Clean Electricity, Dirty Electricity: The Effect on Local House Prices

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Abstract

We study the external effects of large-scale conventional and renewable electric power generation facilities on local house prices. We compare coal, gas, biomass and wind power, combining information on all power plants and wind turbines in the Netherlands with house price data from 2.3 million housing transactions, covering a period of 30 years. Using a hedonic, difference-in-difference, and repeated sales model to explain price effects, we document negative external price effects for gas plants and wind turbines, but positive effects for biomass plants, conditionally upon an ex-ante lower priced location. These external effects of power generating facilities on local housing markets are important to consider, especially with the current focus of public policies on the expansion of renewable energy generation.

Keywords: Renewable energy, energy policy, externalities, wind power, coal plants, housing markets, residential real estate

JEL codes: O13, Q42, Q43, Q51, R31, R52

1 Introduction

Electricity consumption in the European Union is set to increase by 0.5 to 1 percent per year between 2015 and 2030 (European Commission, 2013). To reliably handle this energy demand, a large fraction of electricity is currently generated by coal and gas-fired power plants, which leads to significant environmental externalities. However, there is a strong desire among policy makers to become less dependent on fossil fuels, and to decrease carbon emissions from power generation, mostly through the increasing use of renewable energy sources. In Europe, the European Commission passed its Europe 2020 strategy, which binds all E.U. member states to reduce greenhouse gas emissions by 20 percent and to increase the share of renewable electricity production to 20 percent by the year 2020. Over the past years, the share of renewable electricity production in the EU-28 increased from 12.6 percent in 2003 to 22.4 percent in 2014 (European Commission, 2015, 2016; Eurostat, 2015b, 2015a). But, this average comes with significant variation across individual member states, putting pressure on some countries to more rapidly increase their share of renewables. Whether renewable (or ”green”) electricity generation is a superior solution to conventional generation is a multi-dimensional question that involves a comprehensive cost-benefit analysis regarding electricity prices and production costs, available capacity, and environmental aspects. In order to compare the total costs of different types of electricity production, externalities should also be incorporated in the calculations, in addition to direct costs (Ayres & Kneese, 1969; Roth & Ambs, 2004). Besides global environmental externalities, local effects of power generation on public health, as well as the effects of noise and sight for the nearby population are important to consider. Local externalities often lead to popular opposition when governments consider expanding renewable electricity generation (Breukers & Wolsink, 2007; Wolsink, 2000, 2007; Wüstenhagen et al., 2007). However, EU member states have initiated a multitude of national policies to increase the share of renewable energy, often ignoring these local externalities. In this paper, we analyze the local external effects of electricity-generating facilities on local housing markets, in order to determine the costs of different types of electricity generation for local home owners. We address a comparability problem, since the current literature is mostly limited to studies focusing on the external effects of a single type of electricity generation (typically nuclear or wind) or the general effect of power plants, not distinguishing between the type of generation. Furthermore, existing studies often analyze just a few power plants at the time, use different and incomparable analytical tools, or employ asking prices rather than transaction prices to assess effects on local house prices (Blomquist, 1974; Clark et al., 1997; Davis, 2011; Dröes & Koster, 2016; Gamble & Downing, 1982; Gibbons, 2015; Heintzelman & Tuttle, 2012; Lang & Opaluch, 2013; Sunak & Madlener, 2016). Moreover, the literature mostly employs hedonic models, neglecting endogeneity in power plant location choices. It is therefore difficult to draw a coherent conclusion about the relative effects of different types of electricity generation on local housing markets. This paper fills the research lacuna by analyzing the external effect of conventional power plants (coal and gas) and renewable power plants (wind and biomass) on local housing prices, employing a comparable analytical framework within similar housing markets, and using an extensive, longitudinal dataset of actual transaction prices. We focus on simple proximity effects as well as on opening and closing effects of different energy generation types, comparing different estimation models and examining the importance of ex-ante location controls. In any study of externalities and house prices, endogeneity is a critical issue in properly identifying effects. In our analysis, an endogeneity problem arises from the fact that placement decisions of power plants and wind turbines depend on factors like available infrastructure and local politics, but also on land values. Since electricity production requires significant space, land prices are a considerable factor in setup costs. Land value is also determining house prices, so it could be argued that land values and house prices in affected areas are likely to already be lower before the placement of a power plant or wind turbine. This leads to an identification problem that is often neglected in the existing literature, using hedonic models (Sunak & Madlener, 2016). To cope with this selection problem and to show the effects of neglecting ex-ante price differences, we exploit both a difference-in-difference (DID) estimation and a repeated sales model. However, we also employ a classic hedonic pricing model to compare estimation results and because there are certain tradeoffs to make when using a difference-in-difference setup, as compared to a standard hedonic model. This issue is mostly related to the paucity of available data, since a DID model focuses on observations around openings / closings only, neglecting observations in areas with facilities that opened / closed before the sample period. It can be challenging to obtain informative results, given that the number of facility openings and closings is unbalanced for different energy types, and housing transactions nearby some facility types are limited. We therefore combine three different estimation methods to investigate the variation in the predictive power of the different models, showing that the number of observations shrinks significantly with model accuracy. This study focuses on the Netherlands, which is lagging behind other European countries in terms of renewable electricity generation. The share of Dutch renewable electricity production was 6 percent in 2014. Among renewables, biomass/renewable waste (5.3 percent) and wind (0.7 percent) are the dominant energy sources (Eurostat, 2015b). However, a critical goal of Dutch energy policy is to rapidly increase the share of renewable electricity sources. As wind is abundant along the Dutch coast, the plan is to significantly increase the number of new wind turbines, as well as to partly replace older, less efficient wind turbines, with the goal to have 6,000 megawatt (MW) of onshore wind capacity installed by 2020 (Londo & Boot, 2013). However, as the Netherlands is one of the most densely populated countries in Europe, electricity generation and urban areas will further converge.

Therefore, a critical policy question is whether electricity generation has external effects on local house prices and how the effects of different generation types compare to each other.

We employ an extensive dataset of 2.3 million Dutch housing transactions between 1985 and 2015. In addition, we have access to data regarding all wind turbines, biomass plants and conventional power plants in the Netherlands. We focus on coal, gas, biomass and wind electricity generation facilities, since these are most significant for the Dutch electricity market.[1] We match these information sources in order to measure the effects of proximity to electricity generation facilities on house prices, calculating distance measures for each individual transaction, using a variety of models to control for individual housing characteristics.

We document different external effects on nearby house prices for different energy types. External effects of the same energy type differ with model specification and for openings and closings, indicating an endogeneity problem in the placement decision. We find negative external effects for gas plants and wind turbines throughout nearly all model specifications. For biomass plants, we find positive price effects, conditionally on placement in ex-ante lower priced areas. We do not find any significant price effects for coal plants. All external effects are generally negative in urban areas. Most effects are robust over time and do not vary with plant size. As plant size plays no role, the general negative effect might at least partially come from perception. We document furthermore that the standard hedonic model cannot capture ex-ante locational price effects of electricity generation facilities.

The remainder of this paper starts with a short discussion of the literature regarding the external effects of electricity generation on local housing markets. Section three presents a theoretical framework and the underlying methodology, which

[1]Nuclear power contributes to the Dutch electricity market, but there is only one power plant in the Netherlands (the Borssele nuclear power plant). Due to its singularity, observations within externality distance would be limited and potential results hardly generalizable. We therefore exclude the nuclear plant from our analysis.

is followed by section four, providing the data and descriptive statistics. Sections five describe the results and section six of the paper offers a short conclusion.

2 Literature Review

2.1 Definition of external effects

The challenging question is to define the source of externalities and being able to attach a price to all externalities of a certain (dis)amenity. Focusing on air pollutants, Roth and Ambs (2004) provide a meta-study to quantify the externality costs of 14 different electricity generation types. The authors find a wide range of damage cost estimations of individual air pollutants, such as for carbon dioxide (CO_2), ranging from $9.90 to $41.60 per ton, with coal power plants having the highest external costs, followed by gas and combined cycle power plants. In contrast, biomass and wind appear to have only limited external costs. These results are in line with those from a study conducted by the European Commission (2003). Despite a common agreement in the literature over the rank of air pollution emission among electricity generation types, the pricing of different gas emissions varies widely, showing the difficulty of pricing the external costs of electricity generation.

Despite the lack of air pollution stemming from wind turbines, these generation facilities have significant noise and visual effects. Reported health effects such as sleep disturbance, headache, anger fatigue and loss of motivation are acknowledged in the literature as factors that can be caused by the noise from wind turbines (Farboud et al., 2013).[2] Visual effects seem to have an even stronger impact than noise (Bakker et al., 2012). People located near wind turbines have reported health effects, claiming those effects were due to photo-induced seizures (photosensitive epilepsy) and wind

[2]Other health effects mentioned in the study are: visceral, vibratory and/or vestibular dysfunction, dizziness, vertigo, unsteadiness, tinnitus, ear pressure or pain, external auditory canal sensation, memory and concentration deficits, and irritability.

turbine blade flicker (Harding et al., 2008). In addition, households located nearby report a decrease in life-satisfaction after the installation of wind turbines (Krekel & Zerrahn, 2017).

The increased number of self-reported health effects by people living near wind turbines merely seems to be caused by the annoyance over the presence of wind turbines itself, rather than originating from one aspect in particular, highlighting the difficulty to identify individual externalities (Pedersen & Waye, 2007). People generally support wind energy, but oppose it if facilities are installed close to their homes (Breukers & Wolsink, 2007; Wolsink, 2000, 2007; Wüstenhagen et al., 2007). Wolsink (2007) states that local residents are willing to except wind turbines in their vicinity as long as they perceive the general distribution of wind turbines as "fair". However, in the Netherlands local residents do not have the perception that they can influence the distribution of new wind turbine sites (Wüstenhagen et al., 2007).[3] Similar results are found in the United Kingdom (Bell et al., 2005), the United States (Pasqualetti, 2011b), and Mexico (Pasqualetti, 2011a).

2.2 Power plants and external effects on housing

Since residential real estate is fixed in location, prices are highly sensitive to factors disrupting location quality (Hilber, 2005), which makes real estate a good identifier of local utility or disutility from e.g. externalities. All these effects should be incorporated in house prices (Rosen, 1974) as people choose a location according to their preferences and aversions (Tiebout, 1956), allowing for the translation of (dis)utility of proximity to power plants into a monetary amount.[4] Since it is practically impossible to account for all external effect sources of different electricity generation facilities and incorporate them in the Rosen (1974) framework, we focus

[3]This perception is confirmed by the fact that the *Dutch Ministry of Infrastructure and the Environment* centrally determined eleven areas for the construction of new wind parks in 2014. The official selection criteria were population density and wind speed (Feld et al., 2014).

[4]The main assumption is that people are free in their location choice.

on research literature, using distance (proximity) as a proxy for the exposure to all external effects, theoretically reflecting the net external effect (Nelson, 2008).

The research focusing on local housing market effects of power plants dates back more than 40 years. Most studies focus on the effects of individual power plants in small regional markets (Blomquist, 1974; Clark et al., 1997; Gamble & Downing, 1982; Sunak & Madlener, 2016). Large-scale studies use different measures of property prices, some transaction-based (Dröes & Koster, 2016), and some survey-based (Davis, 2011), and tend to investigate just one type of electricity production. In addition, different control variables are often used, leading to widely varying empirical models. Due to the heterogeneous characteristics of housing markets, changes in electricity generation technology over time, and the typical focus on a single type of electricity generation, it is hard to draw a coherent conclusion about the relative effects of different electricity generation types on local house prices.

Most of the observed external effects for conventional power plants and wind turbines are either negative or not significant. Blomquist (1974) finds a price decrease of 0.9 percent per 500 feet, within a 2-mile distance of a coal power plant. Davis (2011) finds a discount of 3 to 7 percent within 2 miles of plants, increasing with proximity and capacity. For wind turbines, negative external effects range between 5 percent within 0.5 miles (Lang & Opaluch, 2013), 2 to 16 percent within 3 miles (Heintzelman & Tuttle, 2012), 1.2 to 2.6 percent within 2 kilometers (Dröes & Koster, 2016) and 5 to 6 percent within 2 kilometers (Gibbons, 2015). Other studies find no significant effects (Carter, 2011; Hoen, 2014; Sims et al., 2008). Since the methodology, number of observations, research area and control variables differ widely between studies, it is not possible to directly compare these findings and to draw firm conclusions regarding the relative externality costs of different forms of electricity generation.[5]

Overall, there is no study that simultaneously includes different types of

[5] In comparison, focusing on general industrial plants, Currie et al. (2015) find an 11 percent decline in house prices within 0.5 miles for the opening of an industrial plant.

electricity generation technology, uses a large number of observations, measures transaction-based house prices, and accounts for sufficient control variables to quantify external effects in a comparable manner. Furthermore, in any study addressing the effect of locally desirable or undesirable externalities on house prices, the main challenge is identification - what is the counterfactual for the location? In the case of power plants, both renewable and conventional, the locational choice is often driven by factors such as land values and (local) politics, rather than being fully random or based on exogenous factors such as proximity to waterways or exposure to a stiff breeze. Only a few, recent studies address this issue (Davis, 2011; Dröes & Koster, 2016).

