartments with a good efficiency label that are rented out for a premium p_1, the second block includes apartments with a medium efficiency label that are rented out at a premium of p_2, and the third block with units rated to be less efficient that are rented out at a premium of p_3.

2.2. Third-Degree Price Discrimination: Local Market Segregation

Depending on the prevailing housing market conditions, price premiums for equivalent quality characteristics of apartments can be higher or lower. Thus, the question arises how landlords determine the optimal premiums to charge in each local market segment. In hot housing markets, landlords have high market power because of tenants' higher demand resulting in a generally greater willingness to pay. This higher willingness to pay is anticipated by landlords and gives them considerably freedom in setting prices. Thus, the optimal pricing policy for landlords with high market power is to rent out labeled apartments at a higher premium to the high-willingness-to-pay market segment. However, they must be able to separate the high-demand market and the more price sensitive low-demand market. Price discrimination in cold housing markets becomes more difficult due to the better market position of consumers. This pricing strategy is also referred to as **third-degree price discrimination** (Bergemann et al., 2015). Third-degree price discrimination is a practice of charging different rental price premiums to different consumers for the same quality of energy efficiency label. In third-degree price discrimination, landlords identify separable market segments, each of which possesses its own demand for high energy efficiency labels. Landlords then set a rental price premium for each segment in accordance with that segment's demand elasticity. Other examples for this type of price discrimination include discounts for students and senior citizens in public transportation or museums, theatres etc.

[4] Marginal costs in out model for energy efficiency in the rental housing market are assumed to be costs for the labeling of a building. We assume that marginal costs are constant for each building so that we abstract from economies of scale that are usually anticipated within microeconomics.

Figure 2 illustrates the separation of the housing market according to local market conditions. Consumers are divided into two groups with separate demand curves for hot housing markets and cold housing markets. The optimal price premiums and quantities are identified when the marginal revenue equals the marginal costs for each market segment, respectively. Consumers in cold housing markets with an elastic demand curve $D_{cold\ market}$ are charged a rental price premium $p^*_{cold\ market}$ for an apartment that is labeled to be highly efficient, whereas consumers in hot markets are charged a relatively higher price premium $p^*_{hot\ market}$ based on their more inelastic demand curve $D_{hot\ market}$. Marginal costs are again assumed to be constant.

3. Data and Descriptive Statistics

This study is based on a dataset containing apartment offerings in North Rhine-Westphalia (NRW) from 2011-2015. NRW is the most densely populated federal state in Germany with about 18 million inhabitants and thus, a highly urbanized area that is of industrial and economic importance for whole Europe. The building sector is particularly important for the whole country since at least two of the seven German major cities are located in NRW.[5] The dataset only includes rental apartments since apartments are the dominant housing type within the study area and are more homogeneous in their characteristics compared to other housing types (Statistisches Bundesamt, 2017).[6] Moreover, rental apartments are occupied on shorter horizons and have a higher turnover resulting in a greater accessibility to potential tenants (Bond and Devine, 2016). This is especially important since building or renovating green homes is highly expensive and the existing green housing stock is limited so that only a few buildings are available for resale, making the transaction of a green property more complicated (Bond and Devine, 2015). Environmentally aware households can more easily invest into green rental apartments by simply signing a lease. Furthermore, asking rents respond more dynamically to changes in market situations than existing rents, as changes in rent levels are more flexible to realize when tenants change and during first-time rentals, rents are oriented to market conditions (BBSR, 2017).

We use a detailed and extensive rental apartment dataset provided by the private online platform Immobilienscout24. The data include all rental apartment offerings made by using the online service during the sample period. This amounts to around 80% of all rental apartment offerings within the study area within that time period. The dataset is filtered for duplicates, which are identified when the gap time between different offerings is shorter than 12 month. This results in 350,539 observations included in our analysis. The dataset contains information on typical hedonic characteristics just like apartment size, number of rooms, age and quality. Table 1 presents the included characteristics and descriptive statistics.

[5] This is more than every other German federal state has (on average one or no city of major importance).
[6] The homeownership rate in NRW amounts to 42%.

The distribution of energy efficiency labels in our dataset is representative for the whole German residential housing market, indicating that 1.4% of the apartments included are certified as A^+, 2.2% as A, and 8.3% as B. Thus, only a share of 11% of our sample is rated in the highest efficiency classes, providing evidence that a higher than average energy efficiency label is rather hard to obtain. Environmentally aware tenants usually target apartments rated within these high efficient categories. Most apartments are rated in the medium categories C, D or E, whereas the most common rating is D including 23% of all apartments. The introduction of the 2014 Energy Saving Ordinance has strengthened the role of energy efficiency certificates during the searching period especially due to the expansion of the display obligation. Landlords are required to display key efficiency numbers including the energy consumption, energy source (e.g. oil, gas) for heating, and the heating type within an advertisement. Efficiency labels obtained after May 01, 2014 are also required to display the efficiency class in letters.[7] Landlords, who offer an apartment with an older certification, are required to calculate the class from the consumption value or to just state the consumption value. Exemptions are only made for not commercially announced advertisements or if the advertisement is placed in a point of time where there is no certification available for this specific apartment.

Furthermore, energy costs on zip code level depending on the type of the individual heating system installed in the apartments are used in order to observe the intangible or indirect price effect for the efficiency label.[8] Within the German housing market, tenants pay a monthly fee for energy costs directly to the energy provider. This fee is excluded from other maintenance costs for cleaning service, refuse disposal and administration that are directly charged by the landlord. This makes it easier to control for energy costs. Data on average energy costs are provided for different energy sources including gas, electricity, oil, heat pump and district heat on zip code level. The individual energy consumption is then calculated based on the individual heating type and energy consumption value.

We also merge the dataset based on geographic coordinates of the apartment location with neighborhood characteristics on zip code level containing information on the respective socioeconomic and housing structure.[9] This includes information on average household income, household structure, purchasing power, unemployment rate, and migration rate. Within our study area, neighborhoods can extremely vary in their characteristics on a very small scale and thus, we include the data on zip-code level that is the finest scale available. The relevant impact of including detailed neighborhood characteristics in a hedonic analysis is also underlined in various studies (e.g. Rosen (1974)).

Figure 3 presents the spatial distribution of apartments included in our dataset according to the energy efficiency classes. However, there is no obvious difference in the spatial distribution of high and low energy efficient apartments.

[7] In the German classification system, letters for energy certification are ranging from A+ for the highest efficiency to H for the lowest efficiency level.
[8] Data on energy costs is provided by the Verivox GmbH.
[9] Socioeconomic data is provided by GfK GeoMarketing GmbH.

We account for availability by estimating distances between apartment locations and infrastructural amenities. We use a geographic information system in order to estimate distances in kilometers and travel time, including especially the distance to the nearest park, nearest motorway, nearest education or health facility. Since these infrastructural amenities can affect the valuation of a building and the rental prices that are charged from tenants. Especially accounting for the geographic proximity to amenities that are connected to the environment support the estimation of the pure labeling effect of the energy efficiency certificate.[10]

We also analyze whether there are differences in rental price premiums in different housing market segments based on the varying willingness to pay of tenants. Housing markets in Germany are extremely diverse. Even on a small scale level, including neighboring locations and housing sections, there are significant differences in housing demand and supply, which are accordingly reflected in rental prices. The population development and employment, selective migration, different residential construction activity and a diverse compositions of the housing stock result in a variation of local housing market conditions. Because of the major rental price increase especially within metropolitan areas based on a higher demand due to job positions, educational institutions or infrastructural amenities, a separated analysis becomes necessary. We separate our dataset into five different segments ranging from rather cold housing markets to hot housing markets using a median house price index. Apartments are allocated to be in a specific housing segment if the average increase in rental prices on zip code level is higher compared to the 20th, 40th, 60th, and 80th percentile of the average increase in rental prices in the full sample.

4. Estimation Strategy

For analyzing the impact of residential energy efficiency labels on rental prices, we use a hedonic estimation equation building on the initial work of. Hedonic estimation methods have been used extensively in green environmental and sustainability literature as an instrument to use market prices for determining the willingness to pay of consumers for nonmarket characteristics and thus this method is advantageous over other approaches. The hedonic regression model is based on the idea that different rental prices represent tenants' valuation of different bundles of apartment attributes. Apartments can be described as composite goods with a variety of attributes, and hedonic modelling analyzes how rental prices change as the level of specific attributes change, e.g. the energy efficiency quality, holding all other characteristics constant. This allows us to estimate the marginal willingness to pay for each apartment characteristic, respectively.

Since apartments tend to be clustered in space, spatial dependency among observations in direct geographical proximity is likely to occur. Neighboring apartments are assumed to share various locational, structural, and also socioeconomic characteristics, including average income, ethnicity, or neighborhood quality. Thus, the literature suggests different econometric models that account for

[10] Data is obtained from OpenStreetMap and analyzed using ArcGis.

unobserved spatial characteristics. There are different forms of spatial dependency occurring in property analysis including a spatial lag of the dependent variable, of the explanatory variables, and of the error term. If spatial dependency is ignored in dependent and/or explanatory variables, estimated coefficients will be biased and inconsistent, while neglecting spatial dependence in error terms will result in a loss of efficiency (Anselin and Bera, 1998). To account for spatial dependency within our dataset, we extent the conventional hedonic regression model and use a more advanced spatial Durbin error model (SDEM). The SDEM takes two different sources of spatial dependencies into account, a spatial lag in the explanatory variables and in the error terms (Elhorst, 2010). This model specification is also supported by Lagrange Multiplier (LM) test statistics, likelihood ratio (LR) tests, and different information criteria (AIC and BIC). While the LM test statistics and LR tests identify the source of occurrence of spatial dependency, the AIC and BIC provide a descriptive measure of the overall performance of the model and also take model complexity into account. The SDEM is also preferred since it reaches the highest explanatory power.