3 Method

3.1 Theory & sample construction

We study the effects of different electricity generation methods on house prices within one market: The Netherlands. Our focus is on coal, gas, biomass, and wind energy, due to their significance for the electricity market. Since the findings of previous studies differ widely, we are not only interested in the variation of external effects between different electricity generation facility types, but also in the variation of findings due to different model specifications. We therefore test three specifications: a hedonic approach, a difference-in-difference (DID) approach using average area price changes (e.g. see Dröes & Koster, 2016; Muehlenbachs et al., 2015), and a DID repeated sales model.

For all approaches, we use a similar measure of externality exposure. Since we cannot determine and measure all potential externalities of the different electricity generation facilities, we assume that externalities spread over distance (Nelson, 2008). As we focus on local external effects of electricity generation facilities and neglect global effects, such as CO_2 emissions, we focus on areas directly surrounding electricity generation facilities. However, it might be that different externalities spread differently over distance. In contrast to physical externalities such as noise and sight disturbance, economic externalities, such as employment effects, could reach further, leading to potentially unbalanced external effects over distance. We address this issue by testing the external effects at different distances.

Following the assumption of external effects spreading over distance, exposure to externalities is determined by the geodesic distance to the closest electricity generation facility of every energy type, using longitude and latitude information.[6] Based on a cut-off distance, we consider observations as either affected by externalities (d=*1*) or not affected (d=*0*), indicated by dummy variables. Based on empirical findings on conventional plants (Davis, 2011) and wind turbines (Dröes & Koster, 2016), we start with a cut-off distance of 2.5 km for all types. Due to differences in the production type specifications, such as plant size, cut-off distances might vary for different electricity generation types. We therefore examine the chosen cut-off distances, using a linear distance measure and interval measures.

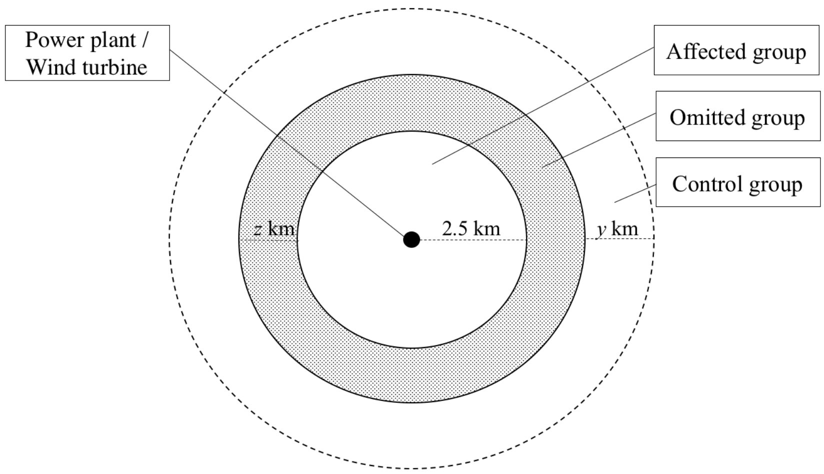
To avoid interference among affected and control observations, we omit observations in a ring-shaped area beyond the cut-off distance. Using the externality cut-off distance of 2.5 km, we consider observations within 2.5 km distance as affected (d=*1*), comparing them with control observations beyond 2.5+z km, where z indicates the width of the omitted area. We start with a distance of 1.5 km for the omitted area, but test different lengths for robustness. Due to the heterogeneity of local residential markets, observations at externality distances do not necessarily share the same locational characteristics with observations far away. We do not only control for location fixed-effects, but also implement a maximum control group distance of

[6]Distances are calculated using the haversine formula, a common way to calculate the great-circle distance of two points on a sphere using longitude and latitude information.

20 km, so $y = 16$ km.[7] Observations beyond y km are omitted from the analysis. Figure 1 illustrates the setup.

We account for confounding factors from other electricity generation facilities. Observations within a 2.5 km distance of a nuclear power plant are omitted, since there is only one active plant in the Netherlands and we argue that the external effects from nuclear power plants differ from those of conventional plants (Gawande & Jenkins-Smith, 2001). Furthermore, we exclude observations within a 2.5 km distance from the German and Belgium border, since we cannot fully account for power plants across the border.[8]

Figure 1
Sample Construction Method



Notes: We cluster observations into affected, omitted and control groups depending on their location relative to a power plant or wind turbine. Observations located in the inner circle around a wind turbine or power plant are considered "affected". We use different radii, ranging from 2.5 km to 4 km. For the omitted group, we use a radius extension of $z = 1.5$ km. We consider all other observations as the control group, limiting the maximum distance to 20 km ($y = 16$km).

[7]We also tested other maximum distances between 10 and 20 km for the control group. This did not markedly affect the results.

[8]There are several wind turbines along the German side of the border and some conventional and nuclear power plants in Belgium, not far from the Dutch border.

3.2 Hedonic approach

After sorting all observations into clusters, we define a hedonic regression model as shown in equation (1), where $\ln(p_{it})$ represents the natural logarithm of the price of property i at time t, α is a constant, S_{it} a vector of structural variables, N_{it} a vector of neighborhood characteristics, E_{it} is a vector of environmental characteristics, such as distance to parks, forests and highways, and T_i is a vector of time-fixed effects. $F_{kit} = 1$ indicates that property i is close to electricity generation facility type k at time t, where k indicates the four tested facility types ($K = 4$). As suggested in the hedonic regression literature (Anselin & Bera, 1998; Kuminoff et al., 2010), we account for potential spatial dependence and omitted variables by including neighborhood-fixed effects in N'_{it} (hereafter referred to as location FE).[9] Furthermore, we include year dummies to control for general house price dynamics (see e.g. Hoen, 2010, 2014).[10] To account for unobserved spatial and temporal correlation, we cluster standard errors by municipality and year.

$$\ln(p_{it}) = \alpha + S'_{it}\beta_1 + N'_{it}\beta_2 + E'_{it}\beta_3 + \sum_{k=1}^{K} \psi_k F_{kit} + T'_i\beta_4 + \epsilon_{it} \tag{1}$$

We first test the explanatory power of the control variables, using a model specification excluding electricity generation externality dummies ($F_{kit} = 0$) for all observations. In the second specification, we do not distinguish between different electricity generation types ($K = 1$), measuring the general external effect of electricity generation facilities and assuming that externalities are similar between different generation types (Davis, 2011). In the third specification, we distinguish between the different electricity generation facility types ($K = 4$), examining whether

[9] We test location fixed effects at 4-digit, 5-digit and 6-digit postcode level, ranging from slightly over 4,000 postcode areas with on average 7,000 households per postcode area to 450,000 postcode areas with 17 households per postcode area.

[10] Additionally, we adjust house prices for inflation, using the CPI from the Dutch Central Statistics Office (CBS)

the external effects on house prices differ between different electricity generation types. In the fourth specification, we test the reach of the external effects, using distance intervals as shown in equation (2), where for every electricity generation type k there are G intervals of 500 m length. We first test intervals up to 4.5 km ($G = 9$) and use observations up to 20 km distance as a control group.

$$\ln(p_{it}) = \alpha + S'_{it}\beta_1 + N'_{it}\beta_2 + E'_{it}\beta_3 + \sum_{k=1}^{K}\sum_{g=1}^{G}\psi_k F_{kgit} + T'_i\beta_4 + \epsilon_{it} \tag{2}$$

To examine the heterogeneity of the external effects and the robustness of our specification, we perform different sub-tests. As property prices differ between urban and rural areas (DiPasquale & Wheaton, 1996), the perception of external effects might differ as well due to the presence of different negative and positive externalities, such as more road noise in cities. We therefore include urban area interaction effects with electricity generation facilities as Dröes and Koster (2016).

We also examine the external effects beyond pricing, investigating time on the market instead of price. On the one hand, the attractiveness of properties nearby power plants may decrease, making them harder to sell. On the other hand, it is possible that price discounts fully reflect any lower attractiveness, leaving the time on the market unaffected, after all price setting is endogenous. To investigate these competing hypotheses, we use the natural logarithm of the time on the market as a dependent variable. Time on the market is determined by calculating the difference between the sales date and the date at which the property first became available for sale.

Due to technical improvements and government regulation, conventional electricity generation facilities typically get cleaner, less noisy, and more efficient over time.[11] It can therefore be assumed that external effects are not persistent, but

[11] See Buhre et al. (2005); Franco and Russo (2002); Meij and te Winkel (2006); Senior and Johnson (2005).

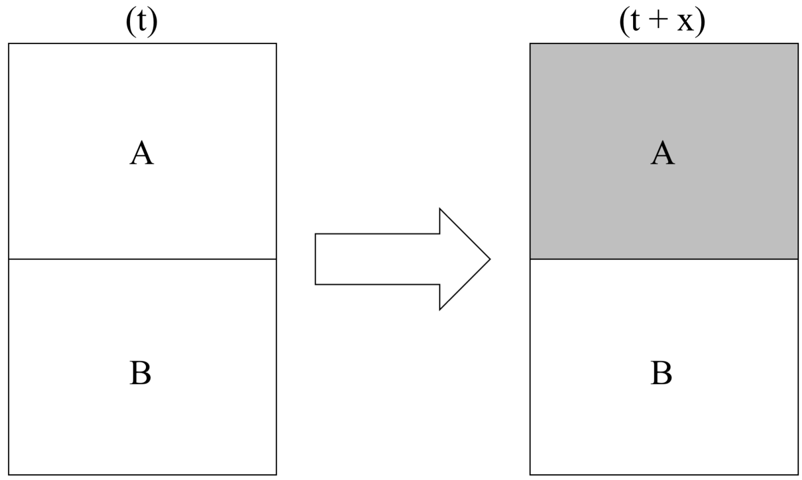
are changing for different periods in time. To measure changes of the external effects over time, we test for time-interaction effects, sorting the treatment into six 5-years time periods.

3.3 Difference-in-difference approach

Since the decision on the location of power plants and wind turbines is not random, a static model might be biased by an economic endogeneity problem of the price-effect relationship. Besides infrastructure factors, such as grid infrastructure or the closeness to gas pipelines and harbors, and political factors, such as local voter opposition, land value may also determine placement decisions. Low land values make it cheaper to build a power plant or to erect a wind turbine, and since land values strongly correlate with house prices (Kok et al., 2014), it is possible that an observed house price discount in the proximity of electricity generation facilities is not the result of an externality, but rather of low ex-ante land prices. This leads to a potential identification problem, which we address by employing a difference-in-difference (DID) model. In addition, the DID approach allows us to investigate the specific effects of facility openings and closings, which we cannot distinguish in a static model setup.

Although our dataset is large, it contains just a limited number of repeated sales pairs for a complete analysis. Due to the preferred placement in remote locations for some facility types (wind and coal) and the imbalance in the number of facility openings and closings (e.g. few coal and biomass plant openings and wind turbine closings), we are not able to perform a DID analysis based on repeated sales for all facility types, for opening and closings. We overcome this problem by using a difference-in-difference model for geographic areas similar to Muehlenbachs et al. (2015), comparing the change in house prices of areas that experience a facility opening / closing (affected areas) and areas nearby that do not experience an opening / closing (control areas), as illustrated in Figure 2.

Figure 2
DID for areas - Setup



Notes: We investigate the average price change of homes in area A comparing it with area B, where observations within area A experience the opening / closing of a electricity generation facility of type k and those in area B do not. We control for individual housing characteristics to avoid capturing systematic changes in housing characteristics of specifc areas.

Equation (3) tests for the effect of facility openings on average property prices in affected areas, where FAC_{ki} indicates an observation i in proximity to an electricity generating facility of type k, either before or after facility type k is opened. $post_{kit}$ (d = *1*) indicates whether a transaction takes place after the opening of the closest facility of type k, and $Treat_{kit} = FAC_{kit} * post_{kit}$ takes a value of *1* for transactions that take place in close proximity to a plant after opening. Therefore, the coefficient of interest is γ_{3k}, measuring, for all facility types k, the effect of a facility opening. The control variable matrix X_{it} accounts for structural, environmental and neighborhood effects, to control for unobserved differences in price-determining factors between the areas over time, using the available controls similar to equation (1). However, we also test for the assumption that the areas compared in the analysis follow a common pretreatment trend (Kuminoff & Pope, 2014).

$$\ln(p_{it}) = \alpha + \sum_{k=1}^{K} \gamma_{1k}(FAC_{kit}) + \sum_{k=1}^{K} \gamma_{2k}(post_{kit}) + \sum_{k=1}^{K} \gamma_{3k}(Treat_{kit}) + X_{it}\gamma_4 + \epsilon_{it} \quad (3)$$

We limit our analysis to facilities that opened during the sample period and exclude observations around plants that were already present. Furthermore, we only consider observations up to 10 years before and after facility openings, as it can be assumed that long-term price effects settle after a certain time.[12] In order to eliminate anticipation effects from construction work, we omit transactions two and one years in advance of facility openings, as well as the opening year itself, depending on facility types.[13] We do not consider areas that are already within externality distance of another facility prior to opening of a new plant. Since the number of affected observations decreases through the filtering process, especially for coal plants, we also test for a 3-km cut-off distance.