We use a spatial weight matrix to control for time-invariant unobserved neighborhood effects that can also be correlated with the efficiency label. For generating this matrix, we use an inverse-distance based *k nearest neighbor* approach and assume that various properties in direct proximity are identified as a relevant property cluster. The adjustment of the spatial weight matrix is based on our assessment of the geographic extent that may share unobserved characteristics resulting in spatial dependency. We have tested a variation of specifications of the spatial weight matrix and results remain to be robust across those variations. We also include quarterly time dummies in order to account for time variations in rental price levels. We estimate the hedonic SDEM using the maximum likelihood method as shown in Equation 1.

$$\begin{gathered} \ln(p_i) = \sum_i \gamma_i E_i + \beta_i X_i + \boldsymbol{W}(X_i + E_i) + \mu_i \\ \mu_i = \lambda \boldsymbol{W} \mu_i + \epsilon_i \end{gathered} \tag{1}$$

where $ln(p_i)$ is the natural logarithm of the rental price of apartment i, X_i is a set of structural, neighborhood and locational variables, E_i is the variable for the energy efficiency label, W is the spatial weight matrix, and μ_i is a vector of independent and identically distributed random error terms. The parameter λ indicates the spatial dependency occurring in the error terms. Coefficients of the SDEM can be interpreted directly as marginal effects (LeSage, 2008). Since the dependent variable is in natural logarithm, coefficients are interpreted as percentages.

To analyze whether rental price effects have changed due to the introduction of the display obligation within advertisements in May 01, 2014, we use a quasi-experimental approach and conduct a spatial differences-in-differences model. Using this model, we are able to obtain casual relationships within the estimation process and control for endogenous impacts or omitted variable biases (Bertrand et al., 2004; Parmeter and Pope, 2013). We define the regulation update in May 01, 2014 as the exogenous change event and compare changes within the treatment group of apartments, which is identified when apartments are offered before the policy change, with changes in the control group including apartments that are offered after the event. For differentiating between rental apartments that are offered before and after the policy change, we use an interaction term that incorporates the energy efficiency label and a binary variable that is equal to 1 if the apartment is offered after the policy change, and 0 otherwise. The SDEM including the differences-in-differences approach is described in Equation 2.

$$\begin{gathered} ln(p_i) = \sum_i \gamma_i E_i + \delta_i T_i \sum_i \eta_i (E_i \times T_i) + \beta_i X_i + \boldsymbol{W}(E_i + T_i + X_i) + \mu_i \\ \mu_i = \lambda \boldsymbol{W} \mu_i + \epsilon_i \end{gathered} \tag{2}$$

where variable descriptions are identical to those mentioned above and T_i is the binary time variable indicating if an apartment is offered before or after the policy change. The interaction incorporating the energy efficiency label and the binary time variable is identified in the term $(E_i \times T_i)$ and provides the coefficients of interest that are interpreted as the marginal change of rental price effects after the event occurs. The parameter λ again indicates the spatial dependency occurring in the error terms.

5. Results

Table 3 presents the results of the spatial model conducted for different model specifications. Since we estimate the pure price effect resulting from the energy efficiency label, further interpretation is based on model (4). The inclusion of maintenance costs has only a marginal impact on the estimated coefficients. Results for Moran's I indicate that there is no spatial correlation left in the dataset. We use an inverse-distance, k-nearest neighbors approach that determines seven properties in direct geographical proximity as a property cluster for defining the spatial weight matrix. Coefficients for structural, neighborhood and locational characteristics have the expected signs and are statistically significant. In model (4), we include maintenance costs including energy costs within our model specification. Results provide evidence that landlords assume a significant higher willingness to pay for apartments that are labeled to be highly energy efficient beside the monetary benefits. Tenants, who are environmentally aware, are assumed to pay a premium of 11.8% for an A^+ labeled apartment, 6.3% for label A, and for label B a premium of 4.3%, whereas D is the reference category. For the medium categories C and E, there is no significant price premium compared to category D. For the lowest label categories F, G and H, there are small discounts of 1.3%, 1.2%, and 2%, respectively.

Reasons for a rental price premium that go beyond the energy costs savings can be identified in consumers, who are environmentally aware and rent an above average labeled apartment, and increase the demand for such apartments. Furthermore, tenants may anticipate a future increase in energy costs. However, landlords anticipate this differentiated willingness to pay and charge high premiums for good energy efficiency labels in order to maximize their profits.

In order to analyze whether there are differences in rental price effects for different regional housing market segments that landlords may use for price discrimination, we separate the dataset into 5 housing market segments according to the yearly average increase in rental prices. Table 5 presents the results, whereas model (1) describes the coldest housing market segment and model (5) the hottest segment. Results indicate that in market segments with a rather hot market, there tends to be a higher price premium for higher labeled apartments. Discounts for a lower efficiency label do not tend into one special direction across market segments. However, the demand for apartments is higher in hot market segments due to working possibilities and infrastructural amenities. Tenants are assumed to be more environmentally aware and thus, pay a premium for energy efficiency even if prices are in general high. Those tenants also invest more into efficient homes that are also an indicator for luxury goods to show-off to the outside that they are aware of environmental impacts and act sustainable. Investors anticipate this behavior and request higher rental price premiums for a good efficiency label as a desirable apartment characteristic. Furthermore, they see the potential for skimming consumer surplus that is larger in hot market segments compared to a cold segments. In rather cold housing market segments, tenants have more market power, so that landlords have to adapt offering rents to the demand side. This is also shown in the estimated price effects: For higher efficiency classes, there is a significant price premium, but it is less high compared to the premium obtained in the hot market. However, price discounts for less efficient homes are exceeding the ones obtained in the hot market.