In line with the static analysis, we investigate the urban-rural heterogeneity effect, by controlling for facility openings in urban areas. As shown in equation (4), we add an urban locational control dummy in the control matrix X_{it} and add an urban-treatment interaction term represented by $(Treat_{kit} * urban_{it})$, where β_{1k} represents the additional effect of facility type k opening in urban areas.

$$\begin{aligned}\ln(p_{it}) = \alpha &+ \sum_{k=1}^{K}\gamma_{1k}(FAC_{kit}) + \sum_{k=1}^{K}\gamma_{2k}(post_{kit}) + \sum_{k=1}^{K}\gamma_{3k}(Treat_{kit}) \\ &+ \sum_{k=1}^{K}\beta_{1k}(Treat_{kit} * urban_{it}) + X_{it}\gamma_4 + \epsilon_{it}\end{aligned} \tag{4}$$

Examining the heterogeneity of opening effects over time, we rerun our opening analysis as shown in equation (3) on subsets of 10-year periods, moving in 5-year steps. We use 10-year periods to have enough observations for every period. This leads to the following periods: 1985 - 1995, 1990 - 2000, 1995 - 2005, 2000 - 2010, and 2005 - 2015.

[12] We also extend this period to 15 years, but do not find a significant difference in results.

[13] The average construction period for conventional plants is two years, whereas the construction period for wind turbines is much shorter, on average. We therefore use one year for wind turbines. Even though projects might be announced earlier, residents in the Netherlands have strong legal power to prolong or abort large projects.

Another potential source of heterogeneity is power plant size (Davis, 2011) and the number of turbines in a wind turbine park (Dröes & Koster, 2016). Davis (2011) argues focusing on power plants above 100 MW, since disamenities are likely to be stronger for these plants. We differentiate for size, using capacity for conventional plants and the number of contiguous wind turbines within a wind park for wind turbines, as capacity differences for individual wind turbines are relatively small compared to power plants. However, due to constraints in size variation, we are only able to examine size effects for gas plants and wind turbines. Based on the available variation, we distinguish three size categories for gas plants (<100MW, 100 - 400 MW, >400MW), and four categories for wind turbines (single turbine, 2 to 9 turbines, 10 to 29 turbines, 30+ turbines).[14]

In a manner similar to openings, we investigate the effect of facility closings to analyze whether the removal of externalities leads to changes in house prices. We focus on areas that are initially nearby an electricity generation facility, but, through closing, are not within externality distance of a plant anymore, and compare the average price change with areas that remain in externality distance of an open facility. Equation (5) shows the underlying model, where $Close_{kit}$ (*=1*) indicates that observations i is close to an closing facility of type k, either before or after closing, $post_{kit}$ (*=1*) indicates that an transaction takes place after the closing of facility type k, and $Treat_{kit} = Close_{kit} * post_{kit}$, identifies observations nearby closing facilities after closing. In the control matrix X_{it}, we control for property characteristics similar to the previous models, but we also add controls for nearby facility types, in order to distinguish the observations remaining nearby generation facilities, our control group, by property type.[15] Despite the relatively small number of observations around closings, we investigate heterogeneity in the effects and test for urban-rural variation,

[14]We use size intervals since external effects do not necessarily increase linearly with capacity.

[15]We argue it is necessary to control for the nearby facility type k of the control group, because of the unbalanced closings per type.

different time periods, and facility size (as before).

$$\ln(p_{it}) = \alpha + \sum_{k=1}^{K} \gamma_{1k}(Close_{kit}) + \sum_{k=1}^{K} \gamma_{2k}(post_{kit}) + \sum_{k=1}^{K} \gamma_{3k}(Treat_{kit}) + X_{it}\gamma_4 + \epsilon_{it} \quad (5)$$

3.4 Repeat sales analysis

Even though the regional difference-in-difference approach allows for clearer causal identification, it is based on the assumption of similar house sales over time. Even though we control for housing characteristics, we cannot completely rule out the fact that transactions in affected or control areas systematically differ over time, leading to an unobserved variable bias. To overcome this issue, we use repeated sales of the same property. Within our sample data, there are 457,547 observations with at least one repeated sale throughout the sample period, of which 109,692 observations are sold three times, 23,959 sold four times, and 4,749 sold five times. We analyze plant openings and closings separately. In the former, we measure the change from no facility present to having a facility nearby, using unaffected properties as a control group, whereas in the latter we use properties that remain close to a facility as a control group. The distance and time restrictions are as before, in order to have a comparable setup.

We follow the approach of Aydin et al. (2016) as shown in equation (6). As a dependent variable, we use the percentage change in price $\Delta p_{i(t+n)}$ of property i between period t and n. Based on the previously defined cut-off distances, we measure whether a facility of type k opened (closed) between the two sales within externality distance, indicated by $\Delta FAC_{ki(t+n)}$ *(=1)*. We control for changes in quality and amenities, using vectors of control variables. We distinguish for positive changes, such as added amenities or improvements in quality, by $\Delta Q'^{+}_{i(t+n)}$ and negative changes by $\Delta Q'^{-}_{i(t+n)}$. We account for time trends by controlling for the sales year Y'_{it}, and the time period between two sales n-t in interaction with the sales year, using a control vector Θ'_{it}.

$$\Delta p_{i(t+n)} = \alpha + \Delta Q'^{+}_{i(t+n)}\gamma_1 + \Delta Q'^{-}_{i(t+n)}\gamma_2 + Y'_{it}\gamma_3 + \Theta'_{it}\gamma_4 + \sum_{k=1}^{K}\beta_k \Delta FAC_{ki(t+n)} + \epsilon_{i(t+n)} \quad (6)$$

It can be assumed that the housing market adjusts to openings / closings over time. In order to investigate the adjustment of the market to the opening / closing of facilities nearby, we control for the time difference between property sales and facility opening / closing years. We measure the year difference of observation i at $t{+}n$ and the opening (closing) year of the nearest facility of all types K, indicated by *z(k).* Since we are interested in time difference effects of treated observations ($\Delta FAC_{ki(t+n)} = 1$), we interact the time difference with $\Delta FAC_{ki(t+n)}$, indicated by $\Lambda_{(t+n)-z(k)}$. The final model is shown in equation (7).

$$\begin{aligned}\Delta p_{i(t+n)} = \alpha + \Delta Q'^{+}_{i(t+n)}\gamma_1 + \Delta Q'^{-}_{i(t+n)}\gamma_2 + Y'_{it}\gamma_3 + \Theta'_{it}\gamma_4 + \sum_{k=1}^{K}\beta_k \Delta FAC_{ki(t+n)} \\ + \sum_{k=1}^{K}\beta_{2k}\Lambda_{(t+n)-z(k)} + \epsilon_{i(t+n)}\end{aligned} \quad (7)$$

In addition, we investigate the robustness of our model performing two sub-tests. In the first sub-test, we estimate our model for different 10-year time periods only. However due to limited variation in closings, we are only able to do so for the opening of facilities. In the second sub-test, we estimate our model for one housing type only, since we do not control for property types in equation (6), which leads to the risk of having systematic differences in property types in the treatment and control group. We therefore focus on single-family houses only, since these are the most common properties within facility distance.

4 Data

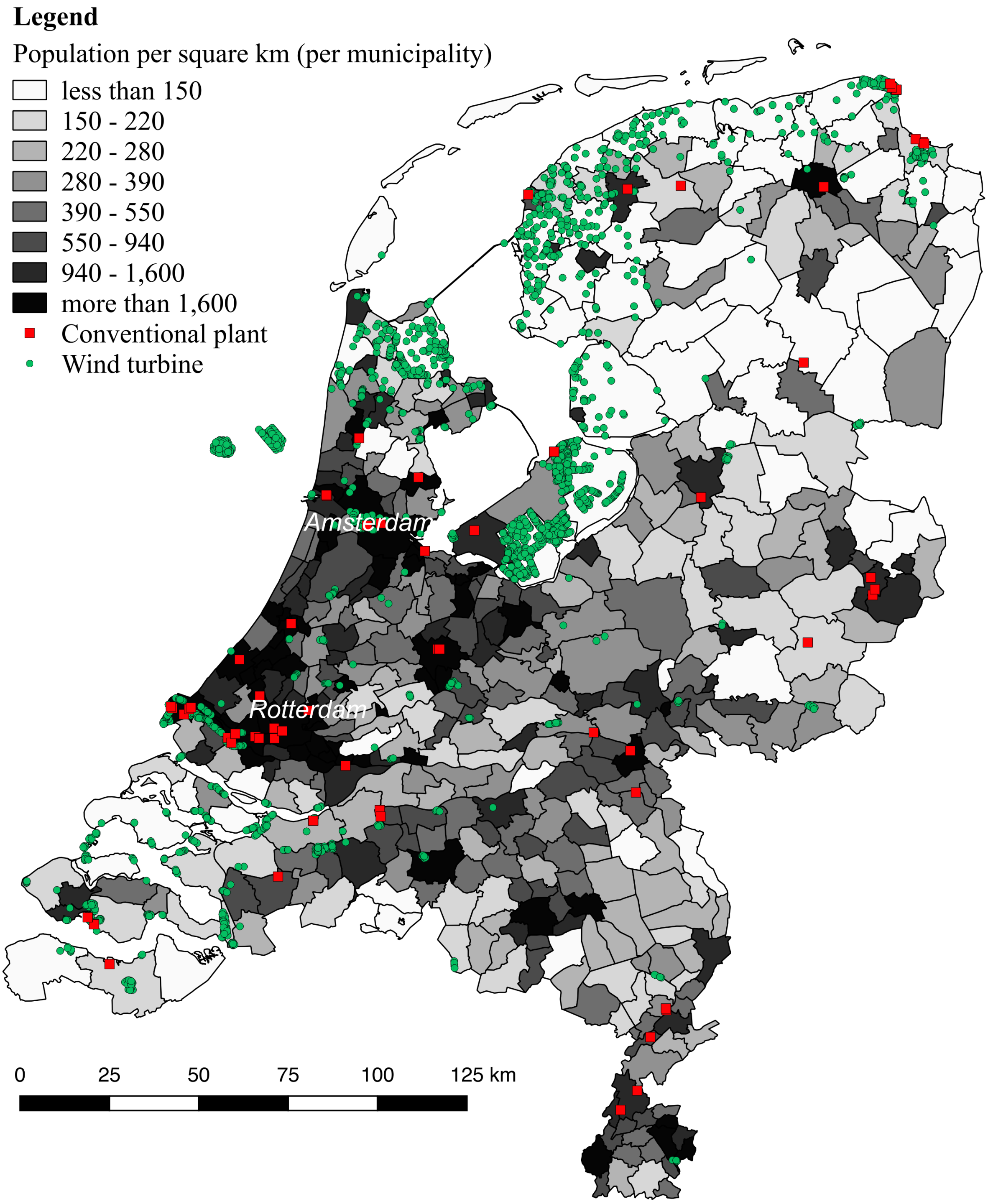
4.1 Power plants

We collect detailed information regarding all major power plants using coal, gas, biomass or a combination thereof, between 1985 and 2015, from various sources.[16] We subsequently sent the collected and filtered plant data to all major electricity suppliers in the Netherlands in order to receive confirmation about data accuracy and completeness. Our dataset contains the number of electricity generation units, fuel types per unit, capacity per unit, year of operational start, year of closing (if applicable), and location. We exclude all cogeneration plants on industrial sites, cogeneration plants focusing primarily on heat generation and plants that do not produce electricity for the public grid (e.g. industrial plants).[17] The final sample includes 119 power generation units located on 45 different plant sites. Figure 3 shows the geographical distribution of the power plants in our sample. Power plants are not systematically located in low population density regions (so as to reduce possible negative externalities), but are placed rather close to urban areas, to keep supply distances in the grid short and to ensure supply stability to urban centers. Another important factor for coal and gas plants is the closeness to fuel transportation infrastructure, such as harbors or pipelines. It is therefore not surprising that a large number of plants are located in the Rotterdam harbor area, assuring direct access to overseas supply of gas and coal.

[16]These sources include:
Bijvoet, N., (n.d.), *Centrale Info*, `http://centraleinfo.net/Europa/Nederland/index.html`
Enipedia, (2010), *Netherlands/Powerplants*, `http://enipedia.tudelft.nl/wiki/Netherlands/Powerplants`
ECN, (2005), *Monitoring Nederlandse elektriciteitscentrales 2000-2004*, retrieved 2015 from: `https://www.ecn.nl/docs/library/report/2005/c05090.pdf`

[17]Cogeneration plants on industrial sites use hot steam to generate electricity. But the electricity generating unit tends not to be recognizable within the industry complex and would distort the results.

Figure 3
Distribution of Wind Turbines, Power Plants and Population Density



Notes: The map shows the sample area (The Netherlands). Population density per municipality is illustrated by 2006 data, retrieved from the Central Statistics Office (CBS). Offshore wind parks are illustrated on the map, but not considered in the analysis.

Panel A of Table I provides an overview of the number of sampled power plants per primary fuel type, and their capacity. In terms of numbers (column 1) and total capacity (column 2), gas and coal plants are most prevalent, with coal providing more than ten times as much power as biomass, and gas almost three times as much as coal. Columns 3, 4 and 5 provide minimum, mean, and maximum capacity per primary fuel type. These numbers show that capacity differences across power plants, for given fuel types, are quite large. For example, the smallest gas plant in the sample has a capacity of 13 MW, while the largest produces almost 100 times that. On the other hand, capacity distributions do not seem to differ very much between fuel types.[18]

Panel A of Figure 4 shows the installed capacity and the respective number of electricity generation units per fuel type per year. The majority of installed units during the sample period are gas units. The first plant primarily running on biomass was installed in 2000. The popularity of coal energy decreased over the same period, with no new facilities added for nearly 20 years between 1994 and 2014. Only in 2015 did the utility company Essent start operating the newly built *Eemshavencentrale*, the Netherlands' biggest and most modern coal plant.

[18] While there are some plants that can use two fuel types, we classify plants by primary fuel type only. To determine the primary fuel type, electricity generation units must run at least 50 percent on that fuel type. Most plants were renovated and upgraded over time, to allow for a secondary fuel type. We argue that the perception and knowledge in the surrounding area is anchored to the primary fuel type (e.g. a local resident would not necessarily notice when a coal plant partly switches to biomass fuel).

Table I
Conventional Power Plants and Wind Turbines
Characteristics by Primarily Fuel Type

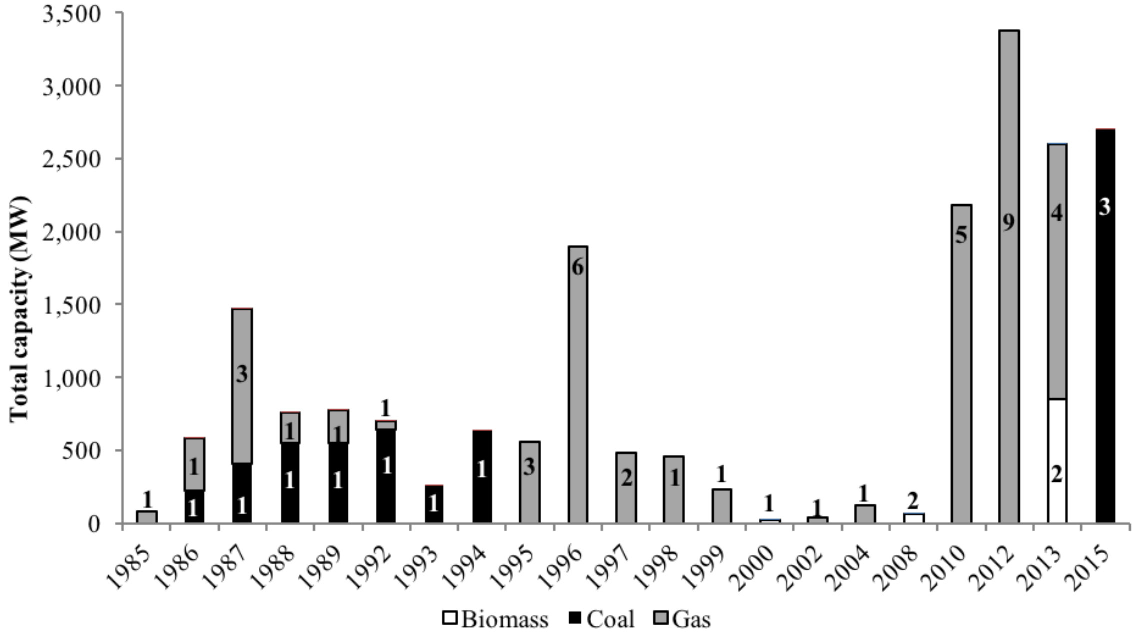
Panel A: Power plant types[a] *(capacity in MW)*					
	(1)	(2)	(3)	(4)	(5)
Type	Number of units	Total capacity	Min. capacity	Mean capacity [SD]	Max. capacity
Gas	95	22,318	13	235 [203]	1,275
Coal	19	8,313	120	438 [288]	1,100
Biomass	5	936	25	187 [343]	800

Panel B: Wind turbine characteristics					
	(1)	(2)	(3)	(4)	(5)
Characteristics	Number of units	Total capacity	Minimum	Mean [SD]	Maximum
Capacity (in kW)	2,117	2,946,321	15	1,393 [1,066]	7,500
Height (in meter)			18	61.53 [22.24]	136
Rotor diameter (in meter)			9	59.18 [24.07]	127
Years in operation[b]			2	13 [5]	20

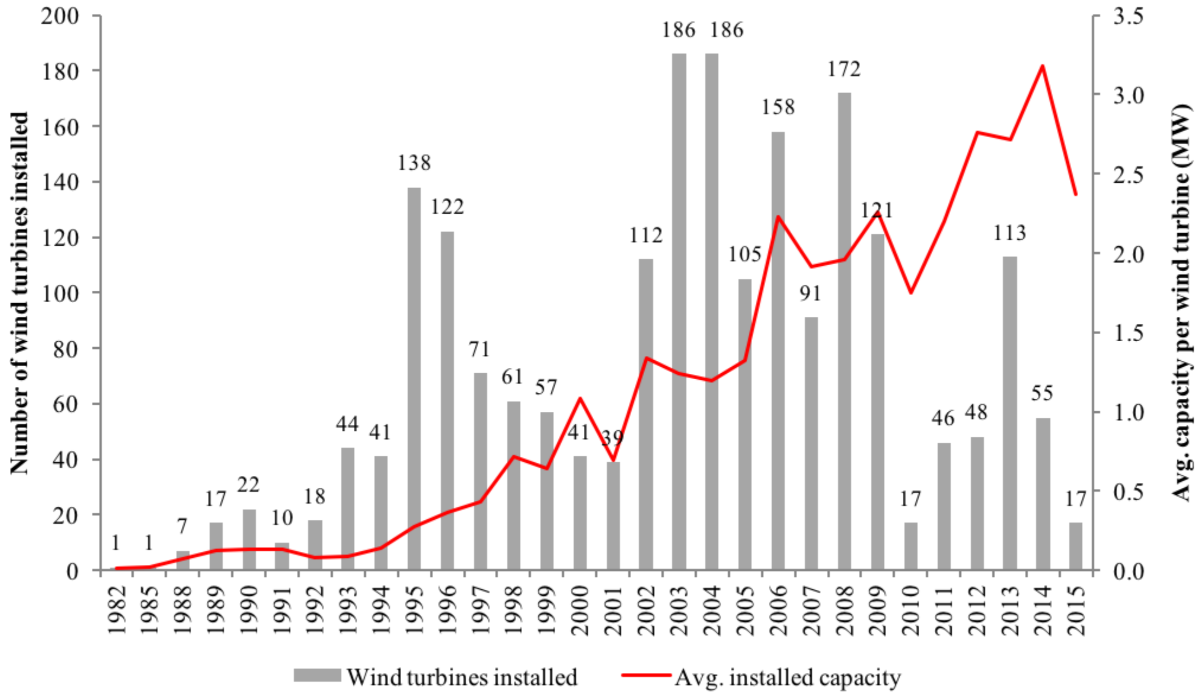
Notes: Standard deviation in brackets.
a Sorted by primary fuel type.
b Based on 61 wind turbines that went out of operation

Figure 4
Yearly Installations of Power Generation Facilities

Panel A: Conventional Installed Capacity (Number of Units in Label) per Type



Panel B: Wind Turbine Placements and Average Capacity per Wind Turbine



Notes: Panel A shows the total yearly installed capacity for biomass, coal and gas plants. In addition, the respective number of electricity generation units are shown to illustrate capacity magnitudes. Since there are years without power plant openings, there are gaps in the timeline.Panel B illustrates the average capacity per wind turbine, per year installed over the respective number of units.

4.2 Wind turbines

Information on wind turbines in the Netherlands is well-documented, including location, capacity, height, rotor diameter, setup year, dismantling year, and park affiliation. Using data from Windstats (2015), we take all wind turbines into account that were operational at some point between 1985 and 2015. This includes 2,117 individual wind turbines, clustered in 217 wind parks. Figure 3 shows the geographical distribution of all wind turbines in the sample, compared to the distribution of conventional power plants and related to population density. Most wind turbines are located in the north-western coastal area. These areas tend to have higher wind speeds than areas in the south-east. The figure shows that wind turbines tend to be placed in relatively low-density areas, but are sometimes located quite close to very densely populated areas.

As shown in Panel B of Table I, the average wind turbine in the Netherlands has a capacity of 1.4 MW, which is considerably smaller than the average conventional power plant. In fact, the largest Dutch wind turbine has a capacity of 7.5 MW, which is still less than the smallest power plant. The capacity distribution is even more widely spread among wind turbines than it is among power plants, with the largest turbine having 500 times more capacity than the smallest. Panel B of Figure 4 shows that the average capacity per wind turbine increases over time. The first wind turbine in 1982 had a capacity of 15 kW, whereas modern wind turbines have an average capacity of around 3 MW. This is due to an increase in size, such as height and rotor diameter, but also due to technical improvements in the generator. The average turbine is 61.5 meters high and has a rotor diameter of 59 meter. During the sample period, 61 wind turbines were dismantled after an average life span of 13 years.

As documented in Panel B of Table I, there is a significant standard deviation in height and rotor diameter, which is due to the technological development of wind turbines over time. Panel B of Figure 4 shows the development of wind turbines installed in the Netherlands and the technological development over time. The first wind turbine in the Netherlands was set up in 1982, and capacity has been added at an increasing rate, especially in the early 2000s, although decreasing drastically during the crisis years.

4.3 Housing transactions

We employ a detailed dataset of housing transactions, consisting initially of nearly 3 million observations between 1985 and the first quarter of 2015. The dataset is provided by the Dutch realtors' association (NVM), which covers around 70 percent of Dutch housing transactions. The dataset contains address, transaction price, structural and environmental information, as well as sales information, such as initial asking price and time on the market. We use Bing Maps through an Application Programming Interface (API) to determine longitude and latitude information per address. After excluding double entries, outliers, and observations with incomplete information, we end up with approximately 2.3 million transactions.

We match data on power plants, wind turbines and housing transactions based on longitude and latitude, using GIS. To control for systematic differences between locations, we add additional information on the municipal level to the dataset. The Dutch Statistics Office (CBS) provides information about population density and land use per municipality, which we use to identify urban centers and rural areas.[19]

[19] We use zoning and land use data, which are available for the years between 1996 and 2015. For older years, we estimate data based on averages and time trends. Land use stays relatively constant over time. Population density data are provided on the municipality level and provide a ranking from "very urbanized" to "rural". We use the first two levels ("very urbanized" and "urbanized") to define urban areas.

4.4 Descriptive Statistics

Given a cut-off distance of 2.5 km for all electricity generation types, and an omission radius of 1.5 km, the number of observations within "external effect" distance is limited for biomass and coal. In total, 339,931 transaction observations are within the externality distance of any type of electricity generation facility, distributed as follows: 1,772 for biomass plants, 10,779 for coal, 152,093 for gas, and 185,598 for wind turbines.[20] The spatial distribution of our sample follows the population distribution as indicated in Figure 3 and is stable over time. Appendix Figure A shows the percentage of affected observations over time. The number of observations close to coal, gas and biomass plants does not change significantly over time, whereas the number of observations close to wind turbines changes markedly. Since the spatial distribution of transactions is relatively stable over time, this implies that more wind turbines get positioned close to housing over time, confirming the convergence of renewable electricity generation and urban space.

Table II shows the average characteristics of houses and apartments in close proximity to power plants, as well as the characteristics of homes in the control sample ($4\ km < d < 20\ km$). There are relatively more apartments in the affected group than in the control group. While apartments in both groups have roughly the same size, houses in the affected group are smaller compared to houses in the control group. Apartments and houses tend to be cheaper in the affected group, both in absolute terms and on a per square meter basis. However, this is not necessarily due to quality characteristics or an urban location, as both characteristics show that properties in affected areas are on average of better quality and more likely to be in an urban area.[21]

[20]Some observations are within externality distance of different electricity generation facility types (e.g. coal and wind), thus the sum of individual electricity generation facility exposures does not match the overall number of affected observations. We test for the interaction effect of being in external distance of different electricity generation facilities, but we do not find a significant effect.