Policy changes can increase the transparency of the energy efficiency certificate and support tenants in making an informed decision for an energy efficient apartment. Based on an information source that is easy to understand, tenants' position can be strengthened during the rental-process. To underline the impact of external policy changes on dealing with the energy efficiency label by tenants, we analyze whether there is a change in premiums for the energy efficiency label after the introduction of the display obligation within advertisements in May 01, 2014. Thus, we differentiate between rental apartments that are offered before and after the policy change and use an interaction term that incorporates the energy efficiency label and a binary variable that is equal to 1 if the apartment is offered after the policy change, and 0 otherwise. Table 5 presents the estimated results. Pricing impacts in all efficiency classes increase, while rental price premiums for the highest efficiency labels A^{+}, A, and B increase most by xx%, xx%, and xx% respectively. Thus, landlords use the mandatory information in the rental process in order to adequately account for the energy efficiency label and maximize their benefit.

6. Robustness Check

We also determine if there is a higher demand and thus, a higher willingness to pay for apartments with a better energy efficiency label by measuring the liquidity of these units.[11] To estimate the liquidity of a highly rated apartment as an additional incentive for landlords to offer highly efficient apartments, we implement a parametric proportional cox hazard model, where the response variable is the time an apartment is offered on the market in weeks. Thus, it is assumed that the shorter the time on market, the higher the demand for this apartment. Survival methods have been rarely used within green housing literature. The survival model includes the hedonic housing characteristics used within the decision-making process of tenants[12] and especially information on the quality of the energy efficiency label. The survival model estimates the elasticity of the time on market with respect to energy efficiency categories (Cajias et al., 2016). Survival models can be estimated using the survivor function or the hazard rate function. While the survivor function estimates the probability of each observation of surviving the event in dependence of the time elapsed, the hazard rate function estimates the rate of occurrence per unit of time of an event. For interpretability, we compute hazard ratios by exponentiating the parameter estimates. The estimated coefficients represent the change in the expected log of the hazard ratio relative to a one unit change in the independent variable, holding all other variables constant (Cajias et al., 2016). The inclusion of maintenance costs has again only a marginal impact on the estimated coefficients. Since there are tenants who are environmentally aware and are only interested in apartments with a good energy label and are willing to pay a premium for this characteristic, a higher efficiency label is expected to speed up the renting process. On the other hand, landlords may overestimate the willingness to pay for a high efficiency label and have to subsequently lower their required green premium. This would also lower the liquidity of highly efficient apartments.

Table 5 presents the results for the same model specifications as used in the rental price approach. We define the reference category in this model to be label A^+. All coefficients for low energy efficiency labels in model (4) are below one and statistically significant indicating that this characteristic decreases the risk of being withdrawn from the market and thus, increases the survival time on the market.[13] This indicates a longer time on market for less efficient apartments compared to highly efficient units, referring to a higher demand for highly efficient units. More precisely, estimation results indicate that low efficient apartments are longer on the market compared to less efficient apartments. Hazard ratios for efficiency classes G and H suggest that apartments are 0.908 (10%) and 0.913 (11%) times more likely to have a shorter survival time compared to apartments in class A^+, *ceteris paribus*.

[11] Demand and willingness to pay of tenants can only be directly measured using surveys.

[12] Those characteristics where also used within the rental price regression in table 4.

[13] Coefficients of a cox hazard model cannot be interpreted as those in OLS regression models since they estimate the survival time as a probability function.

7. Conclusion

The importance of energy efficiency labels increases since policy holders are focusing more on a sustainable development of the residential housing sector in order to fulfil the energy goals. However, it is not clear whether landlords exploit tenants' environmental awareness in order to extract consumer surplus and maximize their benefit. Extracting all consumer surplus can also result in a loss of welfare effects and is negatively associated for all stakeholders of the residential housing market. In this study, we analyze whether higher energy efficiency labels are associated with higher rental price premiums that landlords may use for price discrimination of tenants. We assume that there are different pricing strategies of landlords including the self-selection of tenants by choosing the apartment with their preferred efficiency label and the grouping of tenants according to local market segments. Results indicate that there are significant price premiums for highly rated apartments and discounts for apartments with a low efficiency label. Price premiums for a high efficiency certificate are slightly larger in local market segments in rather hot conditions while there are no significant differences in the discounts for low efficiency labels. Landlords require an extra premium in hot market segments since their bargaining power is high and thus, they assume that tenants are in general willing a pay more for an otherwise similar apartment. They raise rental premiums beyond the pure economic benefits of a higher efficiency label and take advantage of tenants' inferior market position in order to increase their profits. The determination of the degree of price discrimination and tenants' price elasticities is not part of this study and open for further research.

Since the energy certificate is a rather new instrument for increasing the transparency of energy related characteristics within the housing market, tenants are sometimes not able to fully understand the information about resulting benefits. However, the policy change in May 01, 2014 results in tightened price premiums for highly efficient buildings. These results can support future policy implications in adapting regulations to specific market conditions and support tenants during the rental process.

8. References

Anselin, L., Bera, A.K., 1998. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. Statistics Textbooks and Monographs 155, 237–290.

BBSR, 2017. Mieten und Preise: Wohnimmobilien. http://www.bbsr.bund.de/BBSR/DE/WohnenImmobilien/Immobilienmarktbeobachtung/ProjekteFachbeitraege/MietenPreise/Mieten/Mieten.html. Accessed 15 January 2017.