[21]Using Welch's t-test, all differences are statistically significant.

Table II
Descriptive Statistics:
Housing Sample 1985 – 2015

	Generation facility (<2.5 km)		Generation facility (>4 km)	
Variable	**Houses**	**Apartments**	**Houses**	**Apartments**
No. of Observations	*222,399*	*117,532*	*1,082,446*	*372,865*
Size	126	86	134	86
(in m2)	[42]	[27]	[43]	[26]
Price	248,018	174,943	269,667	200,462
(in Euro)	[145,761]	[83,094]	[178,426]	[119,280]
Price per m2	1,946	2,058	1,974	2,344
(in Euro)	[727]	[717]	[842]	[995]
Housing inside quality	3.04	2.96	2.98	2.83
(1 = worst, 9 = best)	[1.18]	[1.20]	[1.17]	[1.13]
Housing outside quality	3.01	2.91	2.95	2.79
(1 = worst, 9 = best)	[1.09]	[0.93]	[1.10]	[0.88]
Highway within 200m	0.08	0.11	0.07	0.11
(1 = yes)	[0.27]	[0.31]	[0.26]	[0.32]
Urbanization	2.58	1.38	2.98	1.87
(1 = highest, 5 = lowest)	[1.38]	[0.72]	[1.10]	[0.94]

Notes: Standard deviation in brackets. All property type mean differences between groups are significant using Welch's t-test. Inside and outside quality are ratings performed by NVM on the overall condition of the property. Both variables are measured on a scale from 1 = best, to 9 = worst. Highway measures whether there is a highway within 200 meters of the observation. A higher average value, shows a higher likelihood of having a highway close to the observation. Urbanization measure the level of urbanization of the respective municipality on a scale from 1 (highest) to 5 (lowest). The externality group is defined by 2.5 km cut-off distance for all electricity generation types. The omission corridor is of 1.5 km length and the control group is included up to a distance of 20 km.

5 Results

5.1 Hedonic regression results

We first estimate the baseline model, excluding any power plant proximity dummies, as shown in Appendix Table I. Excluding the omission group, we consider 1,757,810 observations in our analysis and find an adjusted R-squared of 0.88. The control variables are mostly in line with the literature (see e.g. Brounen & Kok, 2011; Dröes & Koster, 2016), showing e.g. that a villa sells at a premium of 21.8 percent compared to a simple row house. In addition to the listed control variables, we also control for location based on 4-digit postcode level, inside and outside quality based on a scale assessment, sales year, and age by interacting building period and sales year.

Table III provides the hedonic results, including measures for proximity to electricity generation facilities. Not differentiating between electricity generating types, column 1 shows that the average effect of power plants on house prices is -0.9 percent within a 2.5 km distance. However, decomposing the effect, we find different effects per electricity generation type (column 2). For coal plants, we find a negative price effect, but it is not significant, whereas proximity to gas and biomass plants seems to have a positive effect on local house prices of 2.5 percent and 2 percent (significant at 10 %), respectively. In contrast, wind turbine proximity leads to a significantly negative local price effect of -1.6 percent.

As we document in Appendix Table II, the results are robust for different cut-off distances, using price per m^2 as a dependent variable and for 5-digit and 6-digit postcode level fixed-effects. However, we observe that for different cut-off distances and fixed-effects, coal proximity sometimes shows a significantly positive effect between 5.6 percent to 10 percent, which might be the result of the small number of observations.

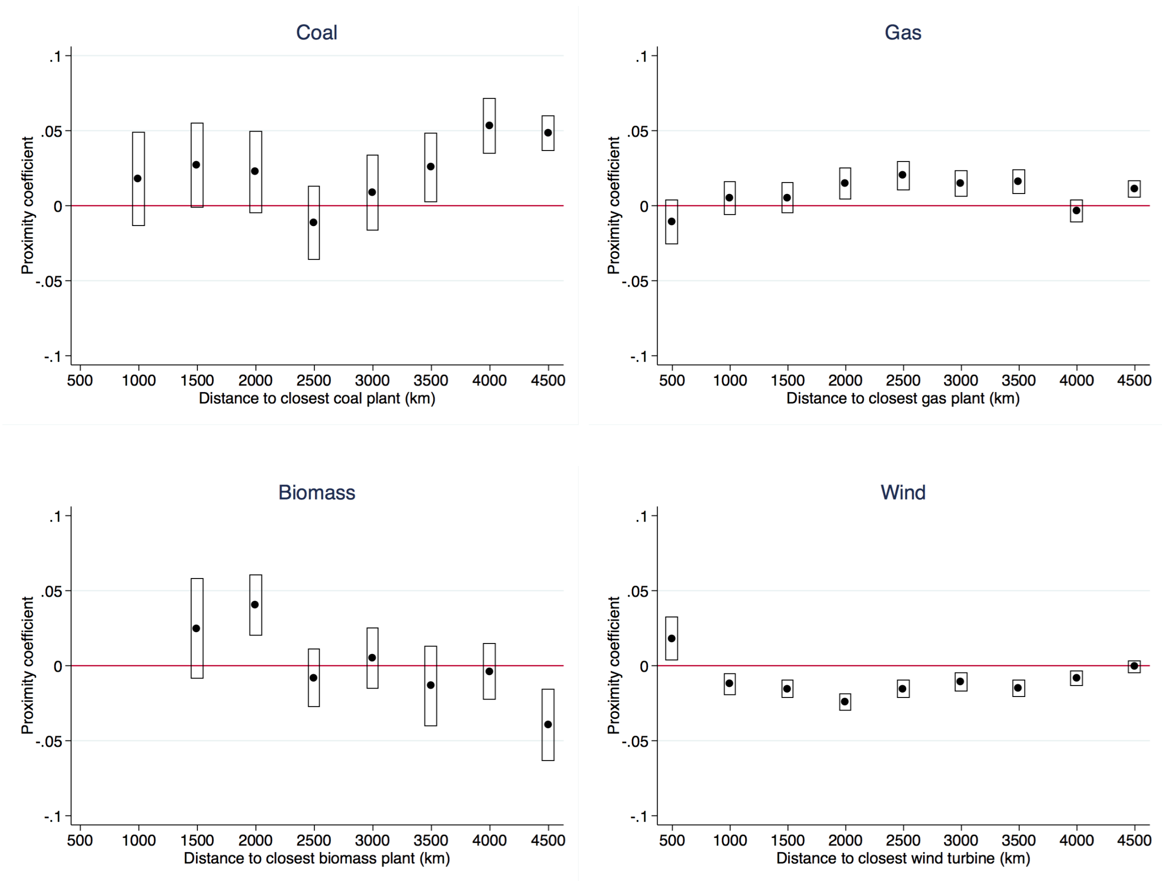
Table III
Results Hedonic approach

Proximity to:	(1) General effect	(2) Energy type	(3) Urban interaction	(4) Time on market
Electricity generation facility	-0.009***			
(1 = yes)	[0.003]			
Coal plant		-0.027	0.023	-0.170**
(1 = yes)		[0.020]	[0.021]	[0.076]
Gas plant		0.025***	0.048***	0.006
(1 = yes)		[0.007]	[0.008]	[0.030]
Biomass plant		0.020*	0.042***	-0.128***
(1 = yes)		[0.010]	[0.010]	[0.045]
Wind turbine		-0.016***	-0.008**	0.022*
(1 = yes)		[0.004]	[0.003]	[0.013]
Coal plant in urban area			-0.116***	
(1 = yes)			[0.035]	
Gas plant in urban area			-0.028***	
(1 = yes)			[0.008]	
Biomass plant in urban area			-0.155***	
(1 = yes)			[0.024]	
Wind turbine in urban area			-0.014**	
(1 = yes)			[0.005]	
Observations	1,757,810	1,757,810	1,757,810	1,730,315
Adj. R-squared	0.877	0.877	0.877	0.189
Quality controls	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Dependent Var.	lnPrice	lnPrice	lnPrice	lnToM
Cut-off distance	2.5	2.5	2.5	2.5
Holdout distance	1.5	1.5	1.5	1.5
Max. distance	20	20	20	20

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All distances in km. Urban area is defined by the level of urbanization of the respective municipality: scale from 1 (highest) to 5 (lowest). We define municipalities above a scale of 3 as urbanized. In column (4), the dependent variable is the natural logarithm of time on the market. A positive coefficient indicates an increase in time on the market of properties. We exclude observations with missing or incorrect time on the market information.

Examining the external effect over distance, Figure 5 shows the estimates for different 500 m intervals over a distance of 4.5 km, including 10 % confidence intervals. We ignore intervals with less than 10 observations in our estimation and do not add an omission corridor, so the control group is within 4.5 km - 20 km. For coal plants, we find no significant effect up to 4 km distance and a positive effect thereafter. For gas plants, we find positive effects for the range of 2 km to 3.5 km. For biomass plants, we only have a limited number of observations in short distance, which forces us to exclude the distance up to 1.5 km. Thereafter, we only find a significant positive effect in the range of 2 km distance and a negative effect in the range of 4.5 km. Lastly, for wind turbines we find a positive effect within 500 m, however this is based on a small number of observations. Thereafter, we find negative effects up to 4 km, becoming insignificant after. These results are in line with the estimations for different cut-off distances documented in Appendix Table II.

Figure 5
Hedonic Approach: Interval Estimation



Notes: We test the effect of proximity to electricity generation facilities over 500 m length intervals, up to 4.5 km. The control group is within 4.5 km – 20 km distance from facilities. Bars illustrate interval coefficients with 10% confidence intervals. Intervals with less than 10 observations are excluded.

Column 3 of Table III shows that the effects of electricity generation on house prices are quite different in urban areas as compared to rural areas. In rural areas, we find somewhat more positive price effects for proximity to electricity generation facilities, while urban house prices are negatively affected. In urban areas, we find, on average, a combined effect of -11.6 percent for coal plants, 2.0 percent (4.8 + -2.8) for gas plants, -11.3 for biomass plants, and -2.2 for wind turbines.

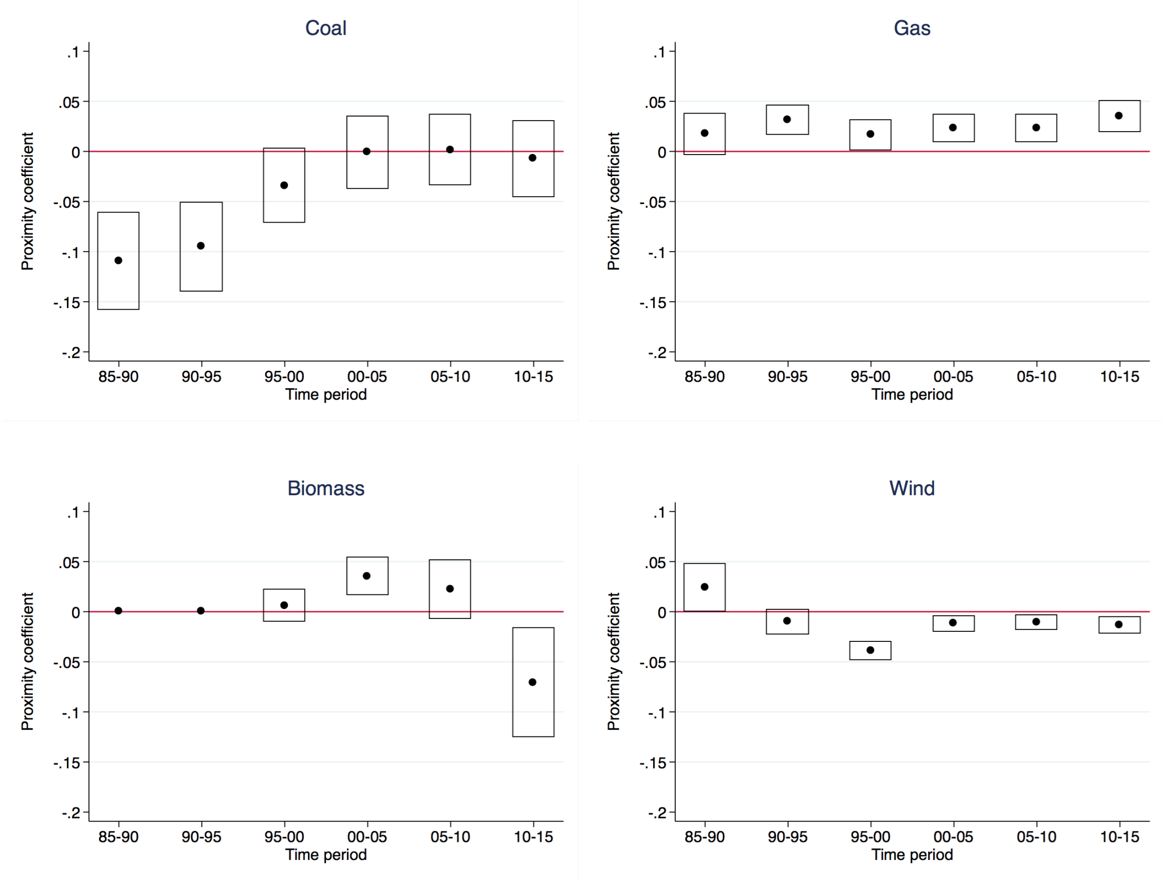
Focusing on the effect on time on the market in column 4 of Table III, we find that the predictability of the model is much smaller with an adjusted R-squared of 0.19.[22] For coal and biomass plants, we find a decreased time-on-the-market of 17 percent and 12.8 percent, respectively. For wind turbines we find an increase of 2.2 percent (significant at 10 %). The average time-on-the-market is 100 days.

Last, we investigate the heterogeneity of the proximity effect over time. Figure 6 shows the estimations of the time-period-proximity interaction effect. We find negative proximity effects for coal plants between 1985 and 1995, which become insignificant as of 1995. For gas plants, we find positive or insignificant effects throughout all time periods. The first biomass plant only opened around 2000, so we cannot estimate proximity effects for earlier periods. Thereafter the effects after rather mixed, from positive to negative. For wind turbines, the proximity effects are insignificant in the early years and become negative as of 1995. Overall, we argue that the proximity effects are constant over time for gas plants and wind turbines, but change for coal and biomass plants.

Overall, we notice that different electricity generation facilities show different price effects on the local property market. Even though empirical evidence about conventional power plants is limited, we find, surprisingly, positive proximity price effects on properties for gas and biomass plants. In contrast, for wind turbines we find negative property price effects, in line with the empirical literature (Gibbons, 2015; Dröes & Koster, 2016). However, using a hedonic approach, causality cannot be established, since a measure that is static in time does not account for the potential correlation between ex-ante land values and facility placement.

[22]We test for the correlation between time-on-the-market and price, documenting an correlation of 0.094.

Figure 6
Hedonic Approach: Time Interaction



Notes: Investigating the proximity effect over time, we form interaction dummies for different sample time periods. The first biomass plant only opens in 2000. Bars illustrate time interaction coefficients with 10% confidence intervals.

5.2 Difference-in-difference results

Table III in the Appendix provides the number of observations that we can employ for the DID analysis per group and fuel type, given a maximum distance of 20 km and an omission corridor length of 1.5 km. We note that the number of observations is quite low for some facility types and times. For the opening analysis, we have enough observations for all types except coal plants. This has three main reasons: the remote location of coal plants in general, the combined location with other facility types, such as gas plants, and the dearth of new coal plant openings over our sample period. For facility closings, we have a limited number of observations for nearly all facility types, except for gas plants. Figure B in the Appendix investigates the simultaneous trend assumption, showing the average price per square meter per year over time to facility openings and closings. As we documented, pre-opening and pre-closing trends follow a quite similar trend, even though there is a systematic price gap for some facility type areas.[23]

Documented in Table IV, we find no significant location discount for biomass plant and wind turbine plant areas at a 2.5 km cut-off distance, but a location discount for biomass plan areas at a 3 km cut-off distance. For gas plant areas, we find a significant positive location effect at both cut-off distances. For openings, we find a negative price effect of -3.3 percent (significant at 10 %) to -4.4 percent for gas plant openings and a negative price effect of -1.4 percent to -1.7 percent for wind turbines openings. In contrast, for biomass plant openings, we find a positive price effect of 6.5 percent to 7.2 percent.

As in the static model, we examine the heterogeneity of the effect, differentiating between urban and rural areas. We document a change in location effects, resulting in significant location discounts for biomass plant areas (for both cut-off distances) and a significant location discount for wind turbine areas at a 2.5 km cut-off distance. The location discount for gas plant areas becomes insignificant.[24] We find no significant opening effect for gas plant areas in rural regions, but a significant discount between -7.5 percent to -4.2 percent in urban areas. The opening effect for biomass plant areas remains constant in rural regions, with an opening effect between 8.4 percent to 9 percent, but shows negative effects between -8.2 percent to -6.4 percent in urban areas. For rural wind turbine areas, we only find a negative effect of -0.8 percent at 3 km cut-off distance. However, we find negative effects in urban wind turbine areas between -1.8 percent and -1.1 percent. Differentiating for gas plant size, we find no

[23] We exclude coal plants from our analysis since we do not have enough observations per year.

[24] We find that 92 percent of gas plants are located in urban areas, compared to 55 percent for wind turbines and 25 percent for biomass plants, suggesting that differentiating for urban locations is important.

significant opening effect for gas plants below 100 MW capacity. Above this level, we find significantly negative opening effects of -6.9 percent (100 - 400 MW) and -5.3 percent (>400MW). For wind turbine areas, we document negative opening effect of -2.1 percent for single turbines, -1.5 percent for parks up to 10 turbines, and -1.6 percent for parks with more than 30 turbines. We do not find a significant effect for wind parks with 10 to 30 turbines.

To see if the perception of different electricity generation facilities changes over time, we rerun our analysis on different sub-periods of 10 years length as shown in Appendix Table IV. For gas plant areas, we find significantly negative effects for the time around 1995 (90 - 00) and around 2010 (05 - 15), showing that the results are robust over time. The positive price effect of biomass plants is significant for all time periods with available data. For wind turbines, we find negative opening effects of -2.5 percent for the time period around 2000 only and no significant effects in other periods. These results are in line with the hedonic results for different time periods, presented in Figure 6, which shows that the perception towards wind turbines has changed.

Table V presents the results for the closing analysis. We find no significant closing effect for coal plant areas. For gas plant areas, we find a significant negative effect of -3.8 percent at a 3 km cut-off distance. For biomass plant areas, we find a significant negative effect between -7.4 percent and -5.8 percent. For wind turbine areas, we find a positive closing effect of 6.5 percent at a 2.5 km cut-off distance.

Table IV
Results Area DID opening

	(1) Opening effect	(2) Opening effect	(3) Urban interaction	(4) Urban interaction	(5) Gas size	(6) Wind size
Gas plant area	0.038**	0.044***	-0.010	0.002	0.039**	0.038**
	[0.017]	[0.016]	[0.013]	[0.016]	[0.017]	[0.017]
Biomass plant area	-0.018	-0.024**	-0.052***	-0.057***	-0.018	-0.018
	[0.012]	[0.012]	[0.012]	[0.013]	[0.012]	[0.012]
Wind turbine area	-0.001	-0.001	-0.010***	-0.003	-0.001	-0.001
	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]
Gas plant opening	-0.033*	-0.044**	0.026	0.005		-0.033*
	[0.020]	[0.018]	[0.018]	[0.020]		[0.020]
Biomass plant opening	0.065***	0.072***	0.084***	0.090***	0.064***	0.065***
	[0.009]	[0.010]	[0.011]	[0.011]	[0.009]	[0.009]
Wind turbine opening	-0.014***	-0.017***	-0.004	-0.008**	-0.013***	
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	
Urban openings:						
Gas plant urban			-0.075***	-0.042**		
			[0.027]	[0.021]		
Biomass plant urban			-0.082**	-0.064***		
			[0.042]	[0.023]		
Wind turbine urban			-0.018***	-0.011**		
			[0.006]	[0.005]		
Facility size effect:						
Gas plant (<100 MW)					-0.001	
					[0.018]	
Gas plant (100 - 400 MW)					-0.069**	
					[0.031]	
Gas plant (>400 MW)					-0.053**	
					[0.026]	
Wind turbine single						-0.021***
(n = 1)						[0.005]
Wind turbines small						-0.015***
(1 <n <10)						[0.005]
Wind turbines medium						-0.004
(10 <= n <30)						[0.009]
Wind turbines large						-0.016***
(n >= 30)						[0.005]
Observations	1,535,120	1,455,944	1,535,120	1,455,944	1,535,120	1,535,120
Adj. R-squared	0.939	0.940	0.877	0.878	0.939	0.939
Quality controls	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Var.	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice
Cut-off distance	2.5	3	2.5	3	2.5	2.5

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All distances in km. The maximum distance considered is 20 km, the holdout distance is 1.5 km. The opening effect dummy for coal plants is omitted, due to the small group size. Urban effects are estimated by additional urban-treatment interaction terms. Urban area is defined by the level of urbanization of the respective municipality: scale from 1 (highest) to 5 (lowest). We define municipalities above a scale of 3 as urbanized. Column (5) distinguished for different gas plant sizes, using capacity as a size indicator. Column (6) uses the number of wind turbines per park. The results of column (5) and (6) are robust for a 3 km cut-off distance, but not reported due to space limitations.

Table V
Results Area DID closing

	(1) Closing effect	(2) Closing effect	(3) Urban interaction	(4) Urban interaction	(5) Gas size	(6) Gas size
Coal plant closing	-0.047	-0.020	-0.067	-0.044	-0.047	-0.017
	[0.045]	[0.033]	[0.044]	[0.032]	[0.043]	[0.032]
Gas plant closing	-0.028	-0.038***	0.040	-0.001		
	[0.018]	[0.014]	[0.028]	[0.019]		
Biomass plant closing	-0.074***	-0.058***	-0.075***	-0.056**	-0.066***	-0.051**
	[0.021]	[0.021]	[0.022]	[0.022]	[0.020]	[0.020]
Wind turbine closing	0.065**	0.024	0.004	-0.006	0.057*	0.017
	[0.032]	[0.024]	[0.074]	[0.070]	[0.032]	[0.023]
Urban closings:						
Coal plant urban			0.086*	0.065*		
			[0.047]	[0.034]		
Gas plant urban			-0.064***	-0.034**		
			[0.024]	[0.015]		
Biomass plant urban			0.006	-0.032		
			[0.026]	[0.024]		
Wind turbine urban			0.059	0.030		
			[0.070]	[0.069]		
Facility size interaction:						
Gas plant (<100 MW)					-0.012	-0.023*
					[0.017]	[0.013]
Gas plant (>100 MW)					-0.053**	-0.064***
					[0.022]	[0.019]
Observations	93,478	123,476	93,478	123,476	93,478	123,476
R-squared	0.884	0.884	0.884	0.884	0.884	0.884
Quality controls	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Var.	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice
Cut-off distance	2.5	3	2.5	3	2.5	3
N affected by closing:						
Coal	134	132	134	132	134	132
Gas	18,814	23,688	18,814	23,688	18,814	23,688
Biomass	463	585	463	585	463	585
Wind	416	339	416	339	416	339

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All distances in km. The maximum distance considered is 20 km, the holdout distance is 1.5 km. The closing effect dummy for coal plants was omitted, due to the small group size. Urban effects are estimated by additional urban-treatment interaction terms. Urban area is defined by the level of urbanization of the respective municipality: scale from 1 (highest) to 5 (lowest). We define municipalities above a scale of 3 as urbanized. Due to limited variation in size (only 30 observations with >400 MW), we sort gas plants around the 100 MW cut-off. For wind turbines, we do not observe closings for parks with more than 10 turbines.

Disentangling the effect for urban and rural areas, we only find a significant closing effect in rural regions for biomass plants, ranging between -7.5 percent and -5.6

percent. However, in urban areas we document a slightly positive effect for coal plant areas between 8.6 percent and 6.5 percent (both significant at 10 %), and a negative effect for gas plant areas between -6.4 percent and -3.4 percent. Examining size effects, the results are robust for gas plants above 100 MW size, but not for plants below 100 MW. In Appendix Table V, we estimate our closing model for three different time periods of 10 years length. We document that the closing effect mainly results from the last decade and find a strong positive closing effect of 5.3 percent for wind turbine areas and a strong negative effect of -8.6 percent for biomass areas. For gas plant areas, we find a negative effect of -2.5 percent for the period 1995 - 2005.

5.3 Repeated sales results

Since our model for the repeated sales analysis differs slightly from the previous specification, we first examine the fit of our model. As shown in Appendix Table VI, the explanatory power is only slightly lower than of our previous model specifications, despite using less observations controls. The coefficients make intuitive sense and are in line with the former findings. In general, adding amenities or increasing quality increases property value.

As documented in Table VI, we find a significant price effect of -9.5 percentage points for observations that experience a gas plant opening between sales. For wind turbines, we find a significant opening effect of -2.7 percentage points. The effect is robust for a 2.5 km, as well as for a 3 km cut-off distance, as indicated in Appendix Table VII. Controlling for the time between facility openings and property transactions, we find a negative effect on house prices of -10.7 and -3.6 percentage points for gas plants and wind turbine openings, respectively. However, the effect diminishes over time, with an average effect of 1.1 and 0.4 percentage points per year for gas plants and wind turbines, respectively. For closings, we focus on gas plant closings only, since we do not have enough observations to investigate other closings.