Bergemann, D., Brooks, B., Morris, S., 2015. The limits of price discrimination. The American Economic Review 105 (3), 921–957.

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Quaterly Journal of Economics (119(1)), 249–275.

Bond, S.A., Devine, A., 2016. Certification matters: Is green talk cheap talk? The Journal of Real Estate Finance and Economics 52 (2), 117–140.

Brounen, D., Kok, N., 2011. On the economics of energy labels in the housing market. Journal of Environmental Economics and Management 62 (2), 166–179.

Cajias, M., Fuerst, F., Bienert, S., 2016. Are energy efficiency ratings ignored in the German housing market? Evidence from a large-sample hedonic study. Working Paper.

Cajias, M., Piazolo, D., 2013. Green performs better: Energy efficiency and financial return on buildings. Journal of Corporate Real Estate 15 (1), 53–72.

Chegut, A., Eichholtz, P., Kok, N., 2013. Supply, demand and the value of green buildings. Urban Studies, 0042098013484526.

Chernobai, E., Hossain, T., 2012. House search duration in hot and cold residential markets. Real Estate Economics 40 (4), 809–841.

Eichholtz, P., Kok, N., Quigley, J.M., 2010. Doing well by doing good? Green office buildings. The American Economic Review 100 (5), 2492–2509.

Elhorst, J.P., 2010. Applied spatial econometrics: Raising the bar. Spatial Economic Analysis 5 (1), 9–28.

Fuerst, F., McAllister, P., Nanda, A., Wyatt, P., 2015. Does energy efficiency matter to home-buyers? An investigation of EPC ratings and transaction prices in England. Energy Economics 48, 145–156.

Fuerst, F., Oikarinen, E., Harjunen, O., 2016. Green signalling effects in the market for energy-efficient residential buildings. Applied Energy 180, 560–571.

Giaume, S., Guillou, S., 2004. Price discrimination and concentration in European airline markets. Journal of Air Transport Management 10 (5), 305–310.

Goldberg, P.K., Verboven, F., 2001. The evolution of price dispersion in the European car market. The Review of Economic Studies 68 (4), 811–848.

Hyland, M., Lyons, R.C., Lyons, S., 2013. The value of domestic building energy efficiency - Evidence from Ireland. Energy Economics 40, 943–952.

Kok, N., Jennen, M., 2012. The impact of energy labels and accessibility on office rents. Energy Policy 46, 489–497.

Krainer, J., 2001. A theory of liquidity in residential real estate markets. Journal of Urban Economics 49 (1), 32–53.

LeSage, J.P., 2008. An introduction to spatial econometrics. Revue d'économie industrielle (3), 19–44.

Novy-Marx, R., 2009. Hot and cold markets. Real Estate Economics 37 (1), 1–22.

Parmeter, C.F., Pope, J.C., 2013. Quasi-experiments and hedonic property value methods, UK.

Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. Journal of Political Economy 82 (1), 34–55.

Statistisches Bundesamt, 2017. Eigentümerquote nach Bundesländern im Zeitvergleich. https://www.destatis.de/DE/ZahlenFakten/GesellschaftStaat/EinkommenKonsumLebensbedingungen/Wohnen/Tabellen/EntwicklungEigentuemerquote.html. Accessed 15 January 2017.

Stavins, J., 2001. Price discrimination in the airline market: The effect of market concentration. Review of Economics and Statistics 83 (1), 200–202.

Verboven, F., 1996. International price discrimination in the European car market. The RAND Journal of Economics, 240–268.

Figure 1.

Second-degree price discrimination

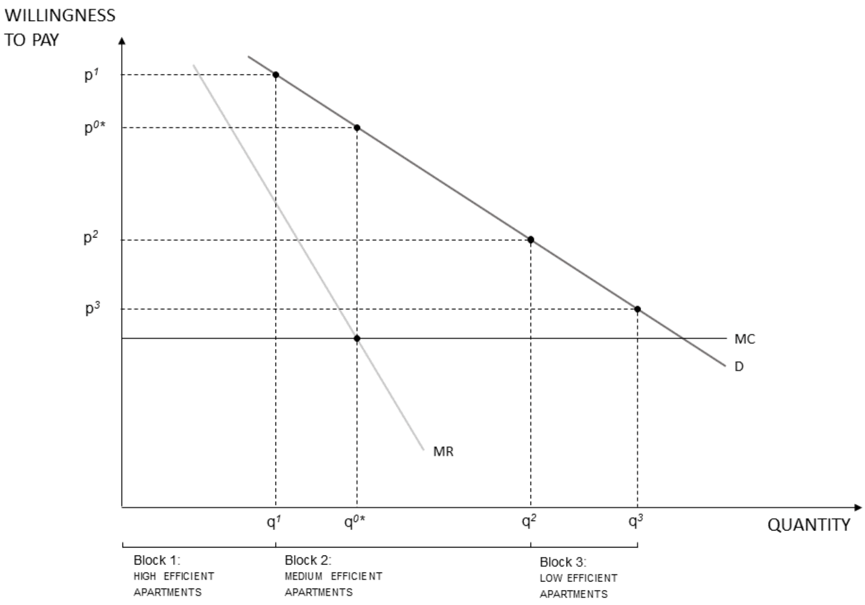


Figure 2.

Third-degree price discrimination

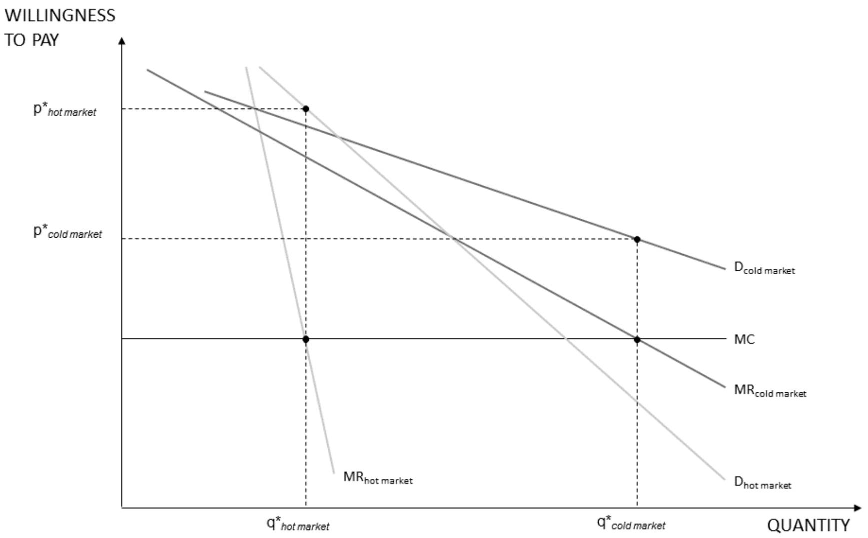
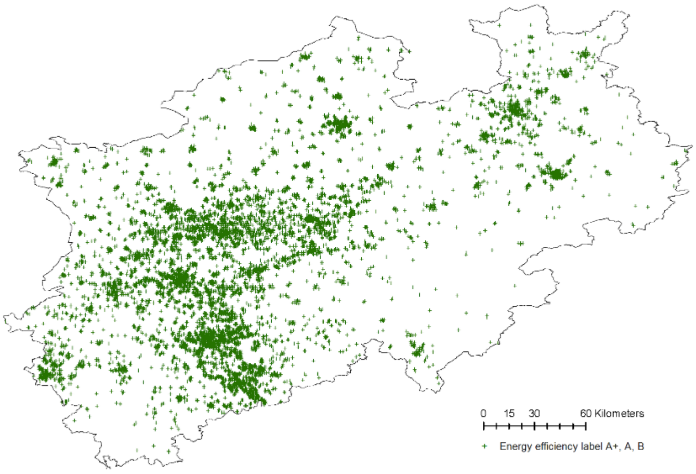
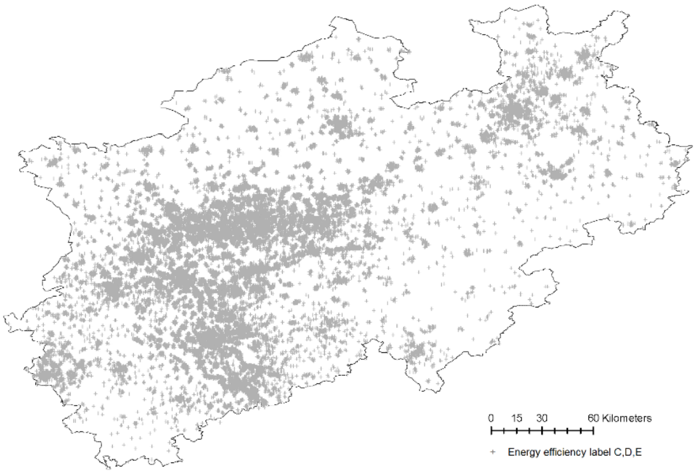


Figure 3.

Spatial distribution of apartments included in our dataset





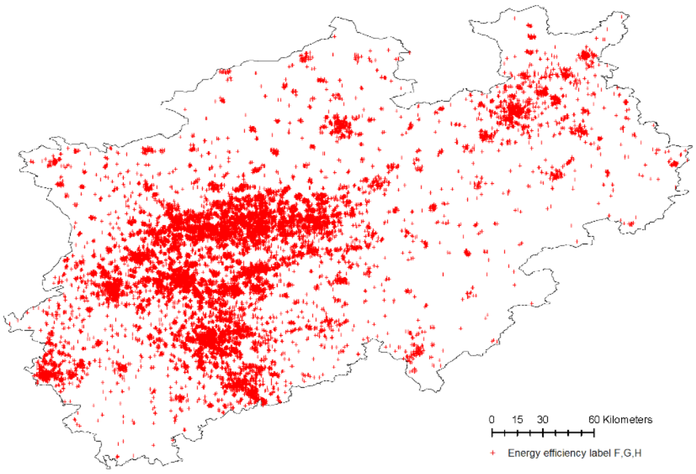


Table 1

Descriptive Statistics

	Mean	Std. dev.	Min	Max
Rental price (€/m^2/month)	6.87	2.23	1	43.1
Time on market (weeks)	4.90	8.50	0.14	364.57
Maintenance costs (€/m^2/month)	2.03	0.74	0.00	31.25
with energy costs (€/m^2/month)	2.98	0.85	0.08	32.06
Energy label (percent)				
A^+	0.01	0.12	0	1
A	0.02	0.15	0	1
B	0.08	0.28	0	1
C	0.14	0.35	0	1
D	0.23	0.42	0	1
E	0.22	0.42	0	1
F	0.18	0.38	0	1
G	0.08	0.26	0	1
H	0.03	0.17	0	1
Structural characteristics				
Living area (m^2)	71.11	25.24	9	470
Number of rooms	2.66	0.88	1	14
Floor	1.84	1.48	-1	41
Age[A]	47.42	25.91	-1	116
Quality (percent)				
Luxury	0.02	0.13	0	1
Good	0.24	0.42	0	1
Normal	0.74	0.44	0	1
Simple	0.01	0.09	0	1

Notes: [A]Also building developments are included that will be finished one year after the study period.