In contrast to the DID closing analysis for areas, we find a strong positive effect of 5.3 to 6.0 percentage points after gas plant closings. The effect does not normalize over time, as we do not find a significant time difference effect. At a cut-off distance of 3 km the closing effects nearly disappears

Table VI
Results Repeated Sales

	(1) Opening	(2) Opening	(3) Closing	(4) Closing
Gas plant opening	-0.095***	-0.107***		
(1 = yes)	[0.026]	[0.028]		
Biomass plant opening	0.021	-0.012		
(1 = yes)	[0.024]	[0.024]		
Wind turbine opening	-0.027***	-0.036***		
(1 = yes)	[0.006]	[0.006]		
Gas plant opening time difference		0.008		
(no. years)		[0.010]		
Biomass plant opening time difference		0.011**		
(no. years)		[0.004]		
Wind turbine opening time difference		0.004**		
(no. years)		[0.002]		
Closing analysis:				
Gas plant closing			0.053**	0.060**
(1 = yes)			[0.024]	[0.027]
Gas plant closing time difference				0.004
(no. years)				[0.004]
Observations	228,632	228,632	15,318	15,318
Adj. R-squared	0.726	0.726	0.715	0.715
Location FE	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes
Dependent Var.	ΔPrice	ΔPrice	ΔPrice	ΔPrice
Cut-off distance	2.5	2.5	2.5	2.5
Holdout distance	1.5	1.5	1.5	1.5
Max. distance	20	20	20	20

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the percentage change in price between sales. The time difference accounts for the time between the opening / closing and a sale, if an observation was affected by an opening / closing. We only have enough observations to examine gas plant closings. The results are robust for a 3 km cut-off distance, as indicated in the Appendix.

We test for robustness by estimating our repeated sales model for different time periods as shown in Appendix Table VIII. We only document a significant negative opening effect for gas plant areas in the last 10 years of the sample period. For wind turbines, we find negative opening effects of -3.5 and -1.1 percentage points for the last two periods. For biomass plants, we find mixed effects, ranging from -6.3 to 6.3 percentage points. Focusing on single-family houses only, Appendix Table IX shows that the opening results are robust for wind turbines, but not for gas plants. For gas plant closings, the effects are robust and even of a bigger magnitude than before.

6 Discussion and conclusion

This is the first study analyzing the effects of different electricity generation types on house prices, using an extensive dataset and testing different model specifications for plant openings and closings. Our results are generally in line with the literature (e.g. Davis, 2011; Dröes & Koster, 2016; Gibbons, 2015), but also show that heterogeneity should be considered. Coal, gas, and biomass plants show different opening and proximity effects on house prices, ranging from negative to positive. In contrast, wind turbines show a consistently negative effect throughout all specifications. When considering facility closings, the effects are not necessarily reversed.

Comparing different model setups, we conclude using a hedonic model for externality studies with potential endogeneity problems leads to unstable outcomes. The results for most energy types are in line with the DID model or repeated sales model, which shows that the hedonic model is not necessarily wrong, but just cannot capture ex-ante effects and precise magnitudes. But of course, one advantage of the hedonic model is lower data requirements.

Considering different energy generation types, we document insignificant to negative effects for coal plants, changing over time and for urban and rural areas. For gas plants, the most common plant type in the Netherlands, we find negative opening effects, which are higher in urban areas. Plants below the suggested cut-off capacity of 100 MW (Davis, 2011) show no significant effects, whereas bigger plants do, but not increasing with size. The results are robust throughout several model setups. However, for gas plant closings the results are not consistent, ranging from negative to positive effects. Biomass plant openings show insignificant or positive price effects, depending on the model setup. Biomass plants seem more likely to be in rural areas with a discount, for which they create a positive effect, whereas the effect is negative in urban areas. Closings then lead to a negative price effect on the area. Finally, wind turbines show negative opening effects in all specifications, which are strongest in urban areas and for the renewable "boom years" around 2000. Wind turbine closings show positive to insignificant price effects. The documented differences in external effects can have different reasons, such as environmental externalities (e.g. air pollution), perception, and economic effects. Especially the latter play a big role in plant locations, since power plants generally create employment and infrastructure (e.g. see Tourkolias et al., 2009). In contrast, wind turbines create limited local employment and infrastructure. Even though the allocation of wind turbines is centrally planned (Dröes & Koster, 2016), considerations about environmental effects are lower than for conventional plants, as wind turbines are perceived as non-polluting. The results documented in this paper are useful for policymakers that are currently considering the diffusion of power plants across regions – whether is it renewable or conventional.

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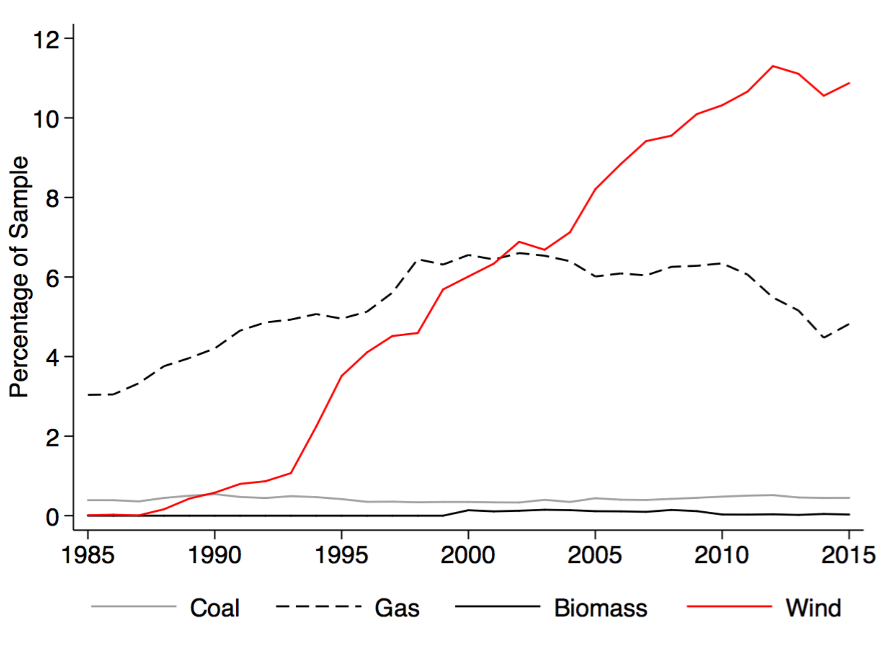
Appendix

Figure A
Percentage of Observations Affected by Externalities (per Year)

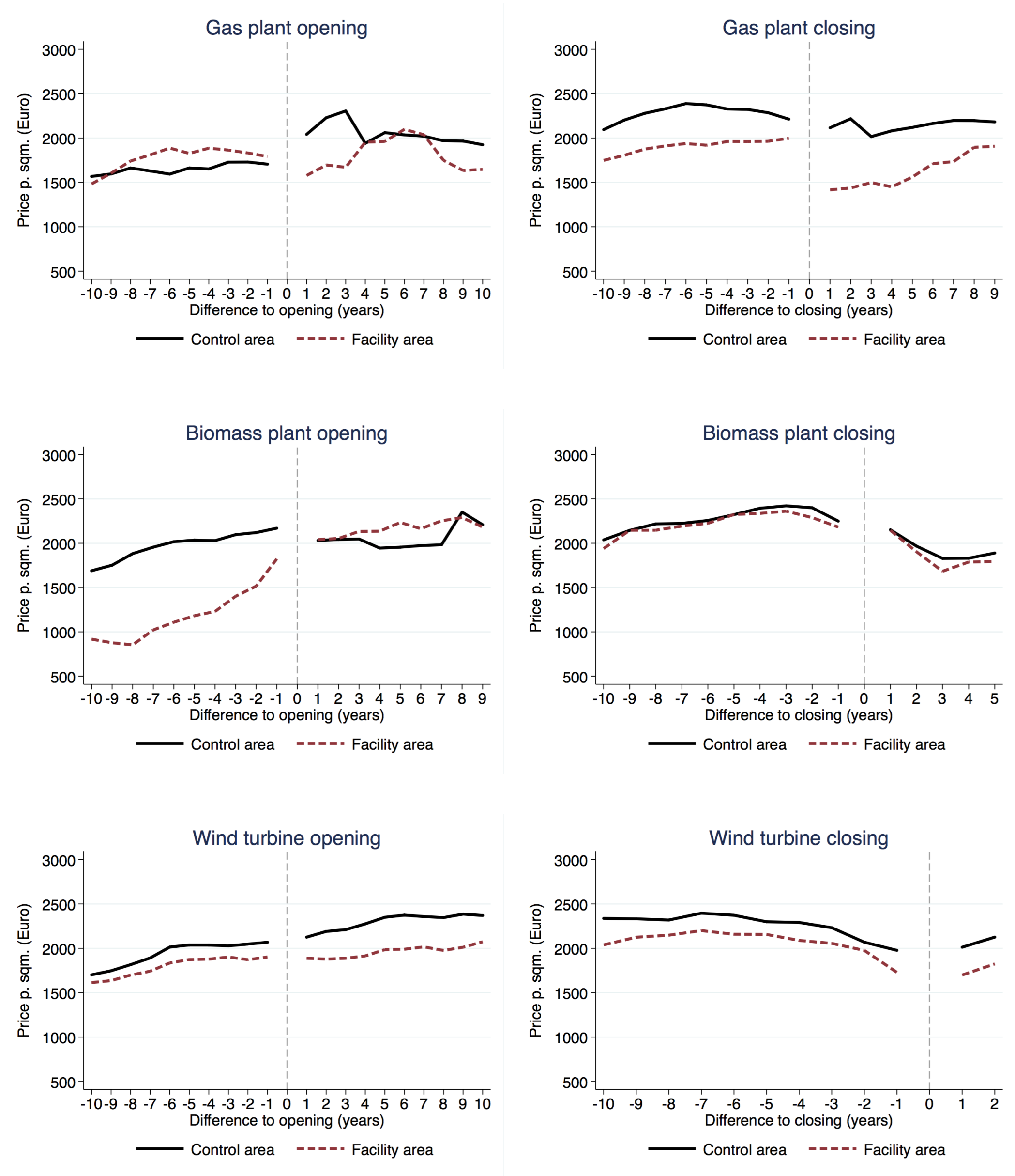


Notes: This figure shows the installation of new power plants and wind turbines, analyzing the convergence of energy generation and urban space. The yearly percentage of observations within externality distance (2.5 km) is illustrated.

Figure B

Simultaneous Trend Analysis

Average price per m^2 around facility openings & closings



Notes: We compare the average price per m^2 in the plant/turbine areas, prior to facility opening, with the average price per m^2 in respective control areas nearby. Due to the limited number of observations, we exclude coal plant areas from the analysis. We do not have observations for all years around openings and closings, e.g. we only have observations two years after wind turbine closings. The opening / closing year is excluded from the analysis.