Table 2

Estimation results for maintenance costs

All Sample	
Energy label	
A^+	-0.308***
	[0.00496]
A	-0.226***
	[0.00340]
B	-0.140***
	[0.00179]
C	-0.0653***
	[0.00134]
E	0.0719***
	[0.00109]
F	0.153***
	[0.00115]
G	0.245***
	[0.00146]
H	0.381***
	[0.00240]
N	350,539
Adj. R^2	0.369
Year quarter fixed effects	Yes
Postal code fixed effects	Yes
Structural characteristics	Yes
Neighborhood characteristics	Yes
Locational characteristics	Yes

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Dependent variable is the natural logarithm of maintenance costs per square meter and month (€/m^2/month).

Table 3

Estimation results for rental price

All Sample	(1)	(2)	(3)	(4)
Energy label				
A^{+}	0.102***	0.107***	0.108***	0.118***
	[0.00296]	[0.00274]	[0.00273]	[0.00276]
A	0.0512***	0.0548***	0.0556***	0.0633***
	[0.00230]	[0.00212]	[0.00213]	[0.00214]
B	0.0381***	0.0378***	0.0381***	0.0430***
	[0.00127]	[0.00117]	[0.00117]	[0.00118]
C	0.00424***	0.00685***	0.00691***	0.00935***
	[0.000952]	[0.000868]	[0.000867]	[0.000874]
E	-0.000141	0.00127	0.00101	-0.00151*
	[0.000796]	[0.000730]	[0.000730]	[0.000736]
F	-0.00864***	-0.00689***	-0.00736***	-0.0128***
	[0.000852]	[0.000779]	[0.000779]	[0.000804]
G	-0.00297**	-0.00291**	-0.00368***	-0.0124***
	[0.00115]	[0.00104]	[0.00105]	[0.00109]
H	-0.00708***	-0.00504**	-0.00557***	-0.0197***
	[0.00171]	[0.00160]	[0.00160]	[0.00167]
Log(maintenance costs without energy/m2)			0.0131***	
			[0.00124]	
Log(maintenance costs with energy/m2)				0.0386***
				[0.00138]
N	350,539	350,539	350,539	350,539
Adj. R^2	0.694	0.744	0.744	0.745
λ	.474	.478	.463	.478
Log Likelihood	70,893	71,398	69,983	70,935
AIC	-283235.7	-345880.3	-346461.6	-347054.7
BIC	-282255.9	-344620.6	-345191.0	-345784.1
Residuals Moran's I	-0.034	-0.036	-0.029	-0.036
Year quarter fixed effects	Yes	Yes	Yes	Yes
Structural characteristics	Yes	Yes	Yes	Yes
Neighborhood characteristics		Yes	Yes	Yes
Locational characteristics		Yes	Yes	Yes
Maintenance costs (without energy)			Yes	
Maintenance costs (with energy)				Yes

Notes: * p<0.05, ** p<0.01, *** p<0.001. Dependent variable is the natural logarithm of rental price per square meter per month (€/m^2/month).

Table 4

Estimation results for market separation

Market segments	(1)	(2)	(3)	(4)	(5)
Energy label					
A^+	0.117***	0.134***	0.111***	0.0962***	0.134***
	[0.00594]	[0.00716]	[0.00657]	[0.00576]	[0.00545]
A	0.0483***	0.0602***	0.0622***	0.0736***	0.0716***
	[0.00521]	[0.00515]	[0.00492]	[0.00460]	[0.00399]
B	0.0340***	0.0309***	0.0447***	0.0439***	0.0555***
	[0.00268]	[0.00246]	[0.00262]	[0.00276]	[0.00260]
C	-0.000176	0.0115***	0.00870***	0.0126***	0.0176***
	[0.00186]	[0.00186]	[0.00197]	[0.00201]	[0.00197]
E	0.000371	-0.000101	-0.00113	-0.00127	-0.00421*
	[0.00159]	[0.00162]	[0.00157]	[0.00164]	[0.00177]
F	-0.00820***	-0.0108***	-0.0113***	-0.0162***	-0.0144***
	[0.00172]	[0.00173]	[0.00176]	[0.00179]	[0.00194]
G	-0.0108***	-0.0107***	-0.0112***	-0.0212***	-0.00490
	[0.00234]	[0.00234]	[0.00236]	[0.00245]	[0.00266]
H	-0.00918**	-0.0255***	-0.0200***	-0.0264***	-0.0201***
	[0.00346]	[0.00335]	[0.00416]	[0.00377]	[0.00390]
Log(maintenance costs with energy/m2)	0.0198***	0.0362***	0.0292***	0.0362***	0.0623***
	[0.00283]	[0.00300]	[0.00316]	[0.00339]	[0.00297]
N	70,986	68,754	69,276	69,518	70,533
Adj. R^2	0.690	0.759	0.734	0.752	0.762
λ	0.583	0.581	0.602	0.615	0.601
Log Likelihood	73,173	74,328	73,196	74,684	74,529
AIC	-73866.1	-74882.1	-72093.1	-71472.7	-64621.4
BIC	-72784.0	-73803.8	-71013.9	-70393.1	-63540.1
Residuals Moran's I	-0.033	-0.031	-0.022	-0.035	-0.024
Year quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Structural characteristics	Yes	Yes	Yes	Yes	Yes
Neighborhood characteristics	Yes	Yes	Yes	Yes	Yes
Locational characteristics	Yes	Yes	Yes	Yes	Yes
Maintenance costs (with energy)	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.05, ** p<0.01, *** p<0.001. Dependent variable is the natural logarithm of rental price per square meter per month (€/m^2/month).