Table I

Baseline Model – Control Variables

VARIABLES		VARIABLES	
Size (m^2)	0.004***	*Apartment type (dummy)*	
	[0.000]	Upstairs apartment	-0.046***
Number of floors	0.000	(1 = yes)	[0.005]
	[0.001]	Two-floor apartment	-0.054***
Number of rooms	0.025***	(1 = yes)	[0.003]
	[0.000]	Maisonette apartment	-0.068***
Number of bathrooms	0.029***	(1 = yes)	[0.004]
	[0.001]	Old block apartment	-0.089***
Construction period (dummy)		(1 = yes)	[0.004]
Construction 1906 - 1930	-0.007**	New block apartment (suburb)	0.065***
(1 = yes)	[0.003]	(1 = yes)	[0.008]
Construction 1931 - 1945	0.094***		
(1 = yes)	[0.008]	Apart. quality normal	0.066***
Construction 1945 - 1959	0.042***	(1 = yes)	[0.003]
(1 = yes)	[0.011]	Apart. quality luxurious	0.203***
Construction 1960 - 1970	-0.030**	(1 = yes)	[0.005]
(1 = yes)	[0.014]		
Construction 1971 - 1980	-0.066***	D: Roof terrace	0.032***
(1 = yes)	[0.018]	(1 = yes)	[0.002]
Construction 1981 - 1990	-0.075***	D: Parking lot	0.100***
(1 = yes)	[0.020]	(1 = yes)	[0.001]
Construction 1991 - 2000	-0.035	D: Garden	0.045***
(1 = yes)	[0.023]	(1 = yes)	[0.002]
Construction 2001 and later	-0.015	D: Garden quality bad	-0.005***
(1 = yes)	[0.025]	(1 = yes)	[0.001]
House type I (dummy)		D: Heating: coal or oven	-0.067***
Terraced house	-0.302***	(1 = yes)	[0.002]
(1 = yes)	[0.002]	D: Heating: central or tele-heating	0.018***
Corner house	-0.217***	(1 = yes)	[0.002]
(1 = yes)	[0.002]	D: Heating: AC or solar	0.008
Semi-detached house	-0.256***	(1 = yes)	[0.013]
(1 = yes)	[0.002]	*Isolation (dummy)*	
Detached house	-0.150***	One level of isolation	0.003***
(1 = yes)	[0.001]	(1 = yes)	[0.001]
House type II (dummy)		Two levels of isolation	0.027***
Caravan	-1.126***	(1 = yes)	[0.001]
(1 = yes)	[0.046]	Three levels of isolation	0.029***
Living boat	-0.194***	(1 = yes)	[0.001]
(1 = yes)	[0.013]	Four levels of isolation	0.021***
Recreational home	-0.431***	(1 = yes)	[0.001]
(1 = yes)	[0.013]	Five or more levels of isolation	0.028***
Single home	0.051***	(1 = yes)	[0.001]
(1 = yes)	[0.002]	D: Close to highway (¡200 m)	-0.005***
Grachtenpand (old house at canal)	0.220***	(1 = yes)	[0.001]
(1 = yes)	[0.007]	D: Close to forest (¡500 m)	0.017***
Manor house (without land)	0.137***	(1 = yes)	[0.001]
(1 = yes)	[0.003]	D: Close to park (¡100 m)	0.031***
Old farm house	0.255***	(1 = yes)	[0.001]
(1 = yes)	[0.006]		
Bungalow	0.229***		
(1 = yes)	[0.003]	Observations	1,757,810
Villa	0.218***	Adj. R-squared	0.877
(1 = yes)	[0.005]	Quality controls	Yes
Landhouse	0.276***	Location FE	Yes
(1 = yes)	[0.005]	Housing Age Controls	Yes
Manor house (with land)	0.396***	Time FE	Yes
(1 = yes)	[0.025]	Max distance	20

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by municipality and year. Base values: Construction = Construction before 1906, House type I = row house, House type II = simple house, Apart. type = ground floor, Apart. quality = bad, Garden quality: normal, Heating = no heating, Isolation = no isolation. For quality, we use a scale for internal and one for external quality. Location controls by neighborhood fixed-effects. Age controls in 10 years' intervals. Time fixed effects by sales year.

Table II
Hedonic model
Robustness checks

	(1) Effect by energy type	(2) Effect by energy type	(3) Effect by energy type	(4) General effect	(5) Effect by energy type	(6) 5-digit postcode FE	(7) 6-digit postcode FE
Electricity generation facility				-0.009***			
(1 = yes)				[0.003]			
Coal plant	-0.028	0.068***	0.100***		-0.010	0.064***	0.056***
(1 = yes)	[0.038]	[0.019]	[0.016]		[0.018]	[0.017]	[0.018]
Gas plant	0.030***	0.017***	0.016**		0.026***	0.030***	0.030***
(1 = yes)	[0.007]	[0.006]	[0.007]		[0.007]	[0.007]	[0.008]
Biomass plant	0.051***	0.017*	0.006		0.022**	0.039***	0.036***
(1 = yes)	[0.012]	[0.010]	[0.010]		[0.010]	[0.009]	[0.008]
Wind turbine	-0.019***	-0.012***	-0.014***		-0.016***	-0.018***	-0.017***
(1 = yes)	[0.003]	[0.004]	[0.003]		[0.004]	[0.003]	[0.004]
Observations	1,795,339	1,745,185	1,794,881	1,757,810	1,757,810	1,757,810	1,757,810
Adj. R-squared	0.877	0.877	0.877	0.815	0.815	0.899	0.939
Quality controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent Var.	lnPrice	lnPrice	lnPrice	lnPrice p m^2	lnPrice p m^2	lnPrice	lnPrice
Cut-off distance	2	3	4	2.5	2.5	2.5	2.5
Holdout distance	1.5	1.5	1.5	1.5	1.5	1.5	1.5
Max. distance	20	20	20	20	20	20	20 8

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All distances in km. Column 1 to 3 examine the proximity effect at different cut-off distances. In column 4 and 5 we use the log price per m^2 as a dependent variable. Column 6 and 7 test different location fixed effects levels, where the number of distinct postcodes increases with digit length.

Table III
Time Clustering – Difference-in-Difference Approach

Number of Observations (2.5 km cut-off)			
Electricity generation type	Before opening (-10y to -1y)	Affected (facility present)	After closing (+1y to +10y)
Coal	10	371	118
Gas	3,739	4,458	21,303
Bio	1,316	1,772	463
Wind	86,523	108,413	687
Number of Observations (3 km cut-off)			
Coal	25	560	164
Gas	5,992	6,229	30,100
Bio	2,411	2,678	585
Wind	118,483	151,551	827

Notes: Observations are considered up to a proximity cut-off distance of 3 km for all energy types. We consider 10 years before opening up to 6 years after closing.
[a] Some observations are affected by several facilities of different electricity generation types and therefore counted more than once. Furthermore, some observations are simultaneously in the affected group of one energy type and in the omitted group of another type. Excluding double entries and observations that are simultaneously in an omitted group, 159,009 unique observations are affected.

Table IV
Area DID Opening
Time Sub-tests

	(1) Opening effect around 1990	(2) Opening effect around 1995	(3) Opening effect around 2000	(4) Opening effect around 2005	(5) Opening effect around 2010
Gas plant area	0.041	-0.040***	0.045**	-0.171***	-0.107
(1 = yes)	[0.035]	[0.010]	[0.022]	[0.041]	[0.084]
Biomass plant area	0.005	0.064**	0.034	-0.022***	0.047***
(1 = yes)	[0.016]	[0.028]	[0.035]	[0.007]	[0.011]
Wind turbine area	0.004	-0.004	0.001	0.006	-0.005
(1 = yes)	[0.010]	[0.005]	[0.005]	[0.007]	[0.008]
Opening effect:					
Gas plant opening		-0.091**	0.033	0.013	-0.050***
(1 = yes)		[0.040]	[0.031]	[0.019]	[0.017]
Biomass plant opening		0.024*	0.041***		
(1 = yes)		[0.014]	[0.012]		
Wind turbine opening	-0.009	-0.011	-0.025***	0.000	0.002
(1 = yes)	[0.008]	[0.008]	[0.010]	[0.005]	[0.006]
Observations	231,231	444,924	715,134	828,479	735,262
Adj. R-squared	0.954	0.955	0.949	0.942	0.942
Quality controls	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Dependent Var.	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice
Cut-off distance	2.5	2.5	2.5	2.5	2.5

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All distances in km. We estimate our DID model for openings on different time sub-periods of the sample. The opening effect dummy for coal plants was omitted, due to the small group size.

Table V
Area DID Closing
Time Subtests

	(1) Closing effect around 1990	(2) Closing effect around 2000	(3) Closing effect around 2010
Gas plant area * closed	-0.056	-0.025**	-0.011
(1 = yes)	[0.050]	[0.012]	[0.023]
Biomass plant area * closed			-0.086***
(1 = yes)			[0.016]
Wind turbine area * closed			0.053***
(1 = yes)			[0.019]
Observations	10,591	56,212	34,355
Adj. R-squared	0.840	0.877	0.855
Quality controls	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Dependent Var.	lnPrice	lnPrice	lnPrice
Cut-off distance	2.5	2.5	2.5
Observations per closing:			
Coal	0	36	98
Gas	558	15,823	4,022
Biomass	0	0	463
Wind	0	0	416

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All distances in km. We estimate our DID model for closings on different time sub-periods of the sample. All sub-periods are 10 years long around the respective year, so e.g. around 1990 means from 1985 to 1995.

Table VI
Repeated Sales
Control Variables

VARIABLES	(1) Controls
Δ size (m^2)	0.002***
	[0.000]
Δ rooms	0.013***
(no. rooms)	[0.001]
Roof terrace removed	-0.022***
(1 = yes)	[0.003]
Roof terrace added	0.029***
(1 = yes)	[0.003]
Parking removed	-0.006***
(1 = yes)	[0.002]
Parking added	0.032***
(1 = yes)	[0.003]
Garden removed	0.001
(1 = yes)	[0.006]
Garden added	0.040***
(1 = yes)	[0.005]
Δ layer of isolation (added)	0.012***
(no. layers)	[0.001]
Δ layer of isolation (removed)	-0.009***
(no. layers)	[0.000]
Observations	228,623
Adj. R-squared	0.725
Location FE	Yes
Sales Year FE	Yes
Time difference * sales year	Yes
Quality change	Yes
Dependent Var.	ΔPrice
Cut-off distance	2.5
Holdout distance	1.5
Max. distance	20

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the percentage change in price between sales. We measure the changes in housing characteristics over time. Some houses expand in living area or the number of rooms due to e.g. renovations. We also control for changes in the interior and exterior maintenance quality.

Table VII
Repeated Sales
3 km cut-off distance

VARIABLES	(1) Opening	(2) Opening	(3) Closing	(4) Closing
Gas plant opening	-0.106***	-0.111***		
	[0.025]	[0.028]		
Biomass plant opening	0.015	-0.035		
	[0.024]	[0.025]		
Wind turbine opening	-0.024***	-0.033***		
	[0.005]	[0.006]		
Gas plant opening time differnce		0.003		
		[0.009]		
Biomass plant opening time differnce		0.015***		
		[0.004]		
Wind turbine opening time differnce		0.005***		
		[0.002]		
Gas plant closing			0.043	0.048*
			[0.026]	[0.028]
Gas plant closing time differnce				0.003
				[0.004]
Observations	213,698	213,698	19,307	19,307
Adj. R-squared	0.730	0.730	0.716	0.716
Location FE	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes
Dependent Var.	ΔPrice	ΔPrice	ΔPrice	ΔPrice
Cut-off distance	3	3	3	3
Holdout distance	1.5	1.5	1.5	1.5
Max. distance	20	20	20	20

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the percentage change in price between sales. The time difference accounts for the time between the opening / closing and a sale, if an observation was affected by an opening / closing. We only have enough observations to examine gas plant closings.

Table VIII
Repeated Sales
Time Sub-tests

	(1) Opening effect around 1995	(2) Opening effect around 2000	(3) Opening effect around 2005	(4) Opening effect around 2010
Gas plant opening		-0.019	-0.057	-0.095***
		[0.109]	[0.038]	[0.028]
Biomass plant opening	-0.036	-0.063**	0.013	0.063**
	[0.046]	[0.029]	[0.030]	[0.031]
Wind turbine opening	-0.003	-0.020	-0.035***	-0.011*
	[0.129]	[0.014]	[0.007]	[0.006]
Observations	13,078	108,052	209,750	160,117
Adj. R-squared	0.759	0.734	0.708	0.681
Location FE	Yes	Yes	Yes	Yes
Sales Year FE	Yes	Yes	Yes	Yes
Time difference * sales year	Yes	Yes	Yes	Yes
Quality change	Yes	Yes	Yes	Yes
Dependent Var.	ΔPrice	ΔPrice	ΔPrice	ΔPrice
Cut-off distance	2.5	2.5	2.5	2.5
Affected observations per type:				
Gas	7	56	118	163
Biomass	27	148	244	129
Wind	415	3,314	6,941	5,986

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the percentage change in price between sales. We use 10 years subperiods around the respective year, considering -5 and +5 years from the stated year.

Table IX
Repeated Sales
Single-family houses only

	(1) Opening	(2) Opening	(3) Closing	(4) Closing
Gas plant opening	-0.011	-0.027		
	[0.027]	[0.032]		
Biomass plant opening	0.044*	0.019		
	[0.025]	[0.027]		
Wind turbine opening	-0.025***	-0.035***		
	[0.005]	[0.006]		
Gas plant opening time differnce		0.009		
		[0.009]		
Biomass plant opening time differnce		0.007		
		[0.005]		
Wind turbine opening time differnce		0.006***		
		[0.002]		
Closing analysis:				
Gas plant closing			0.149***	0.159***
			[0.048]	[0.051]
Gas plant closing time differnce				0.004
				[0.006]
Observations	134,936	134,936	3,924	3,924
R-squared	0.765	0.765	0.776	0.777
Location FE	Yes	Yes	Yes	Yes
Sales Year FE	Yes	Yes	Yes	Yes
Time difference * sales year	Yes	Yes	Yes	Yes
Quality change	Yes	Yes	Yes	Yes
Dependent Var.	ΔPrice	ΔPrice	ΔPrice	ΔPrice
Cut-off distance	2.5	2.5	2.5	2.5
Affected observations per type:				
Coal	0	0	0	0
Gas	93	93	346	346
Biomass	199	199	0	0
Wind	5,688	5,688	0	0

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the percentage change in price between sales. We only consider single-family houses. The time difference accounts for the time between the opening / closing and a sale, if an observation was affected by an opening / closing. We only have enough observations to examine gas plant closings.