Table 5

Estimation results after policy change (differences-in-differences)

All Sample	(1)	(2)	(3)	(4)
Energy label				
A^+	0.0974*** [0.00554]	0.104*** [0.00510]	0.106*** [0.00510]	0.117*** [0.00510]
A	0.0167*** [0.00410]	0.0185*** [0.00374]	0.0204*** [0.00376]	0.0295*** [0.00378]
B	0.0185*** [0.00216]	0.0179*** [0.00195]	0.0185*** [0.00195]	0.0241*** [0.00196]
C	0.000599 [0.00182]	0.00446** [0.00166]	0.00473** [0.00166]	0.00754*** [0.00166]
E	-0.00156 [0.00167]	-0.00415** [0.00153]	-0.00424** [0.00153]	-0.00688*** [0.00153]
F	-0.00875*** [0.00187]	-0.0109*** [0.00169]	-0.0112*** [0.00169]	-0.0167*** [0.00170]
G	0.00781** [0.00283]	-0.000270 [0.00251]	-0.000846 [0.00251]	-0.00963*** [0.00253]
H	-0.0109* [0.00528]	-0.0139** [0.00488]	-0.0146** [0.00487]	-0.0289*** [0.00489]
Interaction terms with time dummy				
A^+	0.00699 [0.00642]	0.00380 [0.00592]	0.00307 [0.00591]	0.00138 [0.00588]
A	0.0465*** [0.00475]	0.0488*** [0.00435]	0.0473*** [0.00436]	0.0453*** [0.00436]
B	0.0278*** [0.00257]	0.0279*** [0.00232]	0.0276*** [0.00232]	0.0265*** [0.00232]
C	0.00495* [0.00212]	0.00310 [0.00194]	0.00283 [0.00193]	0.00226 [0.00193]
E	0.00195 [0.00189]	0.00714*** [0.00173]	0.00692*** [0.00173]	0.00709*** [0.00173]
F	0.000389 [0.00208]	0.00542** [0.00189]	0.00520** [0.00189]	0.00536** [0.00189]
G	-0.0126*** [0.00307]	-0.00263 [0.00274]	-0.00287 [0.00274]	-0.00262 [0.00274]
H	0.00493 [0.00556]	0.0111* [0.00515]	0.0111* [0.00514]	0.0115* [0.00513]
Time dummy (rented after 05/2014)	-0.00631* [0.00314]	-0.00808** [0.00284]	-0.00776** [0.00284]	-0.00779** [0.00284]
Log(maintenance costs without energy/m2)			0.0130*** [0.00124]	
Log(maintenance costs with energy/m2)				0.0381*** [0.00138]
N	350,539	350,539	350,539	350,539
Adj. R^2	0.694	0.744	0.745	0.745
λ	0.583	0.581	0.602	0.605
Log Likelihood	74,133	76,365	73,613	71,079
AIC	-283,503.2	-346157.1	-346,728.9	-347,301.8
BIC	-282,426.5	-344800.4	-345,361.5	-345,934.4
Residuals Moran's I	-0.033	-0.031	-0.022	-0.025
Year quarter fixed effects	Yes	Yes	Yes	Yes
Structural characteristics	Yes	Yes	Yes	Yes
Neighborhood characteristics		Yes	Yes	Yes
Locational characteristics		Yes	Yes	Yes
Maintenance costs (without energy)			Yes	
Maintenance costs (with energy)				Yes

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Dependent variable is the natural logarithm of rental price per square meter (€/m^2).

Table 6

Estimation results for market liquidity

All Sample	
Energy label	
A^+	1.042 [.0615]
A	1.082 [.0214]
B	0.982 [.0043]
C	1.027* [.0023]
E	0.947 [.0011]
F	0.982 [.0612]
G	0.908*** [.0013]
H	0.913*** [.0011]
Log(maintenance costs with energy/m2)	0.532*** [.0013]
N	350,539
Pseudo-R^2	0.64
Year quarter fixed effects	Yes
Postal code fixed effects	Yes
Structural characteristics	Yes
Neighborhood characteristics	Yes
Locational characteristics	Yes
Maintenance costs (with energy)	Yes

Notes: * p<0.05, ** p<0.01, *** p<0.001.